

An On-Line Japanese Handwriting Recognition System integrated
into an E-Learning Environment for Kanji

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Summary

In this work, a Japanese handwriting recognition system is being developed. The system is integrated into an e-learning environment in order to provide a Kanji teaching application with automated error correction. Conceptually, the application is an e-learning environment for Japanese characters, intended for the western learner of the Japanese language. Most e-learning systems of Japanese Kanji provide only a multiple choice method for the learner to reproduce characters. The present prototype offers the ability to enter characters with a stylus on a touch screen system.

The study seeks to determine to what extent it is possible to use modern NLP methods for language learning. While other studies mainly focus on grammatical correction, this application is targeted on the Kanji characters. It will be examined if a handwriting recognition engine can generate informed feedback, suitable for a learner. Additionally, the study examines if that feedback helps obtaining the ability to actively reproduce the Kanji characters.

The prototype developed in this work combines e-learning methods with natural language processing applied to the Japanese script. In order to prepare the task of creating an interdisciplinary software that spans across the aforementioned fields of study, the work reviews the structure of the Japanese script, the current state of the art in handwriting recognition methods and e-learning techniques. The recognition engine implements a structural approach to Kanji character identification. The recognition performs partial analysis of substructures and binds the recognised elements together to form a character. Because of the structural approach it becomes possible to create an informed error recognition that considers linguistic units of the Kanji characters.

The study resulted in the knowledge that it is indeed possible to use a handwriting recognition engine for the generation of informed feedback based on the errors made.

Zusammenfassung

In dieser Arbeit wird eine Handschriftenerkennung für japanische Kanji entwickelt. Der Handschriftenerkennung ist in eine E-Learning-Umgebung integriert und liefert eine automatisch generierte Fehlerkorrektur für Lernende.

Das System ist in konzeptioneller Hinsicht eine E-Learning-Anwendung für das Erlernen der japanischen Schrift. Letztere weist aufgrund ihrer morphemischen Struktur einen hohen Komplexitätsgrad auf und benötigt daher besonderen Lernaufwand. Die meisten E-Learning-Systeme für asiatische Schriftzeichen bieten Zeichenabfrage als Multiple-Choice an, da die Eingabe der Zeichen für einen Lernenden sonst ein technisches Problem darstellen würde. Der in dieser Arbeit erstellte Prototyp bietet die Möglichkeit zur handschriftlichen Eingabe von Zeichen auf einer dafür geeigneten Bildschirmoberfläche. Das ist ein Alleinstellungsmerkmal unter den E-Learning-Anwendungen für die japanische Sprache.

Die Studie untersucht, inwieweit es im Bereich des Schrifterwerbs möglich ist, NLP und Lernmethoden zusammenzubringen. Dabei wird nicht mit Parsing-Methoden die grammatische Struktur der Sprache untersucht, sondern vielmehr die interne Struktur der Kanji zugrunde gelegt und durch einen Handschriftenerkennung erfasst. Dabei sollen Schreibfehler strukturell erkannt werden. Intelligentes Feedback soll dem Lernenden dabei helfen, die Fähigkeit der aktiven Reproduktion der Kanji zu erwerben.

Da der Prototyp eine disziplinübergreifende Software ist, die in den Bereichen Handschriftenerkennung und E-Learning angesiedelt ist, wird in der vorliegenden Arbeit der Forschungsstand der beiden untersucht. Weiterhin wird die Struktur der japanischen Schrift linguistisch analysiert und dargestellt. Die Kombination der drei Disziplinen in einer Studie führt dazu, dass die Substrukturen der Kanji überhaupt programmatisch analysiert werden können, wodurch die Fehlererkennung ermöglicht wird.

Das Ergebnis der Studie zeigt, dass es möglich ist, eine Handschriftenerkennung nutzbar zu machen, um einem Lernenden intelligentes Feedback zu geben, basierend auf den Fehlern, die bei der Eingabe gemacht wurden.

Chapter 1

Introduction

1.1 Motivation

In the history of Computational Linguistics there have been a several attempts to integrate natural language processing techniques with existing technologies. That task is complex in many aspects, depending on what is aimed at exactly.

In this study, I will attempt to create a handwriting recognition for Japanese Kanji. That seems interesting because Kanji the characters form a morphemic writing system with a large number of characters. Thus, handwriting recognition (HWR) of Kanji follows different patterns than in alphabetical writing systems like Latin script. The overall methodology of HWR system is similar to systems for Latin characters, but the details of analysis vary strongly.

Studying Japanese language is a complex task, because a new learner has to get used to a new vocabulary that - coming from a European language - has very little in common with the vocabulary of his mother tongue, unlike in European languages where quite often there are several intersections. The learner also needs to learn a new grammar system. Broadly speaking, most of the central European languages follow a subject-verb-object (SVO) structure. Japanese follows a subject-object-verb (SOV) structure. These create additional difficulty, comparable with German reversed subclause structures that are a source of error for many learners of German. Yet, the most notable difference for a language learner with a central European mother tongue is of course the writing system. The Japanese writing system uses three different scripts. The so-called *Kana* scripts *Hiragana* and *Katakana* are syllabic, each character represents a syllable. Each syllable consists of either a vowel, a consonant and a vowel, or a consonant cluster and a vowel. The syllables are called *open*. Hiragana and Katakana represent roughly the same inventory of syllables and both have around 40-50 characters that can be modified with diacritics in order to yield additional syllable representations. Therefore, these scripts are a hurdle for a learner, but relatively unproblematic, due to their limited number of characters. Besides, the two sets of Kana characters look quite distinct, so the problem of confusing one character with another is limited to a relatively short learning period of those two scripts.

The Kanji, on the contrary, form the largest part of a writing system that has around 3,000 characters, which are built up of around 200 subunits called *Radicals*. One part of the complexity lies in the number of characters. The other part lies in the general method of representing an idea or concept with a character instead of attempting to represent the sounds with graphemes in connection with language specific pronunciation rules. Another difficulty lies in cognitively connecting the characters with their pronunciations. Most characters have multiple pronunciations and for a language learner, studying Japanese vocabulary takes at least twice as much effort compared to languages using a Latin or at least some kind of alphabetic writing system. The two tasks of learning the Kanji and studying the vocabulary together can epitomise a very high learning curve. A connected subordinated problem lies in the fact that quite often subjectively 'simple' vocabulary comes with complex Kanji. Some e-learning applications have taken on that issue by creating a learning environment in which a learner can connect learning vocabulary with studying the Kanji characters.

1.1.1 Integrating NLP and E-Learning

In this project, the main focus lies on the creation of an analytical handwriting recognition engine for Kanji. The advantages of such an engine can be applied to e-learning applications. This is exemplified with a sample e-learning application that includes specialised exercises for handwritten input. The novelty about it is a handwriting recognition that gives the learner the ability to actually practise writing the Kanji and get a feedback, instead of the rather limited multiple choice recognition that most other applications use.

The integration of NLP and e-learning relies on the analytical handwriting recognition. Since characters are split into sub units, the generated feedback about the input correctness can guide a user of the e-learning

application precisely to the error. This is an advantage over a binary statement *correct* or *incorrect* that is directly based on recognition success.

The analytical handwriting recognition examines the individual parts of the input and compares them to the individual parts of the database entries. That way, the errors can be identified locally in respect to the full character. The use of this is the improvement of the learning experience. The error messages by the system have a one-to-one correspondence with the character structure that needs to be studied.

Chapter 2

Japanese Script

The Japanese writing system has a long history. It goes back to around 800 A.D. The Japanese script is in fact a writing system, as Japanese is denoted in a combination of three different scripts: *Hiragana*, *Katakana* and *Kanji*. Kanji is a conceptual script, where each character bears the meaning of one or more semantic concepts and represents morphemes. Hiragana and Katakana are both syllabic scripts, and the individual characters do not bear reference to concepts or even words, but merely to phonological units, usually two phonemes.

In this chapter, the development of the script will be reviewed in section 2.1. In section 2.2 the current Japanese writing system will be exemplified, with a focus on the Kanji in section 2.2.2. Hiragana and Katakana will be reviewed in section 2.2.1, which centres around the Kana scripts. Machine processing of the different Japanese scripts and the difficulties that go along will be demonstrated in section 2.2.4. The difficulties of learning to use the Japanese script will be illustrated in section 2.3.

2.1 A Short History of the Japanese Script

The historical development of the Japanese script is tightly connected to the history of the Kanji characters. Kanji, in Japanese 漢字 (Jap. pron. カンジ / Kanji; Eng. lit. *Han characters*) refers to the 'characters of the Han', meaning the Han Dynasty (206 B.C.-220 A.D.; simplified Chinese: 汉朝; traditional Chinese: 漢朝) (Foljanty 1984). In Mandarin the same characters are referred to as *Hànzì* (simplified Chinese: 汉字; trad. Chinese: 漢字). Note, that the first character 漢 (Chin. 'han', Jap. 'kan', Eng. 'Han') of both the words *Han dynasty* and *Kanji* is identical in Japanese and traditional Chinese, even though it has a different reading in the Chinese and Japanese language. In traditional Chinese the character with the same meaning (漢) has a different shape. This apparent oddity will be explained in greater detail in section 2.1.1.

2.1.1 Historical Development

The Kanji script as developed and coined by the Han is in principle still valid today. It is used alone or in combination with phonetic spelling in China, Japan, Taiwan, Hong Kong. In Vietnam it was used before it was replaced with the Vietnamese alphabet (Viet.: 'quốc ngữ', Eng. lit. 'national language', Eng. 'national script'), a script based on the Latin alphabet. In South Korea the Han characters were in use until they were replaced with Hangul (Kor. with Han characters 韓國語; Eng. 'Korean') (Foljanty 1984).

The Kanji characters were brought to Japan by Koreans living in Japan around 300-400 A.D. Since the Kanji were used by the Koreans to write Hangul they also used it to write Japanese. There was no other Japanese script before that time. Reports about an original Japanese script called *Jindai Moji* (Jap. 神代文字; Eng. 'scripts of the age of the gods') could not be proved. They are now assumed to be a political and speculative invention by Japanese Nationalists in the early 19th. century (Foljanty 1984). According to (Lange 1922) the *Kogo Shūi* (Jap. 古語拾遺; a historical record of the Inbe clan), which was written around 800 B.C. denies the presence of a Japanese native script before the introduction of the Han characters. However, the questions seems irrelevant in the sense, that no longer text or document has been found, written in that script.

In the Christian year 712 an ancestral act of writing was performed at Japanese emperor Temmu's court. Hieda no Are, a member of the guild of the *Kataribe* or reciters, basically a Japanese Griot, dictates the *Kojiki* (Jap. 古事記; Eng. 'Record of Ancient Matters') to Ō no Yasumaro. Ō no Yasumaro wrote the *Kojiki*, which is not the first written document found in Japan, however it is Japan's oldest attempt to write down spoken Japanese (Grassmuck 1997; Chamberlain 1982).

At the time the Han characters were first used to write Japanese, they were already a developed script. The script was more than 1,000 years old since the characters stabilised to their modern form within the Han period. The first Chinese characters were found on oracle bones from the Shang Dynasty (Chinese 商朝), which ruled

over China some 500 to 600 years within the time period between 1600 B.C. and 1046 B.C. (Grassmuck 1997; Guo et al. 2000).

According to the Kojiki, a scholar called Wani (Jap. 王仁) from Korea brought two foundational Chinese books to Japan, the *Lunyu* (Simplified Chin. 论语; trad. Chinese: 論語; Eng. 'Analects'), also known as *The Analects of Confucius* and the *Qianziwen* (Chin./Jap. 千字文; Jap. pron. センジブン/senjibun; Eng. 'The Thousand Character Classic'), which is a Chinese poem used as a primer for teaching Chinese characters to children. It contains exactly one thousand unique characters (Grassmuck 1997). However, (?)Lange1922) demurs strongly against this view and assumes an evolving adoption of the Kanji in Japan. This view seems more plausible, since it has been proved that Japan had contact to Korea even in the time before common era and had contact to China at least from the first century A.D. The Chinese language comprehends more than 40,000 Hànzì characters lexicographically. Only around 25% of those including about 250 *Kokuji* (Jap. 国字; Eng. 'national characters') are in Japanese dictionaries. Only around 2,000-3,000 of those are part of the common characters (Foljanty 1984).

The Japanese Ministry of Education issued a list of 1,850 standard Kanji in 1946 under the name of *Tōyō Kanji* (Jap. 当用漢字表; Eng. 'list of Kanji for general use'). The list of Tōyō Kanji was slightly revised and extended in 1981 and comprised 1,945 Kanji as the Jōyō Kanji (Jap. 常用漢字; Eng. 'often used Kanji') (Foljanty 1984). As of 2010 a revised list of 2,131 characters is in official use (Noguchi 2009).

In China there had been a spelling reform in the 1950s, affecting many of the general use characters, resulting in simplified Chinese. In Japan, the Ministry of Education issued its own reform when the Tōyō Kanji list was introduced. However, the Japanese reform affected a smaller set of characters of only a few hundred and resulted in Shinjitai (Jap. shinjitai: 新字体; Jap. kyūjitai: 新字體; Jap. pron. シンジタイ/shinjitai; Eng. 'new character form'), which replaced the Kyūjitai (Jap. shinjitai: 旧字体; Jap. kyūjitai: 舊字體; Jap. pron. キュウジタイ/kyūjitai; Eng. lit. 'old character forms'). This explains how some characters are still identical in traditional Chinese and Japanese, because they were not affected by any spelling reform, like the aforementioned 漢 (Jap. pron. カン/kan; Chin. pron. 'hàn'), while other characters are different, like the simplified Chinese 'hàn': 汉. Henceforth, and throughout this document, all Japanese characters are in the new character form shinjitai.

2.2 The Modern Japanese Writing System

The Japanese writing system has a complex structure. The three scripts *Hiragana* (section 2.2.1.1), *Katakana* (section 2.2.1.2) and *Kanji* (section 2.2.2), are combined to one writing system. Each script has its task within the system:

- Kanji are used to write lexical morphemes, i.e. content-bearing morphemes.
- Katakana are used to transcribe foreign words, borrowings and nonstandard areas.
- Hiragana are used to write grammatical morphemes and anything else that is not written in one of the other two scripts, e.g. the spoken syllables of a word that should be written with a Kanji character unknown to the writer of that word.

The actual writing system is mainly based on Kanji and Hiragana, catenated to Kanji-Kana blended writing.

- (1) a. マリア：山田さん、「火の鳥」というアニメをもう見ました
 Maria: Yamada-San, [Firebird] say anime OBJ-PARTICLE already seen
 か。
 QUESTION-PARTICLE
 'Maria: Ms Yamada, say, have you seen the Firebird cartoon yet?'
 Taken from (Katsuki-Pestemer 2006)
- b. マリア：山田さん、「火の鳥」というアニメをもう見ましたか。

In example (1a), the blending of the different scripts can be seen:

Both the foreign name マリア (Eng. 'Maria') and the borrowing アニメ (*anime*, Jap. short for Eng. 'animation') are written in Katakana. Kanji are used for:

- The Japanese name 山田 (*Yamada*).
- The nouns 火 (Eng. 'fire') and 鳥 (Eng. 'bird').
- The verb stem 見 (Eng. 'see').

The rest is written in Hiragana:

- The politeness ending さん (*san*; Eng. equiv. 'Mr/Ms/Mrs') for addressing a person with their name.
- The genitive particle の (*no*) between 火 (Eng. 'fire') and 鳥 (Eng. 'bird'), to yield 火の鳥 (Eng. 'Fire-bird').
- The interjection とうい (Eng. 'say').
- The object particle を (*wo*).
- The adverb もう (Eng. 'already').
- The past tense conjugation and politeness ending of the verb ました (*mashita*).
- The question particle か (*ka*).

Three different scripts are used next to each other in one sentence, indistinguishable for the untrained eye. Example (1b) shows the sentence as it is printed in (Katsuki-Pestemer 2006). Without prior knowledge of the different Japanese scripts it is hard to even distinguish the individual word tokens, as blanks are usually absent in Japanese writing. Other than actually knowing the words, which is not the usual case for a beginner of learning Japanese, often the change of script is the only way to recognise a new token. However, Kanji and Hiragana are often used within the same word, too.

Despite those complexities, other features of the Japanese writing system are simpler than in latin-based alphabetic scrips. For example, there is no capitals or lowercase letters. Each character has a reserved space of roughly the same size. In the following sections, the different scripts will be presented in greater detail. Their composition and use will be discussed.

2.2.1 Kana かな

If the Japanese had abolished the Chinese characters after formation of the syllabic scripts and used only those, studying the Japanese script would be a less complex task. (Lange 1922) reports about attempts to remove the Kanji from Japanese and use the Kana or even Latin script, so called ロマジ (*Romaji*, a Latin or 'Roman' transcription of Japanese; Eng. lit. 'Roman characters'). However, non of those attempts succeeded and both Kana scripts serve as auxiliary scripts to the predominant Kanji characters.

The Chinese characters have been used in two ways in Japanese. Firstly, in order to express the morphological content of a character, but also in order to use the sound of the character as a syllable. The characters that have been used as syllables were transformed to two separate short-hand notations. One way used cursive writing of the sound Kanji, reducing the character graphically, such that its original shape became virtually in-cognisable. This development resulted in the Hiragana script. An example of that kind of reduction is shown in figure 2.1. The other method of reduction uses only one of the character's Graphemes in order to represent the whole

女 → め
Reduction of 'me'

曾 → そ
Reduction of 'so'

Figure 2.1: Reduction from Kanji to Hiragana

character. That reduction process (see figure 2.2) lead to the development of the Katakana script.

Using cursive or reduced characters became popular in the 9th century already. Both Hiragana ('smoothened Kana') and Katakana ('fragmented Kana') can easily be distinguished from the more complex Kanji. They represent a different linguistic content than the Kanji, namely rather a syllable than a morpheme. The fact that two parallel scripts came into existence can be explained by their use of different social groups. Hiragana are a product of the literately active court ladies, while Katakana were developed in the Buddhist seminaries. The current system knows 46 Hiragana and Katakana for identical syllables (Foljanty 1984). See appendix A.1 for a complete list of characters.

伊 → イ
Reduction of 'i'

加 → カ
Reduction of 'ka'

Figure 2.2: Reduction from Kanji to Katakana

2.2.1.1 Hiragana ひらがな

Hiragana is one of the three syllabic scripts. The third one, *Hentaigana* can be neglected, as it is not in active use any more. In principle each character represents a syllable, which can contain either a vowel (like 'u', う), a consonant and a vowel (like 'ta', た) or the nasal consonant ん ('n'). Hiragana are used for any words for which no Kanji exist, like から (*kara*, Eng. 'from') or grammatical particles like the object particle を (*wo*, works like a case marker). Additionally, Hiragana are used, when the Kanji is not known to the writer or reader (Foljanty 1984).

For instance, a writer may even passively know a Kanji, but not be able to actively produce it. Say the Kanji in question was 新 (Jap. pron. atara/あた and shin/シン; Eng. 'new'). Example (2) shows first the spelling with the Kanji character in (2a), where the Hiragana parts are underlined. Then the alternative spelling without the Kanji character in (2b) (with blanks in between, in order to visualise the individual characters and their readings). The underlined last part is identical, just the Kanji character has been replaced with an alternative Hiragana spelling.

- (2) a. 新しい
atarashii
'new'
- b. あたら し い
a ta ra shi i
'new'

Hiragana can be modified with

- **Dakuten** (濁点, Jap. pron. ダクテン/dakuten; Eng. 'turbid'; Jap. coll. *ten-ten*, Eng. 'dot dot') for syllables with a voiced consonant phoneme. The dakuten glyph (゛) resembles a quotation mark and is directly attached to a character (Foljanty 1984).
- **Handakuten** (半濁点, Jap. pron. ハンダクテン/handakuten; Eng. 'half-turbid'; Jap. coll. *maru*, Eng. 'circle') for syllables with a /p/ morpheme. The glyph for a 'maru' is a little circle (゜) that is directly attached to a character (Foljanty 1984).

- (3) a. た → だ, き → ぎ, ふ → ぶ, へ → べ, そ → ぞ
ta → da, ki → gi, fu → bu, he → be, so → zo
- b. は → ぱ, ひ → ぴ, ふ → ぷ, へ → ぺ, ほ → ぽ
ha → pa, hi → pi, fu → pu, he → pe, ho → po

Example (3) shows the dakuten in use. In (3a) the turbidity, i.e. the transformation from a fortis to a lenis consonant is exemplified. The dakuten can only be applied to characters that begin with the sounds /k/, /s/, /t/ and /h/. For the consonants 'k', 's' and 't' this is natural in the way that the place of articulation remains the same for the consonants 'g', 'z' and 'd' and their corresponding sounds /g/, /z/, /d/, compared to /k/, /s/ and /t/. Assuming the place of articulation, a changed intensity and use or no use of the vocal cords as the natural connection between the characters with and without a *ten-ten*, there is a difference for the sound /b/: Since there is no Hiragana character to match a /p/ sound, the characters with an /h/ sound serve as a basis to form the modified characters with a /b/ sound. Quite logically, since the Handakuten only yields a /p/ sound, the same set of characters, namely, the 'h'-row in the Hiragana character set, is modified in order to obtain the 'p'-row. In (3b) the transformations from the /h/ and /f/ sounds to /p/ are shown in a complete list¹.

¹The /f/ sound in Japanese is 'lighter' than in English. Concretely, the place of articulation for /f/ in English is labio-dental, whereas in Japanese it is virtually bi-labial. Therefore, the phonation stream creates less friction and the allophone of the /f/ phoneme that is typical for the Japanese language sounds similar to an /h/ sound.

2.2.1.2 Katakana カタカナ





















Just like the Hiragana, the Katakana form a syllabic script. They are mainly used to transcribe foreign words like names and borrowings, like マリア (*maria*) and アニメ (*anime*) from example (1). Another use of the Katakana is called *Furigana*, little notations next to Kanji in order to indicate their reading. They were developed around the period of the Heian, from *Manyogana*, Kanji characters that were used to denote pronunciation. For example the character 加, which was used to represent the pronunciation *ka*, was shortened to カ, by leaving out the second part 口 (Hadamitzky 1995). Compare also figure 2.2. For a full table of Katakana characters see appendix A.1.2. The dakuten can be applied to Katakana as well and have the same meaning.

2.2.2 Composition of the Kanji 漢字

2.2.2.1 Typology

In order to study the Kanji and their composition, it is useful to know how they were first indented and built. Integrated as the integral part into the Japanese writing system, despite the reform and the choice different subsets of what is considered the standard character set, the characters are still mainly composed the way as intended by the scholars of the Han period.

From the religious writings on the oracle bones mentioned in section 2.1.1 a secular script emerged. In parallel, the process of graphical abstraction advanced and finished around 100-200 A.D., leaving aside the modern reforms of the 20th century. The invention of the paint-brush around 100 B.C. improved and simplified writing, also the writing surfaces in their order of appearance, bone, stone, metal, wood and then paper, brought further simplification and spreading of writing. Paper and paint-brush offered the possibility to write without hindrance and technical coincidences, therefore it was possible to standardise the characters and improve them from artistic and aesthetic viewpoints.

Picture	→	Kanji	'KUN'	'ON'	Meaning
	→		→	日	ひ [NICHU] sun
	→		→	月	つき [GETSU] moon
	→		→	木	き [MOKU] tree
	→		→	山	やま [SAN] mountain
	→		→	川	かわ ([SEN]) river
	→		→	田	た [DEN] rice field
	→		→	人	ひと [JIN] man
	→		→	口	くち [NIN] person
	→		→	車	くるま [KOU] mouth
	→		→	門	くるま [SHA] car
	→		→	門	(かど) [MON] gate

※ () reading is rarely used.

Figure 2.3: Kanji pictograms

The Kanji can be classified according to their building principle:

1. **Pictograms** are graphically simplified images of real artefacts. The examples in figure 2.3 after Kano et al. (1990) show the graphical reduction process. Pictograms are only a small minority among the Kanji, their number ranges around 120. Another 100 pictograms appear as a part of more complex characters (Foljanty 1984).

Radical 1	Radical 2	Result	Meaning
日 ('sun')	月 ('moon')	明 ('bright')	both the sun and the moon are 'bright'
人 ('man')	木 ('tree')	休 ('rest')	a man is 'resting' beside a tree
田 ('rice field')	力 ('power')	男 ('man, male')	'a man' is powerful on the rice field
女 ('woman')	子 ('child')	好 ('love')	a woman 'loves' a child
木 ('tree')	木 ('tree')	林 ('wood, grove')	two trees make a 'wood'
木 ('tree')	林 ('wood')	森 ('forest')	three trees form a 'forest'
門 ('gate')	日 ('sun')	間 ('between')	the sun can be seen 'between' the doors of the gate

Table 2.1: Kanji ideograms

Class radical	Sound radical /ki/	meaning
土 ('earth')	奇	埼 'spit, promontory, cape'
山 ('mountain')	奇	崎 'promontory, cape, spit'
石 ('stone')	奇	碕 'cape, promontory, spit'
王 ('jade')	奇	琦 'gem, precious stone'
糸 ('thread')	奇	綺 'figured cloth, beautiful'
馬 ('horse')	奇	騎 'riding on horses'
宀 ('roof')	奇	寄 'to gather'
金 ('metal')	奇	錡 'cauldron, chisel' (Chinese only)

Table 2.2: Kanji phonograms

2. **Ideograms** are combinations of two or more pictographical characters. They often bear a more abstract meaning than a simple pictogram. The abstract meaning of the complex character is meant to be associated with the content of the individual parts. The number of ideograms is fairly small, too. Abstract terms like 'top' (Jap. 上, pron. うえ/ue), 'bottom' (Jap. 下, pron. した/shita), 'left' (Jap. 左, pron. ひだり/hidari), 'right' (Jap. 右, pron. みぎ/migi) and numbers like 'one' (Jap. 一, pron. いち/ichi), 'two' (Jap. 二, pron. に/ni), 'three' (Jap. 三, pron. さん/san), 'four' (Jap. 四, pron. し/shi), 'five' (Jap. 五, pron. ご/go) and so forth can be regarded as parts of the ideograms (Foljanty 1984). See table 2.1 (after (Kano et al. 1990)) for some examples on Kanji pictograms.

3. **Phonograms** are combinations of two Kanji characters. One of those refers to a concept class (for *class characters* or *radicals*, see section 2.2.2.2), while the other character exclusively bears a phonetic value. The content of the second part of a phonogram is not relevant and can be ignored.

In table 2.2 the character 奇 (Jap. pron. き/ki, Eng. 'strange') is used for the purpose of pronunciation only (/ki/), while the radical defines an object class. Object classes can be categories like 'human and human actions', 'metal', 'horse', 'roof / under a roof' etc. The semantic identity within the *Morphogram* is assembled with two reference figures. The pronunciation part is identical for all characters, it serves as a selection criterion within a semantic class selected by the class radical (Foljanty 1984).

As a character type, phonograms are predominant among the Hànzì. Therefore, the phonogram concept, including the radical concept, was transferred to all Chinese characters. Pictograms that are class radicals themselves, are interpreted as characters with an empty sound radical. As the phonograms are historically the last development step of the Han characters, they constitute a different quality in the Chinese script. Phonograms mark the transition between a non-linguistic pictographic script that does not represent linguistic units, but rather images of objects, to a linguistic script. In principle, there is no difference to an alphabetical or syllabic script. Except, morphemes are represented instead of phonemes or syllables. However, one character often denotes more than one morpheme (Foljanty 1984).

In Japanese, basically the same relation between the Kanji characters and morphemes can be observed. However, the correspondence between the morphemes and the syllables (and thus the characters and syllables) is often missing. Since Chinese has a monosyllabic morpheme structure, a one-to-one correspondence between morpheme, character and syllable can be observed. Congruence of character, morpheme and syllable in Japanese can only be found for Chinese borrowings, but not all of them. The original Japanese vocabulary has multisyllabic morphemes, therefore some impreciseness arises in the graphical reproduction of the morpheme structure (Foljanty 1984).

2.2.2.2 Radicals

In section 2.2.2.1 the function of the class characters or Radicals has been mentioned. The Radicals usually derive from pictograms. The Chinese systematics with 214 Radicals is used in Japan, as well. Among the 1945 Jōyō Kanji, only around 50% of the 214 Radicals is in autonomous use. 22 of them denominate empty classes, 46 denominate classes of only one Kanji. The Radicals are grouped according to their graphical position inside a Kanji. Figure 2.4 shows the groupings of the Radicals after (Foljanty 1984). The groupings of the Radicals

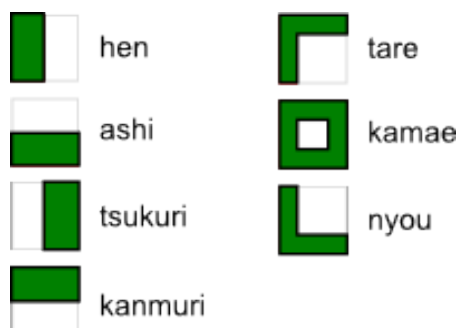


Figure 2.4: Radical positions in Kanji characters

account for a preference of certain Radicals to appear in a certain category. The selection of the class Radical is primarily based on semantic criteria. For example, the character 杉 (Jap. pron. スギ/sugi; Eng. 'cedar') both graphemes have the ability to serve as a class Radical. Therefore there is a choice of using either the Radical 木 (Jap. pron. キ/ki; Eng. 'tree') in the *hen* position, or the Radical 彡 (Jap. pron. カミカザリ/kamikazari; Eng. 'hair ornament') in the *tsukuri* position (see Figure 2.4). This is very pictographic, since the leaves of a cedar are long and thin, (see figure 2.5), therefore the character is most likely an ideogram. Now,



Figure 2.5: Cedar leaves

the categorisation is purely a semantic choice. The cedar has certainly more qualities of a tree than qualities of hair, therefore, the class radical is 木 (tree) and not 彡 (hair). (Hadamitzky 1995) files it under the 木 (tree) class Radical.

2.2.2.3 Readings

Each character has at least one reading. The Kanji script, being a morphemic script does not have a correspondence from character to spoken sound in speech, like alphabetic scripts. Certainly, alphabetic scripts are often far from a one-to-one correspondence between sound and letter, however, the Kanji have their very own ways. There are two main readings of the Kanji:

- *On'yomi* (音読み, Jap. pron. オンヨミ/onyomi; Eng. 'sound reading'), which roughly based on its original Chinese reading.
- *Kun'yomi* (訓読み, Jap. pron. クンヨミ/kunyomi; Eng. 'concept reading, native reading'), which represents the original Japanese word that happens to be written with a Chinese character. The Kun'yomi are further classified into different types of readings.

Because of this, the Kanji that have been developed in Japan only have a Kun-reading. A bit more than half of the official Jōyō-Kanji (999 of 1945) have two readings. The Japanese Kun-reading was part of the adaption process to the Han-characters, where the character was taken for its meaning and underlaid with the Japanese word. The Sino-Japanese reading originated from Chinese borrowings. The complex Chinese pronunciation, however, was adapted to the Japanese phoneme inventory.

Take for example the Kanji 山 (Eng. 'mountain'). The original Japanese word for *mountain* is *yama* (ヤマ), therefore the character 山 has this reading attached as a Kun-reading. The Chinese borrowing is *san* (サン), with the meaning *mountain*. The reading that is used depends on the context (Foljanty 1984). 山 is read Sino-Japanese *san* or in a phonetic assimilation *zan* in:

- 山水, Jap. pron. サンスイ/**sansui**, Eng. 'landscape'
- 火山, Jap. pron. カザン/**kazan**, Eng. 'volcano'
- 下山, Jap. pron. ゲザン/**gezan**, Eng. 'descent'
- 富士山, Jap. pron. フジサン/**fujisan**, Eng. 'Mount Fuji'²

山 is read in the Japanese Kun-reading in:

- 小山, Jap. pron. コヤマ/**koyama**, Eng. 'hill'
- 山山, Jap. pron. ヤマヤマ/**yamayama**, Eng. 'mountains'

(Hadamitzky 1995)

2.2.3 Structure of the Japanese Writing System

Having demonstrated the Hiragana in 2.2.1.1, the Katakana in 2.2.1.2 and the Kanji in section 2.2.2, it is now possible to report about the structure of the writing system as such. It now becomes apparent, why a sentence like the one presented in example (1) in section 2.2 is written and spelt the way it is.

- (4) 帰りたくない
kaeritakunai
go-home-want-not

'I do not want to go home'

An important part of the blended writing in Japanese are the *Okurigana* (送り仮名, Jap. pron. オクリガナ/okurigana; Eng. 'accompanying characters'). Okurigana are Kana that form a word together with a Kanji character (Lange 1922). For instance, the word in example (4) has only one Kanji character: 帰 (Jap. pron. カエ/kae; Eng. 'go-home'), while the other characters are all Kana characters, that are part of the same word and modify the verb.

- り (*ri*): Flexion of the verb used for *tai*
- たく (*taku*): derivation of *tai* = want
- ない (*nai*): Negation ending

Knowing the two syllabic scripts by heart helps distinguish the Kanji from them. Therefore it is possible to use the three scripts next to each other, even without blanks. The Okurigana further help distinguish different versions of the same Kanji, as they sometimes even partially describe the sounds of a verb stem.

- (5) a. 変える
ka-eru
change

'to change something' (transitive)

²'Mount Fuji' is often called 'Fujiyama' in several languages. Thus, the Kun-reading *yama* of 山 has emerged as a borrowing into other languages, even though in Japan the On-reading is used in the particular case of 'Fuji san'.

- b. 変-わる
ka-waru
change

'to change oneself' (reflexive)

Compare for example (5a) and (5b). The Japanese verb ending is る (Hiragana: *ru*). A part of the verb stem are expressed with Hiragana, too. In (5a) it is the え (Hiragana: *e*) while in (5b) it is the わ (Hiragana: *wa*). The Kanji are further used to write nouns, the Hiragana are used for particles and other grammatical functions, while the Katakana are used for foreign words.

2.2.4 Machine Writing of Japanese

Machine processing of the Japanese scripts has been an issue, ever since humans started to automate their writing. Lange (1922) reports in the foreword to the first edition (1896) of his work about difficulties during the printing process. Firstly, there was only one printing office in Germany that was able to print these kind of things at all. Also, there were technical issues, like incompatible letter size and missing characters among the letters available. The manufacturing of the appropriate letters delayed the publication.

Bei der Drucklegung des Werkes in der Reichsdruckerei, der einzigen Druckerei in Deutschland, welche dergleichen zu drucken im stande ist, stellten sich leider einige Übelstände heraus. Einerseits sind die Kana-Zeichen, welche dieselbe besitzt, zu gross, um als erklärende Zeichen bequem neben die chinesischen Zeichen gesetzt werden zu können, andererseits fehlten unter den 10000 chinesischen Zeichen, die aus Shanghai gekommen, eine Anzahl in Japan ganz gebräuchlicher Zeichen. Diese mussten entweder aus den vorhandenen Teilzeichen, die eine andere Form als die übrigen Typen haben, zusammengesetzt werden oder sie mussten erst geschnitten werden; hauptsächlich durch den letzteren Umstand hat sich die Fertigstellung des Werkes verzögert.

When the work was printed in the Reichsdruckerei, the only print shop in Germany capable of printing this kind of work, some mischiefs became obvious. On one hand, the Kana characters that the Reichsdruckerei had were too large to be put next to the Chinese characters as explanatory characters, on the other hand some characters that are very common in Japan were missing among the 10000 Chinese characters that came from Shanghai. The missing characters had to be composed from the partial characters that had a different shape than the other types, others had to be manufactured. Mainly because of the last-mentioned circumstances the completion of the act has been decelerated.

This quote from Lange shows the difficulties an author was facing when trying to print a book. Difficulties in machine writing Japanese also occurred at later stages. The technical and practical problems remain to this day, because of the great number of characters. (Foljanty 1984) reports that in Japan the number of machines needed to print Japanese characters was small, because even business correspondence was mainly done by hand up to the 1970s. Computers worked with Katakana only. There were devices like mechanical-type Japanese typewriters, with around 2000 keys for the different Kanji. A Kanji synthesis system worked with the internal structure of the Kanji. The 'multi-radical lookup' in Breen's (2004) system *WWWJDIC* has a similar concept. A user chooses a number of Radicals from a list and the system computes all Kanji that contain these Radicals. In order to handle word processing the industry standard are Input Method Editors that come with the operating system. Input Method Editors (IME) use Romaji, the Latin transcription of Japanese and a language model in order to generate a Kanji list, appropriate to the spelling of a word. That is necessary since one Kanji can have several readings and Japanese is rich in homophones (Yuan et al. 2005; Hadamitzky 1995). Certainly the most modern input method for Japanese characters is handwriting recognition. The difficulties of other input methods show that there is great need for a better and faster method of input. See section 3.3.7 for a description of research efforts in order to provide technology for using handwriting as an input method for Japanese.

2.3 Difficulties of the Japanese Script for Learners

There are at least four ways to learn the Japanese Script. With *learning the Japanese script* we mean *learning the Kanji*. For the Hiragana and Katakana are only small sets of syllabic characters, the effort to study those is only slightly larger than learning the Latin alphabet. The number of different learning methods and the diversity of advice that can be found on this topic on the Internet and in teaching books suggests that learning the Kanji is regarded a difficult issue. It is apparent that the difficulties lie in the complexity of the Kanji, but also on the structure of the writing system as such. Stahlmann (2004) reports the subjective impression

of many learners that Chinese is among the most challenging languages and even seems daunting. Japanese is no different, as most of the difficulties of the Chinese language are characteristics of Japanese as well. The pronunciation of Japanese is comparatively simple for a European learner, as the phonetic inventory of the language is similar to that of English (Tsujimura 2007). On the other hand, the Japanese writing system with its three different scripts and several readings of a character has other interweavements as demonstrated in the previous sections. Despite the difficulties, the interest in the Japanese language and culture is unbowed:

There are many books available centred around cultural interchange between the western and Japanese culture. For example, (Haschke and Thomas 2008) present German words of Japanese heritage, i.e. a miniature etymological lexicon. The sheer existence of that type of book on the free market suggests that Japanese language and culture radiate fascination into the western world. Therefore, there is a great need for learning methods.

The four groups of learning methods are:

1. **Writing Repetition** - Each Kanji has to be written several times until its meaning and the readings are full known to the learner. Most Kanji books generally follow this concept.
2. **Flash Cards** - Instead of writing the Kanji, the flash card method teaches the passive knowledge. Flash cards for Kanji are readily available and can be home made easily.
3. **Mnemonic methods** - Methods that use mnemonics in order to help a learner memorise the Kanji.
 - (a) **Textual mnemonics** The *Heisig method* assigns a unique mnemonic to each Kanji in order make it more memorable. These mnemonics are little stories oriented toward the shape of a Kanji and do not necessarily have a connection to the actual meaning of a Kanji. They are just mnemonics. The Heisig method is a two-part method. In the first part the learner studies all the Kanji and their translations, in the second part the Japanese readings are introduced (Heisig and Rauther 2007).
 - (b) **Visual mnemonics** *Kanji Pict-O-Graphix* is another mnemonic method. In this method the Kanji are depicted with images that represent the meaning of the Kanji. The stories are therefore more visualised than in the Heisig method (Rowley 1992).

2.3.1 Learner's Problems

1. **Similar Kanji.** In order to be able to distinguish characters like 営 in 営業 and 管 in 管理 a high level of concentration is necessary. Especially, when Japanese is mostly written on the computer and not by hand, the muscular memory does not help any more. Therefore the more Kanji are known, the more difficult it becomes to distinguish similar Kanji.
2. **Compounds.** Often, new vocabulary is studied, rather than new Kanji. The vocabulary are often composed of Kanji characters that are already known. Studying time is needed in order to study the vocabulary and compounds. Therefore it is difficult to study new Kanji at the same time.
3. **Unusual readings.** Since Kanji have several readings, it is useful for a learner to study the most frequent ones. For example, the Kanji 雪 (Eng. 'snow') has two standard readings (see section 2.2.2.3 for more on readings):

The Chinese reading (*on-reading*) is セツ/*setsu*, while the Japanese reading (*kun-reading*) is ヨキ/*yuki*. These two readings occur in very usual Japanese words, having a relation to *snow*. *Setsu* occurs in 雪害 (Jap. reading セツガイ/*setsugai*; Eng. 'damage through snow') and 新雪 (Jap. reading シンセツ/*shinsetsu*; Eng. 'fresh snow'). *Yuki* occurs in 初雪 (Jap. reading ハツユキ/*hatsuyuki*; Eng. 'first snow of the season'), 大雪 (Jap. reading オウユキ/*ouyuki*; Eng. 'heavy snow') and 雪合戦 (Jap. reading ユキガッセン/*yukigassen*; Eng. 'snowball fight'). Similarly, the Kanji 崩 (Eng. 'break down, destroy') has two standard readings:

The Chinese reading (*on-reading*) is ホウ/*hou*, while the Japanese reading (*kun-reading*) is くず/*kuzu*. The Kanji 崩 in the reading *kuzu* does not appear as an individual word, in the following examples it is used as a verb stem only. These two readings occur in Japanese words related to *break down*. *Hou* occurs in 崩御 (Jap. reading ホウギョ/*hougyo*; Eng. 'death of the emperor'). *Kuzu* occurs in 山崩れ (Jap. reading ヤマクズレ/*yamakuzure*; Eng. 'landslide') and 切り崩す (Jap. reading キリクズス/*kirikuzusu*; Eng. 'erode'). The compound of the two, forms a logical unit 雪崩 (Eng. 'avalanche', which could be described semantically as a *'snow landslide'). The reading however, is quite unexpected. Instead of a combination of 'yuki' and 'kuzu(re)' to yield **yukikuzure*, the correct reading is *nadare* (Jap. ナダレ). Unexpected readings like that can be a frustrating and exhausting experience for a learner. The reading *nadare* in this example is a *Jukujikun*. *Jukujikun* (Jap. 熟字訓; pron. ジュクジクン/*jukujikun*; Eng. 'compound kun readings') are specialised Kun-readings that only occur in fixed compounds, comparable to *irregular* words in English (Wydell 1998).

4. **Alternative Kanji.** Some Kanji have the same meaning and reading, yet look differently. For instance the number *one* can be written 一 or simply 一.
5. **Homophones.** Japanese has several homophones. An extreme example is きょう (*kyou*): Around 80 Kanji have at least an alternative reading *kyou*. Also, for example, there are three Kanji that can be read アツイ/*atsui*, namely, 熱い (Eng. 'hot' - for objects or feelings), 暑い (Eng. 'hot' - for the weather) and 厚い (Eng. 'thick' - for clothes; 'kind, warm' - as a characteristic of a person). This can be confusing for a learner.
6. **Infrequent Jōyō Kanji.** There are Kanji that are in the official list of daily use Kanji, but in fact they are actually not frequently used. These can be forgotten easily by a learner, since those Kanji do not appear often in Japanese texts.
7. **Non-Jōyō Kanji.** The fact that a character is not in the list of frequently used characters does not mean that the character is negligible. It may well be necessary to know, at least passively.

Chapter 3

On-Line Handwriting Recognition

3.1 Introduction

Handwriting is a very personal skill to individuals. It consists of graphical marks on a surface and can be used to identify a person. Communication is the main purpose and this is achieved by drawing letters or other *graphemes*, which in turn represent parts of a language. The characters have a certain basic shape, which must be recognisable for a human in order for the communication process to function. There are rules for the combination of letters, which have the ability - if known to the reader - to help recognise a character or word.

Handwriting was developed as a means of communication and to expand one's own memory. With the advent of each new technologies the question arose, if handwriting was going to survive. However, the opposite seems to be the truth: For example, the printing press increased the number of documents available and therefore increased the number of people who learnt to read and write. Through the increased rate of alphabetisation, naturally there was an increased use of handwriting as a means of communication.

In various situations handwriting seems much more practical than typing on a keyboard. For instance children at school are using notepads and pencils or ink pens, which are regarded as a better tool to teach writing by German teachers. Therefore it can be concluded that there is little danger of the extinction of handwriting as a communication tool. In fact, as the length of handwritten messages decreases, the number of people using handwriting increases (Plamondon and Srihari 2000).

3.2 Handwriting Features

Any script of any language has a number of features. The fundamental characteristic of a script is that the differences between the features of different characters are more decisive than the different features of drawing variants of the same letter in individual handwriting styles. There might be exceptions, because *0* (number between '1' and '1') and *O* (letter between 'n' and 'p') or *1* (number between '0' and '2') and *I* (letter between 'h' and 'j') respectively, can be written alike. However, in those cases, context makes clear which one was intended by the writer. Despite the exception, written communication can only work with that fundamental quality (Tappert et al. 1990).

3.2.1 Handwriting Properties of Latin Script

In the Latin script we have 26 letters, each of which has two variants, a capital and a lowercase variant. When writing a character in the Latin script, there are four main areas, in which the character can reside. All characters have their main part between a top line and a ground line. There is also a middle line. Capital characters stretch out to use the full space between the ground line and the top line, whereas lowercase characters usually use the space between the ground line and the middle line. Some lowercase characters (like lowercase *b*, *d*, *f*, *h*, *k*, *l*, *t*) have an ascender and use the area above the middle line as well, some lowercase characters have a descender and use the area below the ground line (like lowercase *g*, *j*, *p*, *q*, *y*). In handwritten cursive script, there are writing variants where also some lowercase letters (*f*, *z*) and certain uppercase characters (*G*, *J*) expand below the ground line. For all latin-based alphabets, usually one character is finished before the next one starts, however, there are exceptions: In cursive handwriting, the dots on *i* and *j* and the crosses of *t* might be delayed until the underlying portions of all the characters of the word are completed. Figure 3.1 shows examples of letters that expand below the ground line with their descender or stretch up to the top line with an ascender.

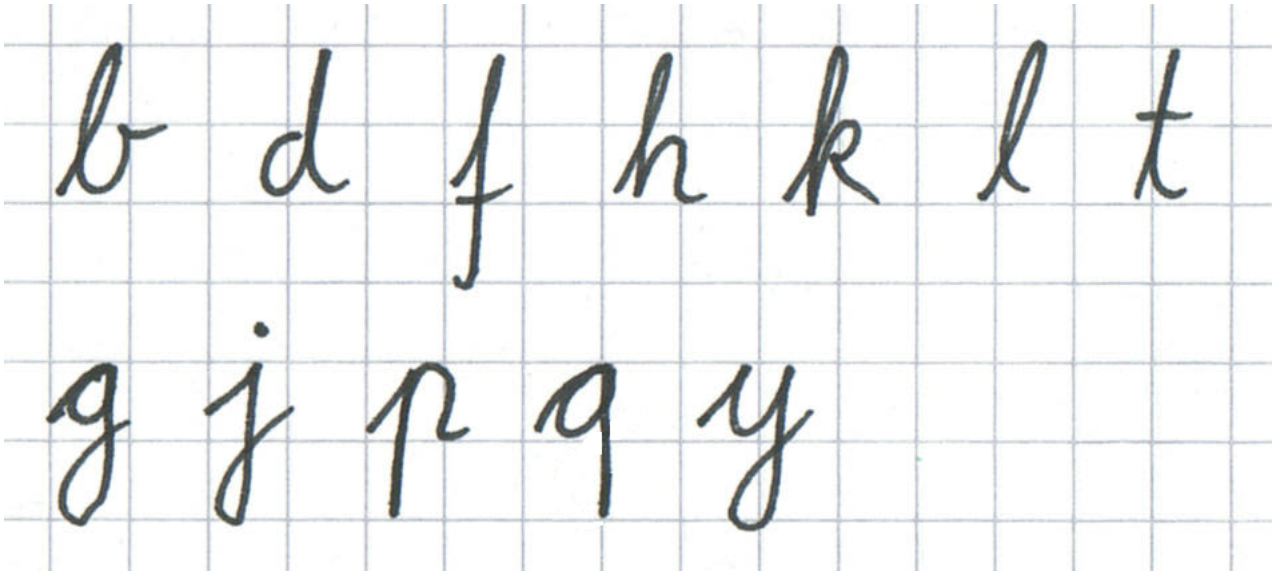


Figure 3.1: Expanding cursive letters

3.2.2 Handwriting Properties of East Asian Scripts

Generally, a handwriting is a formed of a number of strokes, that are drawn in a time sequence. Opposed to the latin-based alphabets, consider Chinese and Japanese script. Chinese has a larger alphabet, up to 50.000 characters, 3.000-5.000 of which are in active use. There are also two writing styles, block style - which corresponds to printed characters in Latin alphabets, even if handwritten. The other style is cursive style. In block style the individual parts of the character are usually written in proper stroke order, and abide by the proper stroke number. In cursive style the characters are written faster, with less care and don't necessarily abide to stroke number or order. In fact, they are usually written with fewer strokes, connecting some block-style strokes by using simpler radical shapes (Tappert et al. 1990).

In Japanese, three different scripts are in active use at the same time, mixed and next to each other. They are called *Hiragana* (ひらがな), *Katakana* (カタカナ) and *Kanji* (漢字). Hiragana and Katakana are syllabic alphabets, each containing 46 characters (see section 2.2.1), whereas Kanji are essentially the Chinese *Hànzi* (汉字) characters as they were imported into the Japanese language (see section 2.1).

The different scripts can even be blended with each other within one word. Take for instance the verb '食べる' (pron. /*taberu*/, Eng. *to eat*). The first character '食' is a Kanji character, pronounced /*ta*/, which also bears the meaning of the word. The second and third characters are the Hiragana characters 'べ' *be* and 'る' *ru*, which are there for conjugation only as well as for phonetic reasons. Without them, the character '食' still bears the meaning of the concept *eat*, but the character alone does not result in the verb *taberu*.

3.3 Automated Recognition of Handwriting

3.3.1 Short History of Handwriting Recognition

Handwriting recognition (HWR) as a technological discipline performed by machines has been around for many years. The quality of the systems recognising handwriting has improved over the decades. It is the key technology to pen-based computer systems. The first research papers concerned with *pattern recognition* on computers were published in the late 1950s, *Handwriting recognition* as an individual subject in the early 1960s. (Goldberg 1915) describes in a US Patent a machine that can recognise alphanumeric characters as early as 1915. However, despite the surprise of how early such a device was invented, it should be taken into consideration that that was before the times of modern computers, therefore the methods he employs are quite different from the algorithms used after the advent of computers, more concretely, computers with screens.

(Tappert et al. 1990) describe in their review the development of handwriting recognition, which was a popular research topic in the early 1970s and then again in the 1980s, due to the increased availability of pen-input devices. Generally speaking, handwriting recognition (HWR) involves automatic conversion of handwritten text into a machine readable character encoding like ASCII or UTF-8. Typical HWR-environments include a pen or stylus that is used for the handwriting, a touch-sensitive surface, which the user writes on and an application that interprets the strokes of the stylus on the surface and converts them into digital text. Usually, the writing surface captures the x-y coordinates of the stylus movement.

3.3.2 Pattern Recognition Problems

The general problem of *pattern recognition* is to take a non-symbolic representation of some pattern, like mouse or pen coordinates and transform it into a symbolic representation like a *rectangle* with its coordinates, or in the case of handwriting recognition, a character. Pattern recognition is a symbol manipulation procedure, that tries to generate discrete structures or sub-sets of discrete structures. Some see it as a game theory problem, where machine 'players' try to match the interpretation of an input produced by machine 'experts' (Zanibbi et al. 2005).

3.3.2.1 Related Problems

There are several related problems, the recognition of equations, line drawings and gestures symbols. The recognition of language symbols includes the different large alphabets of Chinese, the different scripts of Japanese, alphabetic scripts like Greek, or Arabic and other non-alphabetic scripts like the Korean Hangul, but also various writing styles of the latin-based alphabets, and diacritics that are used to denote pronunciation variants in different languages using Latin script, like Turkish or Vietnamese.

Other Problems that are related to handwriting recognition include for example mathematical formula recognition, where mathematical formulae are analysed and put into a computable format (Chan and Yeung 2001). In diagram recognition both the characters and the diagram layout are recognised (Blostein and Haken 1999).

3.3.2.2 Problem of Similar Characters

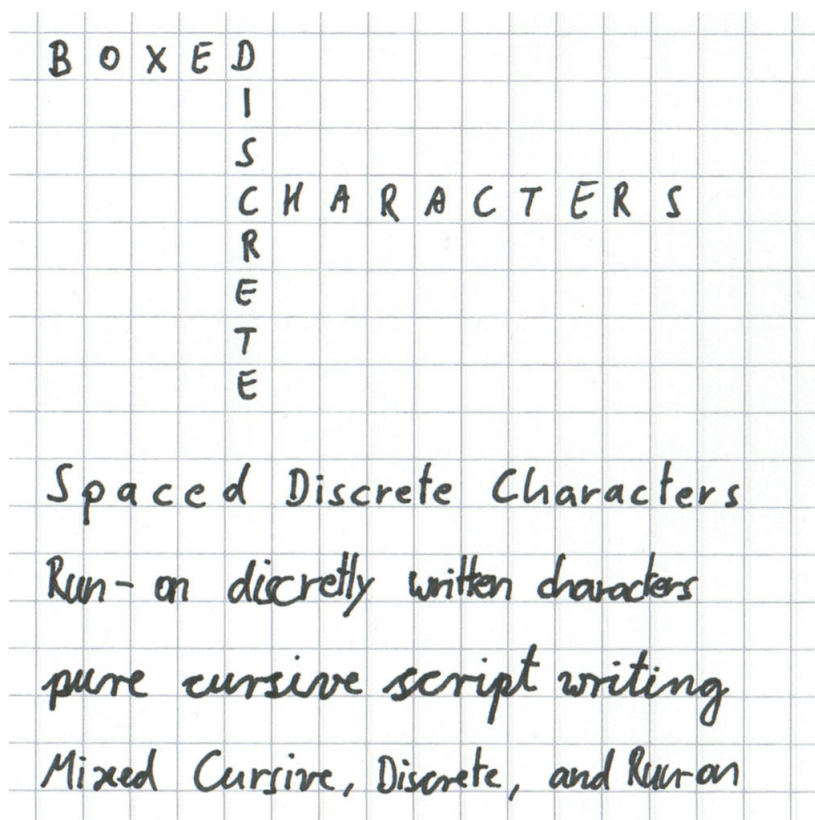


Figure 3.2: Different handwriting styles

There are several subproblems to the task of pattern recognition of a character. Different styles of handwriting after (Tappert et al. 1990) can be seen in figure 3.2. The scripts toward the bottom of figure 3.2 are harder to recognise. In the case of boxed discrete characters, segmentation is done for the machine by the user. Run-on discrete characters are easier to recognise than pure cursive handwriting, because there is a pen-up and pen-down between each character. In cursive handwriting, segmentation between the characters becomes a more difficult task. Some parts of the writing may be delayed, like the crosses of *t* or the dots on *i* or *j*. Besides the segmentation, the discrimination of shapes is often not trivial. Humans may or may not be able to decipher somebody else's handwriting and clearly distinguish between, say *U-V*, but most of the times,

context helps with that task. Other characters have similar shapes, too, like *C-L*, *a-d* and *n-h*. Confusion can arise between characters and numbers like *O-0*, *I-1*, *l-1*, *Z-2*, *S-5*, *G-6*, *I-1*, *Z-2*. Lowercase and uppercase are hard to distinguish in the cases of *C-c*, *K-k*, *O-o*, others are mainly distinguished by their position relative to the base line of the rest of the text: *P-p*, *Y-y*. Therefore, context helps the human reader to identify the correct character. This could be used as an advantage in automated pattern recognition, as well. However, the other characters nearby would have to be recognised first, which creates a (solvable) hen and egg problem. In the Japanese script the problem is taken to another dimension. Consider 本 (root) and 木 (tree) those two characters are only a very basic sample of characters that might lead to confusion of the different symbols. However, due to the hierarchical organisation of the characters with their radicals (see section 2.2) there are many more shapes that look very much alike. From the shape recognition perspective, minor changes to the shape of a character can change its meaning drastically. Compare 嚙 (how, indeed), 撫 (stroke, pat), 蕪 (turnip) and 慥 (disappointment). They all contain the radical 無 (nothingness, none), which doesn't seem to have any semantic connection with the characters, however, it can be seen as the main radical in those characters.

3.3.3 Hardware Requirements

In order to perform on-line handwriting recognition, the handwriting needs to be captured in some way. Special hardware is necessary to perform the task of capturing both the x-y coordinates and the time information of the handwriting input device.

Several different hardware commercial products are available in order to capture the x-y coordinates of a stylus or pen. Graphics tablet like the products of the Wacom Co., Ltd.¹ are popular input devices for hand motions and hand gestures. The use of pen-like input devices has also been recommended, since 42% of mouse users report feelings of weakness, stiffness and general discomfort in the wrist and hand when using the mouse for long periods (Woods et al. 2002). The sampling rates of digital pens are usually around 50-200 Hz. The higher the sampling rate the finer the resolution of the resulting co-ordinates, which leads to more accurate measurement of fast strokes.

Moreover there are PDAs and Tablet PCs, where the writing surface serves as an output device, i.e. an display at the same time. If the pen capturing area is transparent and has an instantaneous display behind that shows immediately whatever input the user drew with the stylus, a high level of interactivity can be reached (Santosh and Nattee 2009). These displays include touch screens, which are a newer development. New generation mobile phones like the notorious iPhone from Apple Inc. also contain touch-displays, but for those it is more common to be operated without a stylus. For the task of handwriting recognition, a stylus can be regarded as the more natural device, since people usually write with pens on paper, therefore a stylus on a display seems more natural than using a finger on a display for writing. In order to interpret user gestures, an input given directly with the fingers is a more natural option. Gestures for zooming into digital pictures, or turning to the next page of a document are interpreted on these devices.

Another rather new development are real-ink digital pens. With those, a user can write on paper with real ink, and the pen stores the movements of the pen-tip on the paper. The movements are transferred to a computer later. It can be expected that with technologies like Bluetooth it may be possible to transfer those data in real-time, not delayed. In a fairly new development accelerometer technology has been used for handwriting recognition, using a mobile phone as a device to write in the air (Agrawal et al. 2009). That approach can be regarded as an area that is only loosely related to classical handwriting recognition, as the phone stores an image of the strokes in the air that were measured by the accelerator device, but does not transform the strokes into characters.

3.3.4 Recognition vs Identification

Handwriting recognition is the task of transforming a spatial language representation into a symbolic representation. In the English language (and many others) the symbolic representation is typically 8-bit ASCII. However, with *Unicode* being around for more than a decade now, storage space on hard disks not being as much of an issue any more and *RAM* being readily available to the Gigabytes, it has become more common to use a *UTF-8* encoding, which is a variable-length character encoding for Unicode (Unicode Consortium 2000). Akin disciplines to handwriting recognition are *handwriting identification*, which is the task of identifying the author of a handwritten text sample from a set of writers, assuming that each handwriting style can be seen as individual to the person who wrote it. The task of *signature verification* is to determine if a given signature stems from the person who's name is given in the signature. Thus, handwriting identification and verification can be used for analysis in the field of jurisdiction. They determine the individual features of a handwritten sample of a specific writer and compare those to samples given by a different or the same writer. By analysing those features one can find out if a piece of handwritten text is authentic or not.

¹www.wacom.com

3.3.5 Interpretation of Handwriting

Handwriting recognition and interpretation are trying to filter out the writer-specific variations and extract the text message only. This conversion process can be a hard task, even for a human. Humans use context knowledge in order to determine the likeliness of a certain message in a certain context. For instance, a handwritten message on a shopping list that could be read as *bread* or *broad* due to the similarities of the characters for 'e' and 'o' in some cursive handwriting styles, will be interpreted as *bread*, since it is a much more likely interpretation in the shopping list domain. However, if the next word on the shopping list is *beans*, the likelihood for the interpretation of the first word as *broad* rises, because the collocation *broad beans* is a sequence that is likely on a shopping list, at least more likely than having the interpretation *bread* and then *beans* without a clear separation between the two. Even with non-handwritten, but printed characters, the human mind can be tricked because of the brain's ability to perform these interpretations within milliseconds without conscious thinking. An example of that are modern T-Shirt inscriptions that state things like *Pozilei* in a white font on a green ground (the German police colours in most federal states are green and white), which German native speakers usually read as *Polizei* (police), because that is the most likely interpretation.

3.3.6 On-Line vs. Off-Line Recognition

3.3.6.1 Basic Features of On-Line Recognition

On-line HWR means that the input is converted in *real-time*, *dynamically*, while the user is writing. This recognition can lag behind the user's writing speed. (Tappert et al. 1990) report average writing rates of 1.5-2.5 characters/s for English alphanumerics or 0.2-2.5 characters/s for Chinese characters. In on-line systems, the data usually comes in as a sequence of coordinate points. Essentially, an on-line system accepts as input a stream of x-y coordinates from an input device that captures those data combined with the appropriate measuring times of those points.

3.3.6.2 Basic Features of Off-Line Recognition

Off-line HWR is the application of a HWR algorithm after the writing. It can be performed at any time after the writing has been completed. That includes recognition of data transferred from the real-ink pens (see section 3.3.3) to a computing device after the writing has been completed. The standard case of off-line HWR, however, is a subset of optical character recognition (OCR). A scanner transfers the physical image on paper into a bitmap, the character recognition is performed on the bitmap. An OCR system can recognise several hundred characters per second. Images are usually binarised by a threshold of its colour pattern, such that the image pixels are either 1 or 0 (Santosh and Nattee 2009).

3.3.6.3 Similarities and Differences of On-Line and Off-Line Recognition

There are two main differences between on-line and off-line handwriting recognition. Firstly, off-line recognition happens, hence the name, after the time of writing. Therefore, a complete piece of writing can be expected as an input by the machine. Secondly, on-line devices also get the dynamic information of the writing as input, since each point coordinate is captured at a specific point of time, which can be provided to the handwriting recogniser along with the point coordinates by the operating system. In addition, the recogniser has information about the input stroke sequence, the stroke direction and the speed of the writing. In the off-line case these pieces of information are not readily available, but can be partially reconstructed from the off-line data (Santosh and Nattee 2009).

All these information can be an advantage for an on-line system, however, off-line systems have used algorithms of line-thinning, such that the data consists of point coordinates, similar to the input of on-line systems (Tappert et al. 1990). When line thinning has been applied, an off-line system could estimate the trajectory of the writing and then use the same algorithm as an on-line system (Plamondon and Srihari 2000). Vice versa, an on-line system can employ algorithms of off-line systems, since it is possible to construct a binary image from mouse coordinates of points. However, only few systems of that kind have been developed. A promising approach was developed in the middle of the 1990s by (Nishida 1995), where an on-line and an off-line system are fully integrated with each other as a *blend system*. (Velek et al. 2002) determine the likelihood of different classifiers in a multi-classifier system, before they are combined and yield a result.

On-line systems can refer interactively to the user in case of an unsuccessful or uncertain recognition. Along these lines, an on-line system can adapt to the way a specific user draws certain characters and a user can adapt to the way a system expects characters to be written distinctively.

3.3.7 HWR of Hànzì (汉字) and Kanji (漢字)

The HWR of the Chinese Hànzì (汉字) and the Japanese Kanji (漢字) in practise are merged as *On-line Chinese Character Recognition* (OLCCR). The techniques are essentially the same, only the language models differ. Hereafter, I'm going to use the term OLCCR for on-line character recognition of both Chinese and Japanese characters.

From the 1990s, On-Line Japanese and Chinese Character Recognition systems have been aiming at loosening the restrictions imposed on the writer when using an OLCCR system. Their focus shifted from recognition of block style script ('regular' script) to fluent style script, which is also called 'cursive' style. Accuracies of up to about 95% are achieved in the different systems.

(Nakagawa et al. 2008) report their recent results of on-line Japanese handwriting recognition and its applications. Their article gives important insights into character modelling, which are employed in this application. Multiple subpatterns of characters are detected and used for character modelling.

3.4 A Typical On-Line HWR Application

A typical HWR application has several parts that follow up on each other in a procedural fashion. The main parts of such an application are the following:

- **Data capturing:** The data is captured through an input device like a writing surface and a stylus. Data capturing is described in section 3.4.1.
- **Preprocessing:** The data is segmented, noise reduction like smoothing and filtering are applied. Preprocessing is described in section 3.4.2.
- **Character Recognition:** Feature analysis, stroke matching, time, direction and curve matching. A description of character recognition can be found in section 3.4.3.

In a typical HWR application there are some intermediate steps that can be regarded as partial processes of the ones mentioned above. In preprocessing, there is often a segmentation step (see 3.4.2.1), most systems perform one or several methods of noise reduction (see 3.4.2.2) and it is common to employ a data normalisation step (see 3.4.2.3). Additionally, some systems that employ a postprocessing step (see 3.4.4).

3.4.1 Data Capturing

Special hardware is needed in order to capture the data necessary for on-line HWR. It is possible to input data with a regular mouse on a regular computer, however the data will be less *noisy*, if a stylus is used for input of the handwriting. See section 3.3.3 for more information on the hardware requirements of HWR. The data that is served by a device driver or the operating system is structured as mouse coordinates. In case of pressure-sensitive input devices the device driver also returns the pressure intensity. However, a typical on-line HWR application uses only the mouse coordinates, not the pressure intensity. Generally, HWR applications work with mouse coordinates, thus the trajectory of the stylus, in accordance with the appropriate time information for each of the sampling points.

3.4.1.1 Sampling

The pen-up and pen-down information is a central part in data capturing. Depending on the sampling rate, there will be between 50 and 200 points per second. Those can be viewed as a function of time. With theses pieces of information, it is possible to track the number and order of strokes drawn by the user. According to the writing speed, the number of coordinates per distance can vary. A fast stroke will have fewer point samples, even if the same distance was covered on the writing surface. Some see this as a problem and *re-sample* the points to be of equal distance to each other and to have a constant number of sample points in every stroke (Santosh and Nattee 2009). (Joshi et al. 2005) re-sample the strokes in a way that they yield a constant number of point samples in space, rather than in time. They propose an approach for Devanāgarī ² characters, where each of the characters is represented by 60 sample points.

²Devanāgarī is a script used to write the Sanskrit, Prākṛit, Hindi, Marathi, and Nepali languages, developed from the North Indian monumental script known as Gupta and ultimately from the Brāhmī alphabet, from which all modern Indian writing systems are derived (Encyclopædia Britannica Inc. 2009).

3.4.2 Preprocessing

Most On-Line HWR systems apply some kind of preprocessing. Generally, preprocessing serves to smoothen the data, eliminate noise and normalise the data, in order to retrieve a more accurate recognition in the next step. (Tappert et al. 1990) distinguish between the phases *external* and *internal segmentation*, a *noise reduction* step that has several sub steps:

Smoothing, filtering, wild point correction, dehooking, dot reduction and *stroke connection*. Some systems also employ a *normalisation* step, that can include *deskewing, baseline drift correction* and *size normalisation*. (Santosh and Nattee 2009) employ a similar perception in their review about several on-line HWR systems. Their *noise elimination* corresponds to *noise reduction* and the aforementioned *normalisation* describes roughly the same techniques that (Tappert et al.) depict. (Santosh and Nattee) also present the additional processing step of *repetition removal*, is comparable to the *dot reduction* mentioned above. In the remainder of this section the typical preprocessing steps are presented in more detail.

3.4.2.1 Segmentation

The term *Segmentation* describes the processing step of segmenting the individual characters or strokes from each other.

External Segmentation *External segmentation* is the step of isolating writing units. That can be single strokes, characters or words respectively. In alphabetic scripts it is sometimes difficult to segment each character externally. In CJK (Chinese, Japanese and Korean) cursive script it is difficult to distinguish individual strokes, however, since it is common to write in boxes, usually each character can be isolated without much processing. The earliest method of external segmentation is an explicit signal from the user, other work used the projection of the trajectories on the X-axis for spatial segmentation. Another method uses temporal information and employs a time-out between the end of one and the beginning of another character. A fairly easy possibility is of course the use of boxed characters, where the user is required to write each character in a separate box. Taking the box idea to the next level of abstraction, some systems provide different boxes on a single screen for different types of characters (Tappert et al. 1990).

Internal Segmentation In cursive script, several strokes are connected together, even several characters can be written without a pen-up movement. Therefore some partial recognition is needed in order to perform the segmentation. In *overlaid handwriting recognition* a sequence of characters is written on the same area, e.g. on a very small display like a wrist watch with a touch screen. In that case, segmentation becomes a problem even for OLCCR systems. (Shimodaira et al. 2003) employ substroke HMMs in a wearable computing environment. They achieved performances of 69.2% with free stroke order and 88% with fixed stroke order characters.

3.4.2.2 Noise Reduction

Any stroke drawn on a device with a pen input contains noise. Digitising errors like limited accuracy of the tablet or erratic pen-down indication or hand fluctuation are sources of noise in the input data. There are different types of noise and different types of filters for elimination of the noise from the data (Santosh and Nattee 2009).

Smoothing *Smoothing* is usually a technique that averages a point with its neighbour point. A common variant of that is only averaging a point with its previous point. That ensures that the recognition can proceed as the input is received (Tappert et al. 1990). (Joshi et al. 2005) employ a 5-tap low pass Gaussian filter in order to smoothen the data. Today, Gaussian filters are often used as a means of smoothing data, despite the fact that *filtering* usually refers to reducing the number of samples in a sequence of points.

Filtering *Filtering* describes a technique that thins out the number of samples in a point sequence. It is sometimes referred to as *thinning* but should not be confused with *line thinning* in off-line HWR. Here, thinning means reducing the number of data samples. Also, duplicate points can be detected and eliminated through filters. The ideal filtering method depends on the recognition method. There are filtering techniques that enforce a minimum distance between points. When a filtering method of that type is used, points tend to be equally spaced. This filtering technique assumes many samples per distance. When a stroke is drawn quickly on a tablet, it can happen, that the distance of the actual sample points is larger than the minimum distance the filter permits. In that case, interpolation can be used in order to introduce new data points in between and achieve equidistant points. Smoothing and filtering can also be performed in one operation for time optimisation (Tappert et al. 1990).

Wild Point Correction *Wild Point Correction* is used for elimination of spurious points. Those points occur usually as a result of errors in data capturing. Acceleration and generally any change of velocity of the hand movement can cause the digitiser tablet to detect wild points (Tappert et al. 1990).

Dehooking Hooks occur at the beginning and more frequently at the end of a stroke. They are recognised by the data capturing device because of inaccurate pen-down detection or random motion when lifting the stylus off the tablet. *Dehooking* is a technique to remove the hooks at the end and at the beginning of a stroke (Tappert et al. 1990).

Repetition Removal *Repetition removal* or *dot reduction* reduces dots to single points (Tappert et al. 1990). Points that are accumulated on a very close area and form a dot, do not improve recognition quality, but rather distort the trajectory. There can even be co-occurring points. Slow handwriting will generate repeating points, and those are generally at the dominant points, such as corners (Santosh and Nattee 2009).

Stroke Connection A *stroke connection* preprocessing method can eliminate pen-up movements that are suspected to be accidental or inaccurately measured. There are different methods to do this, one of which connects strokes if the distance between pen-up and the next pen-down is short in comparison to the size of the character (Tappert et al. 1990).

3.4.2.3 Normalisation

Data *normalisation* is a preprocessing step that prepares data to better match the gold standard and the lexicon entries. It can correct slants or size.

Deskewing is a technique that modifies the slant of an input. Deskewing algorithms can be applied to individual characters or whole words (Tappert et al. 1990). In Chinese and Japanese character recognition, slant correction can be applied in a similar fashion like with latin-based alphabets.

Baseline Drift Correction detects a baseline or horizontal line relative to a word or a set of characters. After detection, that line is corrected to be horizontal (Tappert et al. 1990).

Size Normalisation Adjustment to a standard size can be done with *size normalisation*. This process also normalises for location by relocating the centre of a character (Tappert et al. 1990).

Stroke Length Normalisation sometime called *resampling* normalises the number of points in a stroke or character. Dealing with strokes that were normalised in such a way provides for easy alignment and classification (Tappert et al. 1990).

3.4.3 Character Recognition

Character recognition is a special case of shape recognition. It is the recognition of the shape of writing units. Character recognition falls into different categories, there are methods for the recognition of characters, cursive script, words, gestures, equations, line drawings. Also, there are several different methods for the recognition of the shape of a character. The most common methods include

- **Feature Analysis**, where the distinctive features of characters are taken into account (see 3.4.3.1).
- **Zone Sequences** that code zones on the writing surface (see 3.4.3.2).
- **Stroke Direction** - the individual strokes or substrokes of a character are identified and matched against a stroke sequence database (see 3.4.3.3).
- **Curve Matching** is a method that comes from signal processing and is essentially independent of the alphabet (see 3.4.3.4).
- **HMM Analysis** is independent of the other methods. Basically HMM analysis performs a statistical analysis of the features used, regardless of what they are, i.e. curves, time sequences or writing features of the characters themselves (see 3.4.3.5).

3.4.3.1 Feature Analysis

A character or shape can be represented by a set of features. These features are dependent on the alphabet. Therefore, systems can employ a preconceive analysis of the individual characters of the alphabet. For the Latin alphabet, the systems use features like descender or not descender, dot or no dot (Tappert et al. 1990). Some systems use a decision tree for **binary features**. If there is a descender, for lowercase characters, the recognition choice is reduced to f, g, j, p, q, y, z . If an ascender is present, for lowercase characters, the choice is reduced to b, d, f, h, k, l, t . In case there is an ascender and a descender, the intersection of the two sets leaves only one element, namely the character f . A HWR system can come to similar conclusions by checking if a dot is present i, j , if the character has an open line c, u, v, w, y or a closed line a, b, d, e, g, o, p, q . Systems that perform feature analysis have the potential to use psycholinguistic knowledge and drive the recognition process along the lines humans distinguish characters from each other. The feature analysis method has the disadvantage that it may not produce alternative recognition choices. (Jäger et al. 2001) use ascenders and descenders as features in neural network, where the number of points above or below the baseline is counted.

There are also systems that use **non-binary features**. It is a very common technique in pattern recognition to use a fixed number of non-binary features. A feature space of that kind can be further divided into decision regions (Tappert et al. 1990).

3.4.3.2 Zone Sequences

There are systems that use *zone sequences* in order to represent characters. The zones can be specified by sub-dividing the *bounding box* of a character. The trajectory of the pen that is drawn through the zones is then transformed into a time sequence of zones. That time sequence can be matched against a dictionary of sequences, in which each character is represented (Tappert et al. 1990).

3.4.3.3 Stroke Direction

Stroke direction is another popular feature among HWR systems. The pen-tip motion is captured and each stroke is categorised as a primitive direction (up, down, left, right, other systems also use the diagonal directions and a pen-down, pen-up). (Nakai et al. 2001) and (Tokuno et al. 2002) use the stroke direction feature combined with a pen-coordinate feature. (Okumura et al. 2005) and others follow a similar approach. The substroke approach is very popular in OLCCR, it is often combined with HMMs (see 3.4.3.5).

3.4.3.4 Curve Matching

Curve matching is a set of methods that has been popularised in signal processing. Prototype characters are stored in a database as descriptions of curves. During the recognition process the input curves are matched against the prototypes. It is common to use curves that are functions of time, the direction of the tangent to the stroke or both. Characters have been encoded as a time sequence of eight stroke directions, and as time regions (Tappert et al. 1990). Chinese characters have been encoded as a small number of fixed points, since they consist of mainly straight strokes (Nakagawa et al. 2008). The approach of Jäger and Nakagawa (2001) utilises the Unipen format (Guyon et al. 1994; Unipen Foundation, International 2010) in order to create Japanese character databases.

Elastic matching Curve matching and pattern matching become equivalent in their feature space when there is a constant number of points in a curve and in one-to-one correspondence. However, since many strokes are non-linear the best fit is often not a linear alignment of the points. In order to solve point sequence comparison problem, elastic matching has been used successfully (Tappert et al. 1990). (Joshi et al. 2004a) compare different elastic matching methods for Tamil handwriting recognition. *Dynamic Time Warping* (DTW) is an elastic matching technique that has been applied to handwriting recognition by a number of systems e.g. (Vuori et al. 2001) (for Latin script), (Niels 2004) (for Tamil), (Joshi et al. 2004b) (for Tamil) and (Joshi et al. 2005) (for Devanagari). While the aforementioned systems use it for a single script, (Bharath and Madhvanath 2009) attempt to create a HWR for several Indic scripts using the same technology. (Bahlmann and Burkhardt 2004) use elastic matching combined with HMM modelling for their HWR system. The DTW algorithm yields promising results, especially for the different scripts of the Indian subcontinent, however, due to its complexity, (Keogh and Pazzani 2002), (Chu et al. 2002) as well as (Bashir and Kempf 2008) proposed improvements to the algorithm, mainly through pruning.

3.4.3.5 HMM Analysis

HMM analysis is a technique that is not uncommon among modern systems. It generally follows the standard procedures described in the literature. A detailed description of how On-Line Chinese character recognition can

be done using HMM analysis can be found in the works of Hu et al. (2000), Hu et al. (1996) and also Bahlmann and Burkhardt (2004). In this paper consider section 3.5.4.3 for some details of HMM analysis, embedded into the actual classification process.

3.4.4 Postprocessing

When the recognition process is finished, some systems start another process that takes as input the output of the character recognition. In this postprocessing step, language information can be used to improve the recognition accuracy. Postprocessing is mainly used for continuous character recognition, where more than a single characters is recognised. Since some systems yield a single string of characters others yield a number of alternative recognitions, often in addition with a certainty measure. A postprocessing unit can use the information to calculate estimates for words or even sentences. When the character recogniser yields single choices for characters, the post-processor can apply a correction algorithm, based on a language model (Tappert et al. 1990). (Shimodaira et al. 2003) proposed a method for overlaid handwriting recognition, where the segmentation problem (see 3.4.2.1) is resolved at the end of the recognition process: Alternative choices of characters and character boundaries are generated and probability estimations calculate the most likely sequence of characters, using both the alternative recognition results and a language model for Japanese.

3.5 Overview of a Typical OLCCR system

Typical handwriting recognition systems for Chinese and Japanese characters have broadly the same structure as systems for latin-based alphabets. The process begins with *Character segmentation*, goes on with *Preprocessing*, *Pattern description*, *Pattern recognition* and ends with *Contextual processing*, if applicable. However, there are differences to the standard process, due to the nature of the Chinese characters (see section 3.2.2).

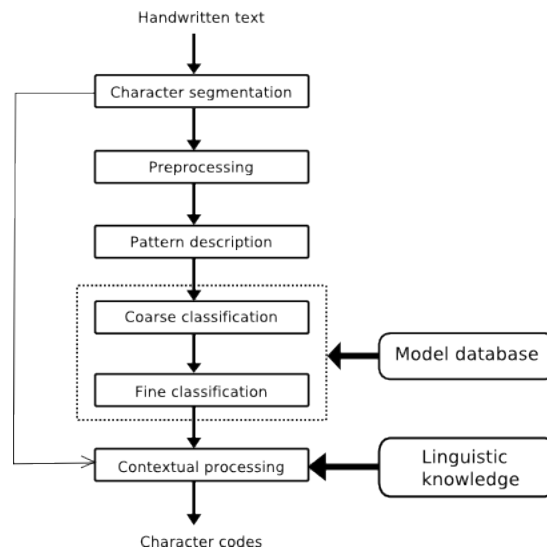


Figure 3.3: Overview of an OLCCR system

A typical OLCCR system is depicted after Liu et al. (2004) in figure 3.3. The first two steps, character segmentation and preprocessing are virtually identical to systems dealing with Latin script. The next step, pattern representation is not only different from Latin script systems, but it has great diversity among the different OLCCR systems. The pattern description is naturally more alike in the systems focusing on Latin characters. This is due to the fact that the Latin alphabet is quite small, but has more variation concerning writing style, whereas the Chinese alphabet has a larger inventory of characters, but less variation in how to write a character. The reason for that is that it is widely agreed upon a standard stroke sequence for a character, even across country borders (Nakai et al. 2003). The next step after the pattern representation is the actual character recognition or classification. Different flavours of comparison methods are applied in different systems, but some systems employ coarse classification first, then a fine classification, whereas other systems try to find the corresponding character model in a model database in just one step. The coarse classification is done to reduce the candidate set, the fine classification is used to find the best match. There are systems that accomplish another step *contextual processing*, which can be regarded as an equivalent to postprocessing (Liu et al. 2004).

3.5.1 Character Segmentation

Character segmentation is a technique that does not apply to OLCCR systems in the same way it does to HWR systems for other scripts. Each character is written separately, even in cursive script. In Chinese characters, *cursive* refers to reduction of lines and lesser pen-up movements within a character. In e.g. Latin script it usually refers to not lifting up the pen before the end of a word (Tappert et al. 1990). Therefore character segmentation is often a trivial task in OLCCR systems, also due to the fact that systems usually only allow writing in boxes - or, in box-free application, assume horizontal character orientation (Nakagawa et al. 2008).

One system attempts to recognise overlaid handwriting characters on a small display, allowing continuous writing for the user. That is essentially boxed writing, but because of the small display, there is only one box in which all characters have to be drawn. The system can therefore be regarded as a continuous character recognition system. In that system, character segmentation is not done as a preprocessing step, but during recognition. The system uses HMM technique, based on substrokes and segments the characters alongside the recognition process (Shimodaira et al. 2003).

The system developed by Nakagawa et al. in 2008 performs continuous character recognition, regardless of the text orientation. The average character size is estimated from all strokes drawn and the estimate defines a threshold for the separation of characters.

3.5.2 Preprocessing

The preprocessing techniques used in OLCCR systems are mainly the same as the ones described in section 3.4.2, in (Tappert et al. 1990) and in (Santosh and Nattee 2009). However, since the input devices offer higher quality input, less noise reduction is necessary and smoothing is enough to remove undesirable points from the input trajectory. Therefore, many OLCCR systems limit preprocessing to the other techniques. Data points are reduced by one of two methods: approximation of lines (by feature points) or resampling (Liu et al. 2004). Size normalisation is realised in most HWR systems, OLCCR systems included.

3.5.3 Pattern Description

An important part of each HWR system is the description of the patterns that need to be recognised. Since the Japanese and Chinese alphabet has a manifold character set, pattern representation faces greater difficulty, because confusion of characters must be avoided. There are three main types of pattern description in OLCCR systems. The classification of characters depends highly on that representation. In the beginning of research into OLCCR systems, *structural* character representation was the natural choice. As systems and computing power evolved, *statistical* character representation became more relevant. In order to optimise for speed and recognition accuracy, system designers started blending the two methods to *hybrid statistical-structural* character representation (Liu et al. 2004). Systems that use statistical character representation usually store the input patterns in feature vectors. The character model database holds the parameters for classification.

3.5.3.1 Statistical Character Representation

In statistical character representation, the central focus lies on transferring input patterns into feature vectors. The model database contains the same type of classification information for the characters. Since each stroke of a character is represented in a feature vector, systems are enabled to perform stroke order free recognition. The trajectory can also be mapped into a 2D image, in order to apply off-line recognition features. An on-line version of the direction feature, commonly used in off-line recognition systems, can be found in several systems (Suen et al. 2003). Generally, using features and a statistical representation, enables the use of several feature extraction techniques that have been developed for off-line systems (Liu et al. 2004).

3.5.3.2 Structural Character Representation

Several different approaches have been proposed to structural character representation. The most basic version of a structured representation is simple point sequences. Systems that use point sequences as a representation, calculate the distance between the strokes. Another approach deals with feature point or line segments. Feature points are calculated from the original point sequence, which is ideal for characters with mostly straight lines. Instead of matching complete point sequences, only feature point sequences need to be matched with the character database (Liu et al. 2004).

Using stroke codes for character representation has been adopted by a number of OLCCR systems. Each of the graphemic strokes of the Kanji stroke inventory is named. A character representation consists of a stroke sequence of the named strokes or a relation between the strokes.

Structured Character Representation is a approach where the characters are structured in their graphemic subcomponents. (Nakagawa et al. 2008) employ basic sub patterns and then structural information about how these are combined to form a full character. That way, the dictionary is smaller, because there is only limited number of sub patterns and their variations. The sub patterns are not chosen randomly, but taken from the inherent hierarchical structure of the Hànzì and Kanji. (Chen and Lee 1996) propose a hierarchical representation for the reference database of on-line handwriting recognition. The characters are organised hierarchically in the way that each one of them is built from the same set of radicals. Therefore the characters can be described as a trees or directed acyclic graphs, using the radical representations. In the dictionary, the radicals are shared between the characters, reducing the dictionary size immensely (Liu et al. 2004). There are around 200 radicals but around 3000 Kanji characters in active use in the Japanese script. Creating a character representation for each one of them is a considerable effort however, using a structured approach can lessen that labour-intensive task. (Breen 2004) proposed a multi-index dictionary that bears the potential to support the creation of structured character databases. Besides the alleviation of the database creation, the storage space used can limited, which will be advantageous when building a system for small computing devices.

3.5.3.3 Statistical-Structural Character Representation

A common example of statistical-structural character representation is the *substroke approach*. (Nakai et al. 2001), (Shimodaira et al. 2003), (Okumura et al. 2005) and others define 8 or more³ stroke types, each of which has its own direction and orientation. These are used to describe input patterns sequentially but also non-sequentially.

In statistical-structural models, characters are described in graph or tree structures. The primitives, e.g. the substrokes and their relations to each other are represented in a probabilistic model. Most of the substroke systems use HMMs. The substrokes are represented by nodes and the transition between strokes is measured probabilistically. Some systems use points or line segments. Other systems use full strokes or even radicals. Attempting to avoid stroke-order dependence of the system, often multiple HMMs are generated with stroke-order variations. The substroke approach responds to that by hierarchical character models, such that the stroke order variations can be stored in a network (Liu et al. 2004).

3.5.4 Classification

Classifying an input pattern representation as an entry found in a pattern database is the kernel of each pattern recognition application. Representing data in the same format as the original patterns (see 3.5.3 is another key task, however the actual classification is the main piece of software. In this section, different kinds of classification are reviewed to fit with the different kinds of pattern description. The two main groups of classification methods are reviewed: *structural classification* and *probabilistic classification*. Additionally, a short section about *coarse classification* shows how to speed up the classification process by preprocessing in the sense of classification preprocessing, not to be confused with the data preprocessing described in section 3.4.2.

3.5.4.1 Coarse Classification

Coarse classification is a name for any method that pre-selects characters to match an input pattern, before the detailed or fine classification is done. There are different coarse classification methods, but nevertheless the overall goal of coarse classification remains the same. Increasing the speed of the classification process. That appears to be necessary due to large vocabulary size. Comparing an input pattern with each pattern in the pattern database is a time-consuming process. Therefore, many system designers subdivide their database into *character classes*. When a new input pattern needs to be analysed, the system first assigns a character class and therefore reduces the search space. This coarse classification method is called *class set partitioning*. Another method of coarse classification is *dynamic candidate selection* (Liu et al. 2004).

Class Set Partitioning methods divide the large set of characters into smaller groups - character classes. These groups can be completely disjoint or sometimes overlap. The system assigns the input pattern to one or more character classes. After that, in the next step of the recognition process, the input pattern is compared to the members of the character class it has been assigned to. The groups are devised in the database design phase (Liu et al. 2004).

Dynamic Candidate Selection methods calculate a matching score between the input pattern and each character class. A subset of character classes is selected for further enquiry. (Liu and Nakagawa 2000) have shown that the increase in recognition speed can be achieved without loss of precision by choosing a variable number of classes according to a confidence value. The dynamic grouping can be based on several different

³Some systems distinguish between short and long strokes and thus use 16 stroke types.

factors. For instance the overall character structure, the basic stroke substructure, the stroke sequence (Liu et al. 2004). Selection the partition classes dynamically is less labour-intensive, because it avoids the training process or manual division of the character classes. Stroke number of the input pattern can also be used as a preselection of characters. Systems that employ structured character representations (see section 3.5.3.2) can also use radical detection. All characters in the database that do not contain the confidently detected radical are ruled out from fine classification. However, the radical detection has a close relation to structural classification (see section 3.5.4.2) and cannot be done without it. Another possibility to perform coarse classification is feature vector matching, where only a subset of the feature vector is compared and thus rules out all character database entries that do not match (Liu et al. 2004).

3.5.4.2 Structural Classification

Structural classification refers to a set of methods for classification or character matching that use the internal structure of the character in order to perform the matching. Input patterns are compared to structural representations of the candidate character classes. The one with the minimum distance measure is considered the resulting character.

The different methods of structural classification can be grouped as follows:

Stroke matching or *stroke correspondence*, *elastic matching* or *DP matching* (*dynamic programming*), *relational matching* and *knowledge-based matching*. Stroke matching compares the strokes that have been drawn with the strokes of the character model in the character database. Elastic matching is performed on ordered stroke sequences and contains stroke deformation techniques. Relational matching considers the strokes and the interstroke relationships, whereas stroke matching only considers the strokes, but not their relations to each other. *Hierarchical matching* and *deformation methods* are connected to these approaches in an orthogonal fashion, i.e. they can be combined with the approaches mentioned above.

Hierarchical Matching can improve recognition speed, because parts of the recognition and representation are done only once for several characters. That approach would of course not be possible without the hierarchical composition of the Kanji characters. The accuracy of that approach is limited in the way that the accuracy of the recognition depends on the accuracy of the radical recognition. However, when a radical has been recognised correctly, the classification can succeed by traversing a decision tree or network (Liu et al. 2004).

Deformation Methods deform the input pattern in a way to better match with a character representation from the database. In order to do that a deformation vector field is computed, based on the stroke correspondence. Then the prototype is deformed by local affine transformations in order to fit the input pattern.

Stroke Matching is a technique where a distance between the input strokes and the strokes in the database are calculated. The distance between an input pattern and a character in the database is the sum of the between stroke distances. When the input strokes are reordered according to domain-specific rules, alternative stroke orders can be matched. The domain-specific rules contain linguistic information such as the stroke order precedence. Alternatively, there can be several database entries for the same character with varying stroke orders. Defining these rules is a labour-intensive task (Liu et al. 2004).

Elastic Matching does not differ much from the general elastic matching techniques described in section 3.4.3.4. Elastic matching searches for the ordered correspondence between primitive symbols, such as coordinate points or line segments. During that process the algorithm seeks to minimise the edit distance (*Levenshtein distance*). A popular elastic matching technique is called *Dynamic time warping* (DTW), which is used by many different systems, especially the concerned with HWR for scripts that have rather curvy characters like Tamil (Niels and Vuurpijl 2005), (Joshi et al. 2004b) or Devanāgarī (Joshi et al. 2005), but has also been applied to HWR of latin-based alphabets (Negussie 2008), (Vuori et al. 2001). (Niels 2004) and (Joshi et al. 2004a) have done research into which elastic matching approach is suitable for HWR, as well as, if DTW is useful for that task at all. Both conclude that the method bears advantages, because certain problems concerning handwritten input, such as stroke length, or number of sample points can be dealt with.

Relational Matching systems search for correspondences between element sets. That is, for example the spatial relationships between strokes in a set of strokes in a character representation. Since the stroke order within radicals tends to be invariant, it is possible to perform elastic matching for the strokes within the radical and use relational matching for the strokes on a character level. Just like elastic matching and stroke matching, relational matching can be performed by systems focusing on character patterns or radicals. The advantage

of relational matching over elastic matching is that it is stroke-order independent. Since the relationship constraint improves the accuracy of the matching, relational matching also has an advantage over stroke matching. However, it is computationally complex and therefore slower than the other two methods (Liu et al. 2004).

Knowledge-Based Matching utilises the knowledge of the internal structure of characters. The knowledge is formulated and represented as heuristic rules or constraints. The constraints reduce the search space of structural matching efficiently. Radical detection and stroke reordering have been performed by rule-based methods. The rules hold the information of permitted basic strokes for a character or fixed spatial feature of strokes. Building knowledge-based systems can be laborious, because of the tasks of acquiring and organising the knowledge. However, even simple heuristics have proved to be valuable. Some heuristics can be acquired in an automatic fashion, or from corpus studies, for example statistical distribution of stroke order for characters. With rule-based heuristics, the overall recognition accuracy of systems based on other classification methods can be improved (Liu et al. 2004).

3.5.4.3 Probabilistic Classification

The use of probabilistic methods for classification has increased. Many modern OLCCR systems use probabilistic methods successfully. For example, the stroke-type probability can help computing the between-stroke distance. Alternatively, if the prototype strokes are modelled as Gaussian density functions, the matching score of an input pattern respective to a character model can be computed using the joint probability of constituent strokes (Liu et al. 2004).

HMM-based Classification has been a popular method in recent years of research in OLCCR systems. The recognition task is the decoding of the observed sequence (i.e. the input sequence) into the most probable state sequence. This is done with the Viterbi algorithm, that is very popular for these types of decoding tasks, such as automated translation (Koehn et al. 2007). Radicals can be represented in HMMs and therefore be shared between different characters in the character database. Hu et al. (1996) have incorporated HMMs into a stochastic language model for Latin characters. Tokuno et al. (2002) employed a substroke model for cursive Kanji and Hiragana handwriting recognition. Their model contains content-dependent substrokes and their character model therefore needs 25 HMMs as opposed to one for each character. The substroke approach became popular, and has been used by (Nakai et al. 2001). In a follow-up article, (Nakai et al. 2003) propose the automated generation of a dictionary for stroke-order free OLCCR. That approach is as well based on substroke HMMs. (Shimodaira et al. 2003) propose a handwriting recognition interface for wearable computing. In their approach the HWR has to be done overlaid, i.e. the user draws sequential characters in the same box. The resulting segmentation problem is solved by using substroke HMMs, where recognition is done in parallel with segmentation. In order to achieve that, a stochastic bi-gram language model is combined with the HMMs. Another system (Okumura et al. 2005) uses not only the pen-direction feature of the other substroke-based HMM approaches, but additionally incorporates the pen-coordinates into the system. This is done at the inter-state transitions of the HMM, whereas the pen-direction feature is utilised at the intra-state transitions.

3.5.5 Postprocessing

3.5.5.1 Contextual Processing During Recognition

OLCCR systems, focus on finding the appropriate candidate for an input pattern. Once the correct character has been found the task is solved. Most systems deal with extraction of features and classification or matching, resulting in scores for individual characters. There are systems that have to deal with multiple character input. That can make the problem more complex, for example when dealing with overlaid handwriting and the accompanying segmentation problem (Shimodaira et al. 2003).

In Japanese, it is possible to write from left to right in lines, while the lines go from top to bottom. It is also possible, to write from top to bottom in columns, while the columns go from right to left. The task of recognising multiple character input becomes more difficult, when attempting to recognise Japanese handwriting without assumptions about the writing direction (Nakagawa et al. 2008). However, it is possible to make use of the linguistic context for contextual processing of already recognised character classes. The context can provide additional information about which character class is the most suitable among a selection of possibilities with their scores. Also, geometric features like size, location or aspect ratio can support the segmentation process.

For page-based recognition processes - especially in the case of off-line recognition, but also when handwriting input can be placed freely on some input device with a stylus-based or touch display - it is important to integrate the segmentation and the recognition modules. Frequently, segmentation can not be done unambiguously before the recognition (Liu et al. 2004).

Some segmentation ambiguities need to be solved during the recognition process. Usually, the systems generate some candidate character classes and verify them by their geometric features, the recognition results and also linguistic knowledge. The candidates can be represented in a network, where the edges denote combinations or segments that build up the candidate pattern. Each path in the pattern represents a segmentation of the input and its recognition result. A dynamic programming search yields the path with the highest probability value. Linguistic knowledge can be used to verify the path or can be inserted into the path scores (Liu et al. 2004).

3.5.5.2 Contextual Processing After Recognition

Linguistic processing of system results after segmentation and recognition is called *postprocessing*. For instance, based on the recognition result, other candidate characters can be given, due to statistical information about confusion of characters. That procedure reduces the risk of excluding the true class from the candidate set.

Additionally to that, there are systems that ruthlessly exploit linguistic knowledge in dictionaries or character-based or word-based n-grams models. Word-based n-gram models usually provide syntactic or semantic classes, for example parts of speech. Using n-gram models involves dividing text into words and some degree of morphological analysis. It is beneficial to use writer-specific dictionaries. Generally, linguistic postprocessing improves the accuracy of the recognition (Liu et al. 2004).

Chapter 4

E-Learning

4.1 Introduction to E-Learning

The term *e-learning* refers to a number of different methods, concepts and techniques. It is therefore difficult to confine the term sharply. Thus, in literature, there are different definitions of what e-learning is and what it is supposed to be. Rosenberg (2006) defines e-learning as follows:

E-learning is the use of Internet technologies to create and deliver a rich learning environment that includes a broad array of instruction and information resources and solutions, the goal of which is to enhance individual and organisational performance.

It can be noted that Rosenberg (2006) defines e-learning purely by terms of instruction and information resources. Further, *the use of Internet technologies* is seen as a necessary condition for e-learning. The definition does not take into account educational software. Seel and Ifenthaler (2009) claim that the terms *e-learning* and *learning on-line* are synonymous.

Richert (2007) criticises the definition of Rosenberg because she sees no reason for such equality of terms. She constitutes her view with the fact that electronic (learning) applications are not limited to the Internet. Richert (2007) defines e-learning as:

Unter E-learning wird das computergestützte Lernen (vorwiegend von Einzelpersonen) mit hypertextbasierten, multimedialen, interaktiven Systemen verstanden, das zeit- und ortsunabhängig sowohl online als auch offline erfolgen kann.

in English:

E-learning is defined as computer-aided learning (mainly by individuals) with hypertext- and multimedia-based interactive systems. The learning process can take place independent of time and location both on-line and offline.

It is important to note that the term is broader than the definition of Rosenberg, but is restricted to *learning systems*. That means concretely that electronic media like dictionaries may be included in e-learning systems as a tool, however, they can only form a part of a more general e-learning environment. Electronic media itself is not necessarily understood as e-learning system.

4.2 Classification of E-Learning Systems

E-learning systems can be classified by their degree of freedom for user interaction. On one end of the scale there are *Drill-and-Practise* programs that do not allow for freedom of interaction. On the other end there are interactive programs allowing the user to interact and control the application. Judged by the definition of Richert this classification does not seem very suitable (Richert 2007).

Another possibility to classify e-learning systems is the kind of storage media used. This classification allows for a distinction between *on-line* and *offline* e-learning systems. *Offline systems* are those systems that are offered on passive storage media like floppy disk, CD-ROM. Offline systems are usually called *Computer Based Training* (CBT) systems. *On-line systems* on the other hand are web server based systems that fall under the category of *Web Based Training* (WBT) systems (Richert 2007).

Additionally, Richert (2007) defines *hybrid systems* that are CBT systems but use the Internet as a means of communication with other learners. Table 4.1 shows the classification of e-learning systems after (Richert 2007).

		Using the WWW for storage	
		Yes	No
Using the WWW for communication	No	WBT	CBT
	Yes	Learning platforms	Hybrid CBT

Table 4.1: Classification of e-learning systems

4.3 Technical Context of E-Learning

4.3.1 Multimedia Systems

The term *Multimedia* has several definitions. Simple versions of multimedia definitions state that multimedia refers to a combination of different forms of information from several sources. Those forms can contain textual information, graphic, video and audio. With a broad definition of that kind any television news report could be regarded as multimedia. Richert (2007) understands *multimedia* more holistically than that. She sees multimedia as a technological concept that allows for the interaction of a user and a multiple media system. More than one sensorial modality should be should be presented by the system.

4.3.2 Classification of Interactivity

Interactivity can be defined in several steps. The concept of *interaction* serves as a basis for the classification, because in a sociological sense there can, by definition, be no mutual interference between man and machine. Interactivity in the sense of interaction comprises the ability to access and control different functionalities of a software system (Richert 2007).

Six classes of interactivity can be described. They differ by their degree of interaction between the user and a software system. The gamut of interactivity is used to evaluate e-learning applications:

1. **View and absorb objects**

The multimedia components can be viewed and played by the user. The user can not further influence the components in any way.

2. **View and absorb multiple displays**

Program components offer more than one display. For instance, a user could click on a picture and be shown a different one. No modification of components is possible.

3. **Varying the form of representation**

On this level, users can gain the feeling they could actively influence the multimedia components. They can scale objects or view them from different perspectives. Users can influence the form of representation but not the content.

4. **Changing the content of a component - parameter or data variation**

Contents of a multimedia component are generated by the user. Users can input data or text. They can not change films or pictures. A usage example of that type could be the selection methods of statistics programs. Users can modify objects and the program yields different results.

5. **Generating objects or the content of a representation**

This mode of interaction is reached by applications that offer tools to create and change content. For example visualise thoughts with mind maps, or render new forms and models.

6. **Constructive and manipulative actions through situation-dependent feedback**

On this level of interaction symbols can be manipulated and the result of the interpretation can be interpreted by the program. That allows for the generation of useful and context-sensitive feedback. User input can be evaluated by the application.

The gamut is described after (Richert 2007).

4.4 Pedagogical Context of E-Learning

The pedagogical context of e-learning is a crucial part of any e-learning environment. The learning targets need to be defined and a conceptual design of a software needs to be based on those.

4.4.1 Learning

The term *learning* is of a complex nature. A definition of learning is therefore never sharply confined. The definition of *learning* by Lefrancois (1994) shows how broad the term can be perceived:

Lernen umfasst alle Verhaltensänderungen, die aufgrund von Erfahrungen zustandekommen.

In English:

Learning compasses all changes in behaviour that are based on experience.

The changes in behaviour include those processes that do not aim at acquiring information, but also those changes in behaviour of an unknown cause (Lefrancois 1994). According to (Richert 2007), this means the acquisition of competences of different kinds.

4.4.1.1 Educational Objectives

Cognitive learning targets comprise all targets that include acquisition of knowledge. Knowledge can refer to both reproduction of content, but also acquiring the ability to solve problems. The area of cognitive learning targets can be differentiated further. Richert (2007) distinguishes the acquisition of:

- **Declarative knowledge or factual knowledge.** Knowledge that can be categorised as *knowing that* as opposed to *knowing how*.
- **Procedural knowledge or dynamic knowledge.** Knowledge that contains approaches to problems and their resolution procedures. Procedural knowledge can be seen as a series of declarative inventory of knowledge, nevertheless it can be categorised as *knowing how*. The distinction to the regular ability of a human to solve problems lies in the fact that declarative knowledge is needed in order to solve specific types of problems. For instance, in order to be able to successfully use a map for navigating, a human needs to know that a certain object is a map, what the symbols on the map mean and where or what the four cardinal points are.
- **Contextual knowledge.** Knowledge that contains application situations. This category is centred around *when and where* to apply knowledge. What abilities and which factual knowledge can be used in which situations?

Affective learning targets are educational objectives that aim at changing behaviour. It is difficult to actualise affective learning targets by cognitive learning only. In order to achieve affective learning targets, feelings, evaluations and attitudes of humans need to be taken into account. In learning situations at school often personal enthusiasm, credibility and charisma of the teacher play a role (Richert 2007).

Psychomotor learning targets is the class of learning targets that aim at the acquisition of manual abilities and motion sequences. That includes playing of musical instruments or using tools. Analogue to the procedural knowledge learning, theoretical knowledge about the objects involved is necessary in order to achieve the psychomotor abilities. That theoretical knowledge is a necessary condition for the psychomotor learning process, but it is not sufficient, psychomotor learning involves practising motor sequences (Richert 2007).

4.4.1.2 Self-Driven Learning

Learning is often seen as a behaviourist stimulus-reaction process. Different views observe an active and constructive process. In the constructionist view on learning there is a continuum from *self-learning* to *autonomous learning*. *Self-driven learning* can be classified by that continuum.

Self-learning defines a type of learning with a focus on the self-initiative and self-responsibility of a learner. Richert (2007) reports of the opinion that it is impossible to not self-learn, because learning always assumes the intention of the learner. This view conjectures that each learner has to accomplish the task of self-construction of knowledge. However, self-learning defines solely the self-initiative of the learner, the learning material is provided by an external source.

Autonomous learning is distinct from self-learning in the way, that it focuses on teacher-independent organisation of learning. While in self-learning, the learner can decide to learn, independently of a teacher, in autonomous learning the learner is self-responsible for defining learning targets and has an analytical view on the learning process (Richert 2007).

Self-driven learning is a type of learning that can be seen somewhere on the continuum from self-learning to autonomous learning. In self-driven learning the learner is given all instructions and decisions concerning the learning process in the learning materials. The self-direction is therefore limited to the location and the time of learning (Richert 2007).

4.4.2 Intelligent Tutorial Systems

Intelligent tutorial systems fall under the paradigm of cognitive learning. The general scheme of such a system is depicted after (Richert 2007) in figure 4.1. The declarative knowledge of a system is stored in the expert module. The student module holds information about the learning progress and the course module holds the lessons of the application. The communication module interacts with the learner. A problem of these systems is that they cannot distinguish between small oversights and serious errors. Prof. Norrick, Prof. Norrick.

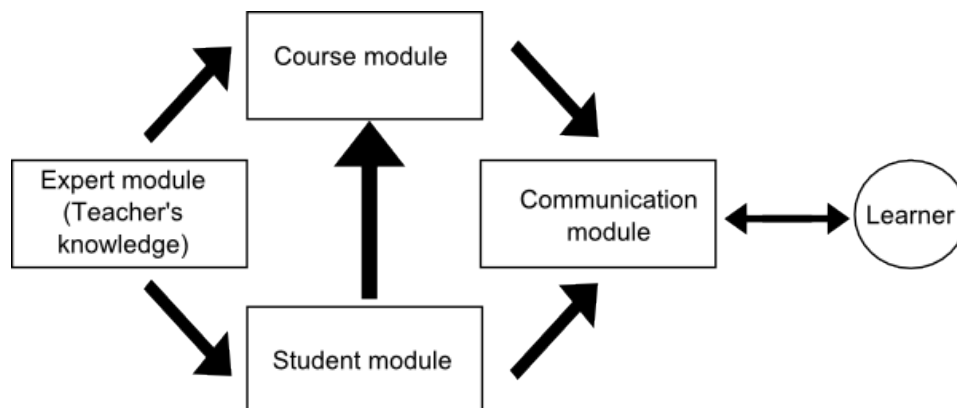


Figure 4.1: General scheme of intelligent tutorial systems

4.5 E-Learning of Languages

In *computer assisted language learning* (CALL) most the systems are not necessarily bound to the key competences for language learning. Richert (2007) defines the following key competences as possible learning foci for the e-learning of languages:

- linguistic (grammatical) competence
- socio-linguistic competence
- discourse competence
- strategic competence
- social competence
- sociocultural competence

E-learning systems can offer specific parts of the language as a learning focus. The learner decides what to learn when. Available systems, however, do not always account for this educational ideal (Richert 2007). Bailey and Meurers (2008) report about an intelligent CALL system that aims at diagnosing meaning errors. Generally, most CALL systems are based on structural analysis of language. Nevertheless, the systems often focus on fixed patterns and rely on repetition. The drill of a certain pattern is meant to automate the reproduction, however, allowing no room for creativity. The problem is that the repetition of stereotype structures is that they are just a form without a function (Richert 2007). Some e-learning systems add little or no value to the learning process, because they focused solely on the management and measurement of the training process (Ismail 2002). However, due to the impersonal nature of e-learning systems compared to face-to-face classroom work, the pedagogical acts can be objectified, free from personal animosities that might occur between a teacher and a learner (Zimmer 2009).

4.5.1 E-Learning of Japanese

4.5.1.1 Japanese CALL Systems

Some efforts for e-learning of Japanese have been made. Nagata (2002) report about the BANZAI system, that is a classical CALL application. It uses syntactical parsing in order to teach grammatical constructs. It does not aim at teaching Japanese characters, but focuses on the structure of the language. There are systems that focus on the e-learning of Japanese Kanji. These systems, by their very nature, do not comply with the key competences of language learning defined by (Richert 2007). The definition of key competences focuses mainly on spoken language, it does not account for the difficulties a learner may have in writing a language. Many Japanese e-learning systems are in fact not systems aiming at teaching the Japanese language as such, but rather only the Kanji.

4.5.1.2 Key Competences for Studying Japanese Script

The key competences¹ defined by Richert (2007) are orthogonal to those types of e-learning system focusing on the script. In addition to the key competences, other competences are needed for writing any language, Japanese in particular². More concretely, the *linguistic competence*, needs to be extended from a purely *grammatical competence* to a more general linguistic competence, including the fields *orthographic competence* and *graphemic competence*. Both are necessary conditions for a successful written communication in a language. Despite the availability of modern technologies like video conference software, and online telephony, the most popular form of both immediate and delayed communication on the internet is still written language. That means, in order for a learner to be able to participate in world-wide communication in a specific language, it is essential to be able to read and write.

¹Presented in section 4.5

²For the complexity of the Japanese writing system, see chapter 2)

Chapter 5

Conceptual Design of Kanji-Coach

5.1 Requirements of a Kanji Teaching E-Learning Application

5.1.1 General Considerations

In order to create a concept for a Kanji teaching application, a number of different aspects need to be taken into consideration. These aspects emerge from the academic background concerning the Japanese script, pedagogical and didactic knowledge about teaching languages and general conceptions of e-learning applications.

Many efforts in designing e-learning applications are focused around the teacher's view on learning. For designing an e-learning application that is useful to students, the students view needs be taken into account (Alexander and Golja 2007). Ivašin (2009) criticises the technical dominance in e-learning and e-teaching processes, as the conceptual software designs are not always supporting the didactic purpose of the software. Therefore, the user view should be taken into account when conceptually designing an e-learning application. The requirement of a *user-focused design* follows directly from this view.

For on-line e-learning, it is a known that readers only scan the textual information displayed. Therefore it is not useful to provide a user with large blocks of text, but rather with smaller chunks that encourage skimming over (Hamid 2001). It can be expected that the fact that an e-learning process happens on-line does not greatly affect the user behaviour. Therefore, the observations made for on-line e-learning can probably be applied to offline desktop application based e-learning. The requirement of *keeping textual information short and concise* derives from that observation.

If e-learning is considered as a learning method in higher education, *blended learning* seems to be the most suitable form of e-learning. Blended learning means combining classroom activities with e-learning methods (Hettinger 2008; Kahiigi et al. 2008). Language learning is not necessarily considered as higher education. In case of studying Japanese, with its specific difficulties in language and the script, language learning is taken to an intellectual level that is at least close to higher education. Thus, an e-learning application for any aspect of the Japanese language should not have the ambition of possessing the capability to *teach Japanese*. Japanese is a complex language with a complex script. E-learning applications should aim at supporting a learner's classroom efforts of studying the language. The requirement of *focusing on a specific language aspect* can be drawn from this reasoning. The prototype system designed in this work does not aim at being a complete e-learning system, but rather offers individual learning components from which a user can choose what type of learning and which component best supports his study.

5.1.2 Conceptual Considerations for E-Learning of Kanji

An e-learning application for Kanji should be an e-learning application for vocabulary at the same time. It is conceptually not useful to split those two learning tasks (Stahlmann 2004). Learning Kanji and Hànzì is a visual task. Learners need to focus on many little details concerning a character. For example, the character 曜 contains 18 strokes that are difficult to distinguish from each other in a regular script size of 11pt. It is those details that make it difficult for a learner to remember a character. Thus, it is important to direct and guide the learner's perception and comprehension of the characters towards a construct of Radicals, rather than a combination of a large number of strokes (Stahlmann 2004). When attempting to split characters into conceptual sub units for the ease of a learner, three different approaches lend themselves to this goal.

Firstly, splitting the characters into certain strokes. There are 26 original strokes in the writing system and each shape in all the characters can be drawn with a combination of those strokes (Foljanty 1984). This approach does not seem to ease the task of memorising the Kanji. It may be fairly easy to memorise 26 strokes, but the fact that around 2,000 Kanji necessary for reading Japanese consist of these strokes, does not imply that memorising those becomes any less difficult.

Secondly, splitting the characters into graphemes. There are several shapes in use in the Japanese and Chinese writing system. There are 79 graphemes in use (Hadamitzky 1995). Using graphemes as a conceptual unit for a learner seems much more useful than employing the strokes as a direct sub unit of the Kanji. Memorising all the graphemes may help a learner to study the Kanji, because all sub shapes of the characters are known. However, graphemes do not necessarily bear a meaning. Seen from a perspective of perception and cognition, the coherence between the different parts of a Kanji would be purely visual. That can help learners with an outstanding visual memory, but probably not the majority with an average visual memory.

Thirdly, splitting the characters into Radicals. Radicals are the conceptual sub units of Kanji characters and they bear a meaning of their own. The number of Radicals is larger than the number of graphemes, but not all Radicals are in use and some graphemes are Radicals themselves at the same time (Hadamitzky 1995). The Radicals do not only bear a meaning, but also have a function in character formation (see section 2.2.2.1 for typology of the Kanji). In order for a learner to memorise the Kanji, it seems useful to grasp the concept of Kanji typology and therefore character formation. Equipped with the rules of character formation and a number of Radicals the brain can link different parts of a Kanji character with other parts and other characters. For example when studying phonograms, the majority of the Kanji characters, knowledge about the pronunciation of the phonetic Radical will help the learner.

Among those three possibilities it seems most suitable to use a combination of the second and the third. Conceptually, the characters will be split into Radicals, but the system must know about the concept of a grapheme, too. Ideally, the system would have data that distinguishes both.

5.1.3 Classification of a Kanji Teaching Application

5.1.3.1 Classification in an E-Learning Context

Different types of e-learning systems have been discussed in section 4.2. In the course of designing a prototype system, design choices need to be made. The design choice for the prototype will be an offline e-learning system that runs on a desktop PC. This design choice does not follow a conceptual requirement, in fact it ignores Ivašin's (2009) criticism of technical dominance in e-learning systems. The choice is a purely technical choice, yet, it is driven by a conceptual requirement. The purpose of the e-learning environment is to test to what extend a handwriting recognition engine can help studying the Kanji. In order to examine that research question, the handwriting recognition needs to be implemented and integrated with the e-learning system. Thus, the design choice for an offline system was inevitable in the sense that the technical limitations of on-line applications form an obstacle for pen input of characters and fast recognition procedures.

According to the definition given by Richert (2007) the Kanji teacher prototype is a *computer based training* (CBT) system, as it does not use the Internet for communication or a web server for storage. According to her research, another criterion for identifying offline systems is that they are offered for distribution on CD-ROM or floppy disk. That criterion can be regarded as obsolete, as it refers to specific storage media. Even if a higher level of abstraction is used to describe the criterion, it is still obsolete, since a *passive storage medium* is not necessary to describe what the criterion actually tries to define. The criteria concerning communication and data storage are useful to confine different types of e-learning applications. Additionally, *installability* can be used as a criterion for offline e-learning systems. *Installability* here refers to *the possibility to install a software on a computer system*, not the *ease of installation*, which is defined in ISO9126 as *installability* as well (Chua and Dyson 2004). The ISO9126 type of installability will be taken into account during the software evaluation, which is reported in chapter 8.

The levels of interactivity as described in section 4.3.2:

1. **View and absorb objects**
2. **View and absorb multiple displays**
3. **Varying the form of representation**
4. **Changing the content of a component - parameter or data variation**
5. **Generating objects or the content of a representation**
6. **Constructive and manipulative actions through situation-dependent feedback**

The prototype designed in this work is aimed at a level higher than level (4) *Changing the content of a component*. It is targeted between the levels (5) *Generating objects or the content of a representation* and (6) *Constructive and manipulative actions through situation-dependent feedback*. Concretely, a user can:

- Change the ideal shape of a character by storing a new gold standard.
- Create new characters and their descriptions

- Receive situation-dependent feedback even on the newly created characters, due to the nature of the error recognition algorithm that evaluates mathematically the distance between a gold standard character and an input. Additionally, characters are analysed structurally, therefore new characters added by the user will automatically be classified and arranged among the other characters in the database of the system.

Thus, based on the levels of interactivity (Richert 2007), it can be concluded that the prototype provides a very high level of interaction. The levels serve as an evaluation measurement for the quality of e-learning applications.

5.1.3.2 Classification of Kanji Coach Among Kanji Teaching Applications

Kanji Coach is an e-learning system for Kanji characters. Its unique features are

- The internal handwriting recognition engine
- The error recognition performed by the handwriting recognition module

The conceptual use of the handwriting recognition engine is dealt with in section 5.3. The error handling concept is presented in section 5.4.

There are several e-learning systems that are centred around learning to read and write Japanese:

1. **JWPce**: <http://www.physics.ucla.edu/~groventh/jwpce.html>
Special text processing editor for Japanese as a foreign language, including dictionaries.
2. **JFC**: <http://www.physics.ucla.edu/~groventh/jfc.html>
Application for learning Kanji.
3. **JapAlpha**: <http://members.aol.com/JapAlpha/private/japa10.htm>
Application for learning the phonetic letters of Japanese.
4. **Hiragana und Katakana online lernen**: <http://www.theiling.de/schrift/#kanatop>
Web site for studying Hiragana and Katakana.
5. **Moji**: <http://moji.mozdev.org/>
Web browser extension for immediate dictionary lookup of Kanji.
6. **KanjiQuick**: <http://www.kanji.de/>
Dictionary for Kanji-German with a translation module and a text to speech module.
7. **Kanji Gold**: <http://web.uvic.ca/kanji-gold/>
E-Learning application for studying Kanji.
8. **KanjiGym Light**: <http://www.kanjigym.de/>
E-Learning application for studying Kanji with the Heisig system.¹
9. **Tagaini vocabulary teacher**: <http://www.tagaini.net/>
Vocabulary teacher for Japanese.
10. **Online vocabulary teacher**: <http://www.vokabeltrainer-online.net/>
General vocabulary teacher for several languages including Japanese.
11. **Kanji Teacher of SZSB**: <http://szsbls3.szs.uni-saarland.de/kanji/>
Online e-learning application for studying Kanji.
12. **Skritter**: <http://www.skritter.com>
Online e-learning application for studying Kanji including a handwriting input.

Among the various e-learning applications centred around Japanese there are three different types of applications.

1. **Dictionaries**. In the dictionary type of applications it is possible to look up a Kanji and receive a translation in a different language, mostly English, sometimes German. Among those JWPCE is the most developed in the sense that it provides a Radical lookup. A user can choose a number of Radicals in a matrix of Radicals and the dictionary finds appropriate characters.
2. **Vocabulary teachers**. Vocabulary teaching applications provide interfaces for word look-up and foreign word input with either Unicode input or Latin transcription of Japanese words.

¹The Heisig system is a method for studying Kanji, discussed in section 2.3.

3. **Script teachers.** Script teaching applications are designed as two different types. Multiple choice applications and handwriting input.

- **Multiple choice.** The large majority of e-learning applications teaching the Japanese script (either the two types of Kana or the Kanji) have to use multiple choice for character input. The reason for that is that modern Input Method Editors (IME) allow for a Latin input of Japanese words and provide the Kanji for the user. If the application would prompt the user with a task like *What Kanji is pronounced 'inu'?* the user would have to type 'I-N-U' in order to be presented with the character 犬 by the IME. In other words there is no cognitive task for the user except reading Latin characters from the screen and typing them on the computer keyboard. Since that does not help with the task of learning the Kanji, the only chance is multiple choice. The user is presented a set of characters and is asked to click on the one that had been asked for.
- **Handwriting input.** There are only two applications that use a handwriting input method in order to teach the Kanji. However, none of the applications performs a handwriting recognition. Those two applications are *Skritter* and *KanjiGym Light*.

Skritter uses a kind of stroke-based similarity measure for individual strokes. When the system prompts the user for a specific character, it allows only the next correct stroke of that character as user input. Concretely, the user can just try to write any stroke. If it is close enough to the next correct stroke, it will be morphed into an idealised picture of that stroke. If not, Skritter will show the correct stroke. The system is clearly not a handwriting recognition system.

Figures:

- Figure 5.1 shows that Skritter does not allow any incorrect input by the user. If the user tries to input an incorrect stroke the correct stroke is shown on the screen. That feature avoids any learning from one's own errors, because the correct stroke is always given.
- Figure 5.2 shows the way Skritter morphs a user input to the correct position. The stroke length is adapted to fit the character. The user's error concerning the stroke length disappears immediately without any comment by the system. The system only comments incorrect stroke direction.
- Figure 5.3 shows the high tolerance that Skritter allows when morphing. The user input stroke has the correct shape and the right direction, but the euclidean distance of the input stroke and the ideal stroke is large. Nevertheless Skritter accepts that stroke as a correct input without a comment or feedback to the user.

KanjiGym Light does not perform a handwriting recognition. The application provides a canvas for writing characters. The user can input a character and then click a button named *check*. The correct character appears next to the user input and leaves it to the user to compare for correctness. There is an accept and a discard button.

- Figure 5.4 shows the user input canvas in KanjiGym Light.
- Figure 5.5 shows the way KanjiGym Light has the user compare his own input with the original character.

5.2 Approaching the Specific Difficulties of the Japanese Script

Section 2.3 deals with the typical problems that learners face when studying the Kanji. The Japanese script inevitably bears some difficulties when attempting to study it. The application should care for these problems by supporting these issues. They can be approached by providing not only a handwriting input for the user but also a handwriting recognition engine that gives informed feedback to the user.

5.2.1 Character Learning Aspects

The specific problems mentioned in section 2.3.1 are:

1. **Similar Kanji**
2. **Compounds**
3. **Unusual readings**

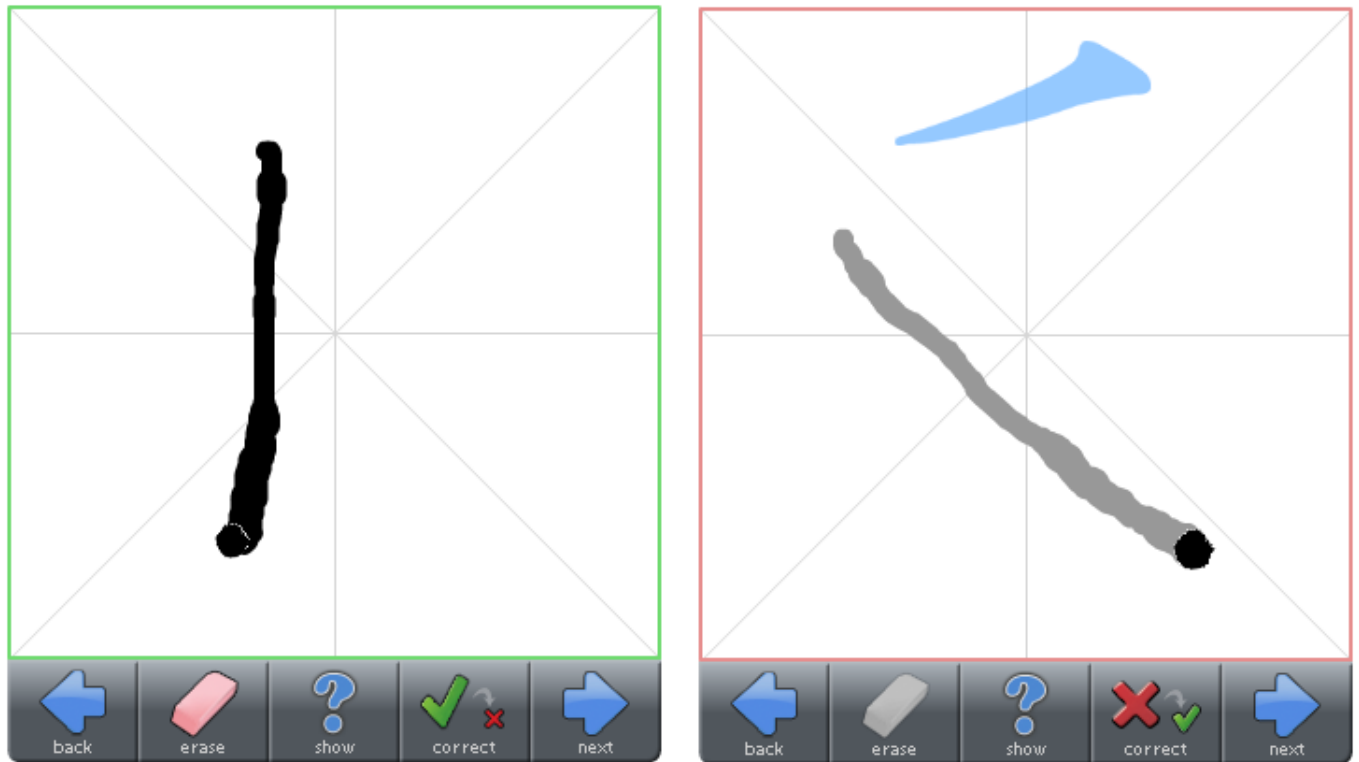


Figure 5.1: Skritter does not allow incorrect input

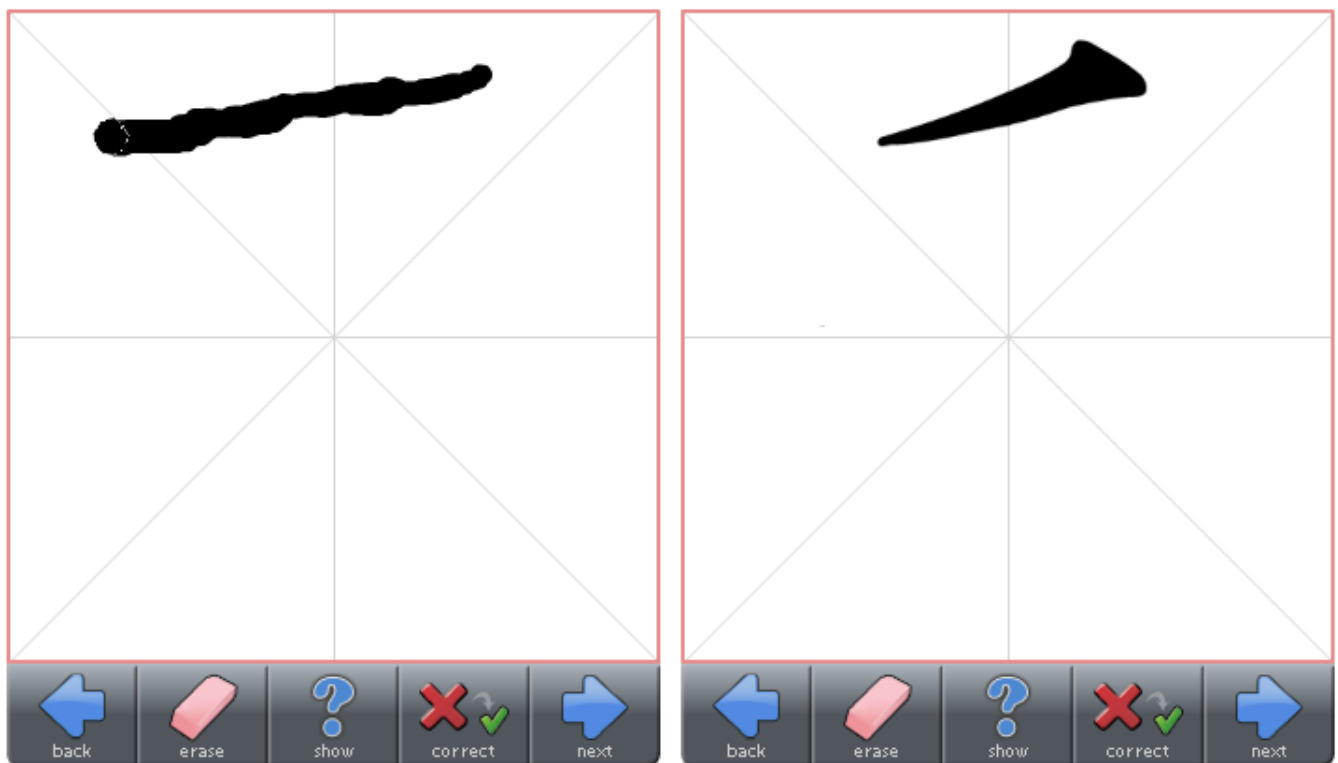


Figure 5.2: Skritter morphs user input to correct strokes

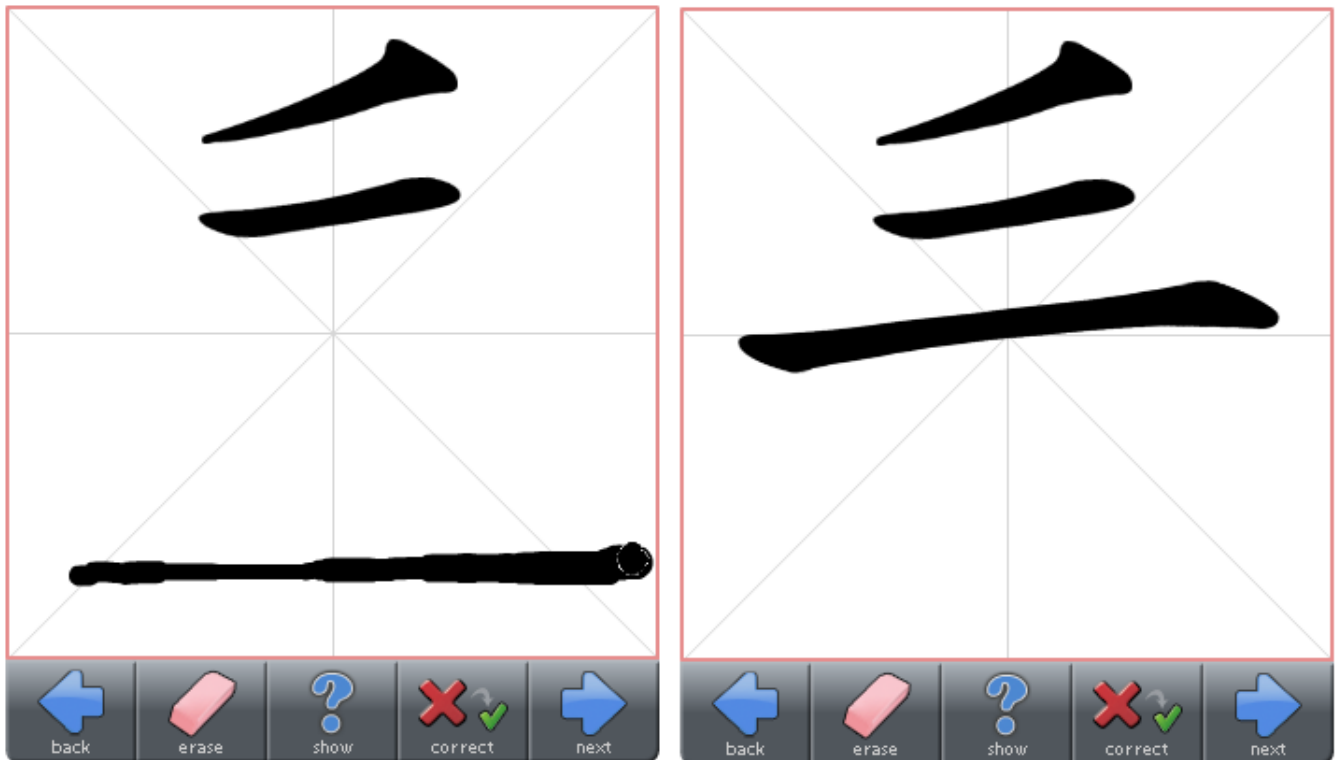


Figure 5.3: Skritter employs a very high tolerance when morphing user input

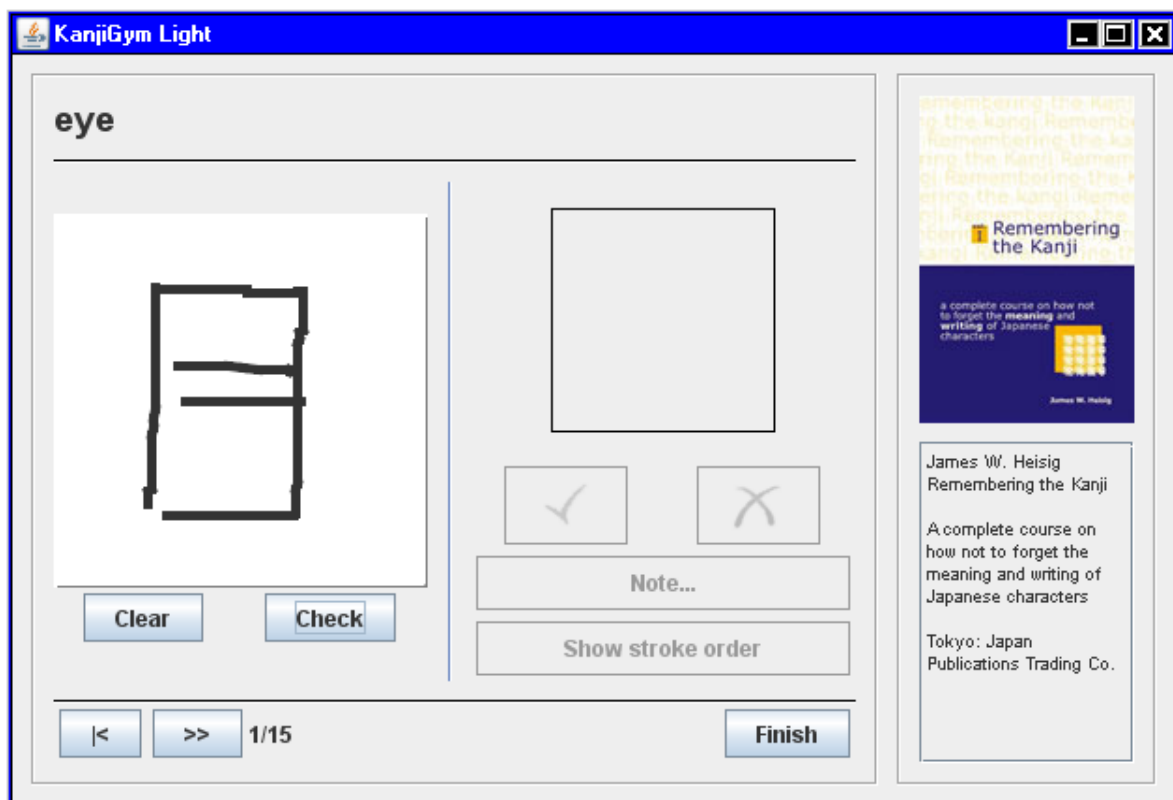


Figure 5.4: KanjiGym Light character input

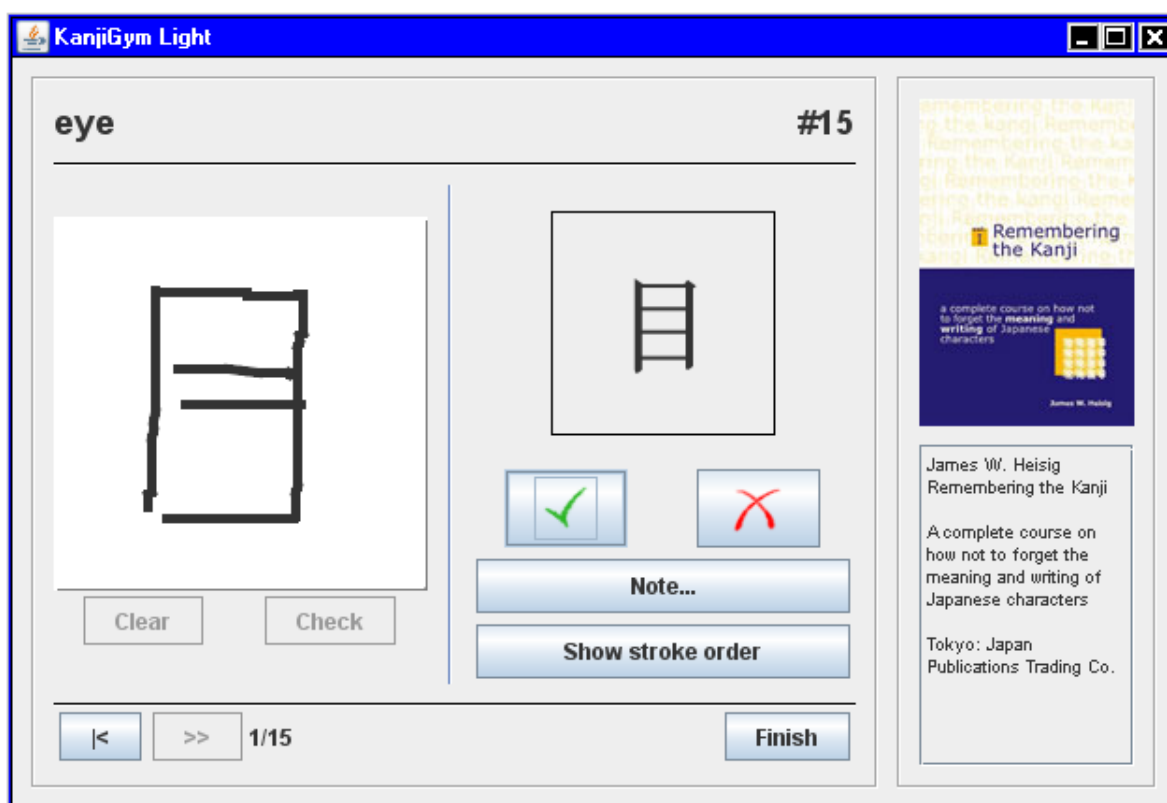


Figure 5.5: KanjiGym Light checking correctness manually

4. **Alternative Kanji**5. **Homophones**6. **Infrequent Jōyō Kanji**7. **Non-Jōyō Kanji****5.2.1.1 Problems Outside the Scope of the Prototype**

A Kanji teaching prototype cannot provide solutions for all of those problems, but for some. It cannot provide a satisfying solution for problem 2 as the prototype deals with single characters only. It is not useful to provide a solution for problem 3 because studying the main reading of a character is most important at the beginning of studying Kanji. Especially, when studying a new character, the learner should focus on the character shape and the main reading, not on unusual alternative readings. Kanji Coach aims at teaching the Japanese script, not the full Japanese language.

Kanji Coach cannot provide a solution for problems 6 and 7, memorising infrequent Jōyō Kanji and Non-Jōyō Kanji. These characters are difficult because they are infrequent. It seems more suitable for a learner to study the frequent characters first in order to learn reading and writing. Thus, it is not plausible to pay special attention to this group of characters by presenting those more often to the learner.

5.2.1.2 Problems Inside the Scope of the Prototype

The two main problems for learners of Japanese Kanji are

- Similar Kanji (problem 1)
- Homophones (problem 5)

Those two will be dealt with in the prototype. Additionally, the problem of

- Alternative Kanji (problem 4)

is targeted by the e-learning application.

Similar Kanji are the major issue for a learner of Japanese. The prototype *Kanji Coach* provides a solution for this difficulty. The solution does not necessarily contain the employment of specialised lessons for similar-looking Kanji. The reason for that is that it is more suitable for the human brain to study material that belongs to the same range of topics. Similar looking Kanji often do not have a connection to each other except their visual similarity. Therefore, studying them together does not seem useful, unless they are semantically similar, too, like for instance the characters for *speaking* 話, *state/give instructions* 誥 and *language* 語 that also belong to the same Kanji class, as their key Radical is the same.

Homophones are a general difficulty for learners of the Japanese language. Many words are phonetically ambiguous. The context can provide a better understanding, but often it is necessary to see the written Kanji character in order to know what is meant with an expression (Foljanty 1984). Therefore, it is essential to deal with problem 5.

Conceptually, this issue can be solved by providing special lessons that focus on homophones. Homophones in Japanese are not necessarily homographs and therefore not homonyms in the strict sense. True homonyms are those word pairs that are both homophones and homographs. In languages using Latin characters, homophones are often homographs at the same time, e.g. German *Schloss* (Eng. castle) and *Schloss* (Eng. lock). This is due to the fact that the spelling roughly mimics the speech. The pairs that are both homophones and homographs are called homonyms. Sometimes, homophones are not homographs, e.g. the verbs *dye* and *die*.

In the course of studying the Kanji, it is part of the study process to learn to distinguish the characters that are pronounced the same. For instance, there are roughly 80 distinct characters that share the pronunciation *kyo*. Table 2.2 on page 16 shows several Kanji that are pronounced *ki*. The prototype provides a lesson that is centred around the homophone Kanji characters and their distinction.

Alternative Kanji is an issue that can be dealt with in an indirect way. Following the concept that frequent characters and the main reading should be studied first, Kanji Coach does not provide any special form of presentation for this group of characters. However, it has the ability to recognise alternative Kanji. In a scenario where a user is asked to input a certain character, an alternative character with the same meaning would be accepted. For instance, if a user is prompted for the character for the number *one*, which is usually written as 一, but enters the character 壱 instead this input would be regarded as correct. Additionally, the user is presented with a hint that another character with the same meaning exists. The focus lies on studying the frequent characters, therefore there are no special lessons concerning alternative Kanji.

5.2.1.3 Character Repetition

In section 4.5 the pure repetition of grammatical structures as a learning method has been criticised. The system should account for that by not just forcing the user to reproduce fixed structures. In fact, it should leave room for creativity. The system does not provide a free-drawing module in order to allow for total creativity. But creativity is given through the use of the handwriting input as such. A user can practise his own writing style. The tolerance thresholds given by the character recognition module allow for an interpretation of the character shape, rather than a pure repetition.

Similar to the multi-radical look-up in JWPCE a learning task for a user of the Kanji e-learning prototype *Kanji Coach* could be the combination of different radicals to a Kanji character. That would allow for creativity and also appeal to the cognition because it is more demanding than merely repeating the shapes that were given before.

5.3 Integration of HWR Into the Learning Process

The learning process of Kanji is driven by understanding the structure and meaning of the characters and memorising the shape (Stahlmann 2004). In order to study and memorise, many learners rely on repeating to write the Kanji. That approach seems most natural and can hardly be replaced by any other method. Nevertheless, the method can be changed to be more challenging to a user and thus create some level of excitement. This is done by combining it with different tasks where the user does not see the character before having to write it.

5.3.1 The Motivation for Using a HWR

The fact that learning to read and learning to write are highly interwoven processes suggests that both should be studied together. In standard class room learning environments that is the case. Learners read texts, learners are presented with new Kanji and learners are asked to reproduce the Kanji when writing essays. An e-learning application can not perform the teaching effort of a full language course. In order to provide a complementary

addition to a language course, the prototype should create an environment that increases the user's regalement for tedious learning tasks.

The repetition of writing characters in order to memorise them does not appeal to the majority of the learners. Especially having to write on paper repeating the same character over and over again does not awake inspiration and creativity. An e-learning application with an integrated handwriting recognition engine that provides corrections for the user input has two main functions:

- Making the repetitive task of training the muscular memory less tedious.
- Helping the learner overcome difficulties in writing the Kanji by giving informed feedback.

In order to train the muscular memory and memorise the Kanji, repetition is needed. The same amount of written characters can seem less repeating simply if the characters are not written in a row. Additionally, using a technical device can be more emotive and help increasing the user's motivation and self-discipline. (Ismail 2002; Richert 2007) criticised that some e-learning applications do not add a value to the learning process.² The prototype proposed in this work does add value to the learning process. Additional value over practising to write characters on paper is added by the following features:

- The general ability of the application to prompt the user with different characters in an ordered or random fashion.
- Presentation new characters, their meanings, pronunciation and stroke order.
- Characters are organised in lessons and related characters are presented in combination with each other in the same lesson.
- The methods
 - Writing a Japanese character after being prompted an English word, instead of purely drawing lines without an additional cognitive anchor.
 - Writing a Japanese character after being prompted a Japanese word.
- The error correction that comes with the handwriting recognition. The user is less dependent on a teacher and can study in his own time and pace, yet still get informed feedback.

5.3.2 Character Recognition

The type of character recognition is crucial for the abilities of the system concerning error processing. Highly optimised handwriting recognition systems perform a fast and reliable handwriting recognition. However, those systems often do not have a record of the internal structure of the characters.³ Since understanding of the structure of the characters is important for a successful learning process, the error correction needs to focus on the internal structure of the Kanji characters. Studying the character shapes can be performed as a purely visual task. Studying the full characters and grasping their construction is a cognitive task that combines visual memory with linguistic information. Thus, the error correction must provide structural error levels, considering the internal character structure. Following that concept even further, the character analysis must be structural as well. The prototype performs a structural character recognition.⁴ Structural character recognition means that it performs a structural analysis of the characters in order to obtain a symbolic value for the character, in this case a unicode value.

5.4 Handling Errors

Having a handwriting recognition that gives informed feedback about the question if the entered character was correct is an approach that allows for additional analysis and feedback. Because of the structural analysis of the characters during the recognition process it becomes possible to provide feedback about errors on a graphemic, phonetic and semantic level.

²For details see section 4.5.

³See chapter 3 for details.

⁴Details about how the character recognition is performed on a technical level can be found in chapter 7.

5.4.1 Motivation for Error Recognition

The motivation for error recognition has been broached in the previous sections. The main reason is that a user needs be given a chance to learn from his own errors. In any relation between a student and a teacher, concerning any subject matter the teacher has the task to inform the student about mistakes. The teacher provides corrections to the errors of the student when trying to fulfil a task. The student can learn by improving what he had done wrong before.

For an e-learning application it is difficult to provide an informed error correction. The reasons for that lie in:

- The limitations of communication between the machine and the user: in the most common scenario the user interaction is limited to typing with the keyboard and clicking with the mouse
- The limitations of user input analysis. For text strings most of the times only exact matches are accepted. Some types of analyses are very difficult to perform, including syntax analysis and handwriting input. That is the reason for most interfaces to perform a simplified or a partial analysis of the user input or no analysis at all.
- Limited knowledge within the application about potential user errors.

In Kanji Coach these limitations shall be weakened. The communication between machine and user is actualised with an intelligent user interface, a canvas that takes handwritten characters as input. The limited user input analysis is approached with the interpretation of the strokes as a Kanji character. Knowledge about possible sources of error is stored in the application's knowledge base, such that the third limitation has a less severe impact into user experience.

5.4.2 Possible Sources of Error When Writing Japanese Characters

There are seven different sources of errors for learners when writing Kanji characters. These error categories are:

- Stroke level errors
- Radical level errors
- Character level errors
- Linguistic level errors
 - Phonological errors
 - Morphological errors
 - Semantic errors
 - Lexical errors

Stroke level errors

- **Stroke length:** A stroke has been drawn by the user with an incorrect length.
- **Stroke direction:** The stroke has been drawn from the opposite direction or the general stroke direction, the absolute angle with respect to the X-axis was deviant.
- **Stroke angle:** If the stroke has a corner the angle of in the corner can deviate from the angle of the original stroke.

Radical level errors

- **Stroke number:** The number of strokes in the Radical is different from the number of strokes in the gold standard Radical.
- **Stroke sequence:** The sequence of strokes within the Radical is different from the ideal stroke sequence.

Character level errors

- **Incorrect Radical:** A Radical used within the character is not correct as it was confused with a different one by the user.
- **Incorrect number of Radicals:** An additional Radical has been added to the character or a Radical is missing.

Linguistic level errors are a super-category of other error category. The errors on a linguistic level do not concern the character input directly but rather the language and the use of the characters. The linguistic errors can be subdivided into phonological, morphological, semantic and lexical errors, where the latter ones have only a subtle distinction.

Phonological errors are errors concerning Kanji readings. If a user writes a character with the same reading as the character in question it is likely to be a confusion based on the phonological features of the two characters. The Japanese language has a large number of homophones that abet this type of confusion.

Morphological errors are mainly concerned with suffixation. If a Kanji character and additional Hiragana characters in order to form a word, these Hiragana characters are called *Okurigana*.⁵ The error of adding incorrect Okurigana to a Kanji character can be classified as a morphological error. As the Kanji Coach prototype deals with single characters only this error type is not applicable.

Semantic errors are those errors where a user confuses two characters with a similar meaning. For example, the words 食べ物 (Jap. pron. タベモノ / tabemono; Eng. lit. *thing for eating*; Eng. *food*) and 飲み物 (Jap. pron. ノミモノ / nomimono; Eng. lit. *thing for drinking*; Eng. *drink*) can be confused easily on a semantic level. The same is true for the individual characters.

Lexical errors are the errors where a user uses a character with the same meaning. Those are not real errors. This falls under *alternative Kanji* that have been discussed in section 5.2.1.2. This type of error can be compared to using a synonym in a vocabulary test. The word was not the word asked but the answer is not incorrect either. Therefore, lexical errors do not need special attention the the prototype application.

5.5 Use Cases

The uses cases presented in this section are oriented towards the conceptual design presented in the previous chapters. The startup screen of the application is presented in figure 5.6. There are four different modes to choose from.

1. View mode
2. Follow mode
3. Exercise mode 1
4. Exercises mode 2

The user can employ different modes for self-directed study. In view mode, the characters and information about those are just presented to the user.

Figure 5.7 shows the view mode. On the left side of the screen the character is presented to the user. On the right side of the screen information about the character are displayed.

The first interactive character learning mode is the follow mode shown in figure 5.8. In follow mode, a character is shown and the user can follow the character lines that are shown on the screen.

The input in follow mode or in the other modes can be drawn on the mobile input area. That guarantees the ability to use a stylus. Figure 5.9 shows a drawing on the mobile device. In exercise mode 1 the user is presented an English word and is asked to draw the appropriate Kanji character. Exercise mode 2 works the same way, just the user is presented the Japanese reading of a character instead of the English word.

Figure 5.10 shows the screen of exercise mode 1 with a user input. The user input is mirrored from the mobile device as shown in figure 5.9 before. After the character recognition and error detection is performed, the application can return an analysis to the user. In this case the input was not quite correct. As seen in figure 5.8 in order to write the character for 'root', which is written 本, there is one stroke missing in figure 5.9 and the mirrored image in figure 5.10.

Incorrect stroke number is one of the errors defined in section 5.4.2. It is in the *Radical error level* as there is a stroke missing in order to finish the Radical. There is no error in character level. In this special case the character is a Radical. The error 'missing stroke' is relevant to the Radical level.

Figure 5.11 shows the error message and the feedback for the user. A missing stroke is just a minor error, therefore the user is presented a positive feedback.

⁵For a detailed description of what Okurigana are, see section 2.2.3.

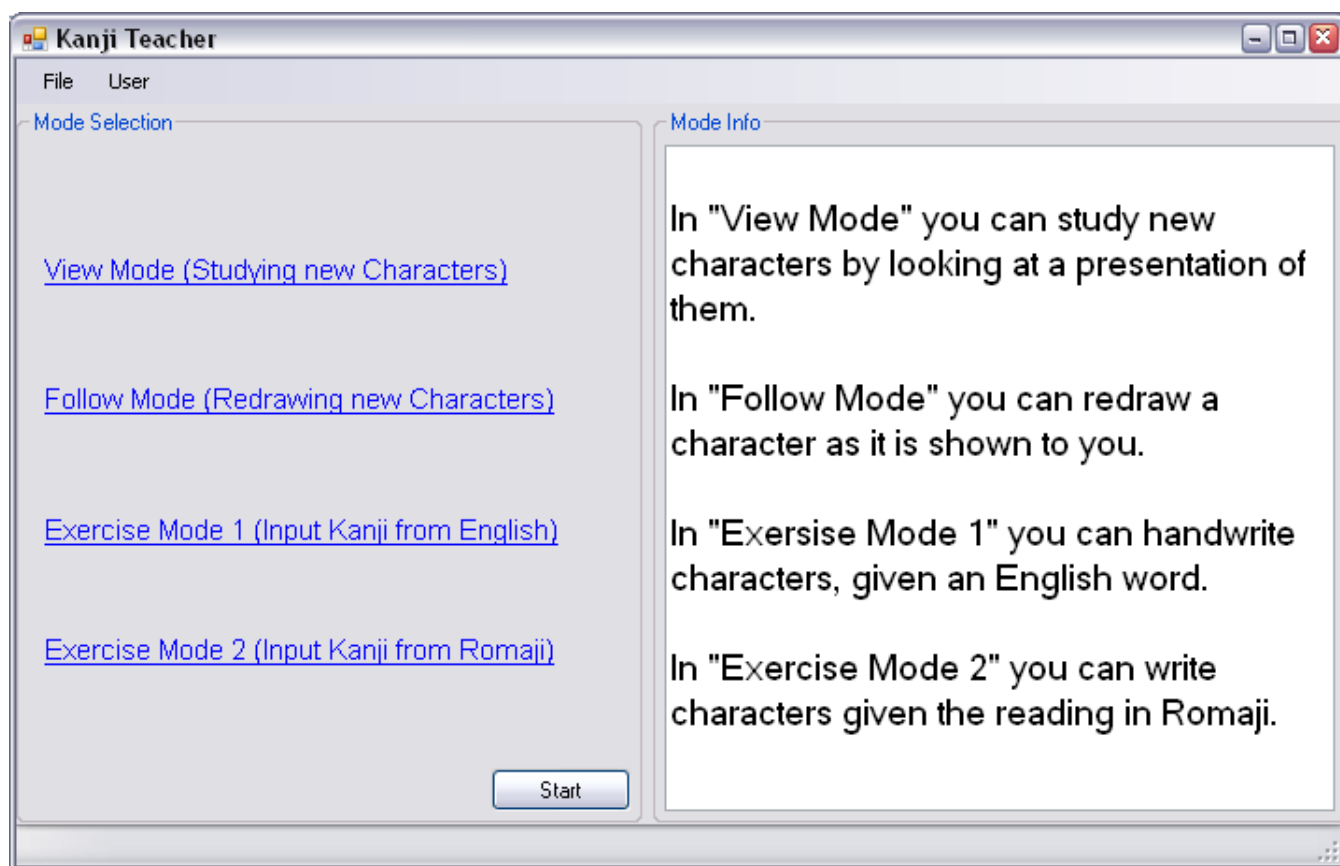


Figure 5.6: Startup screen

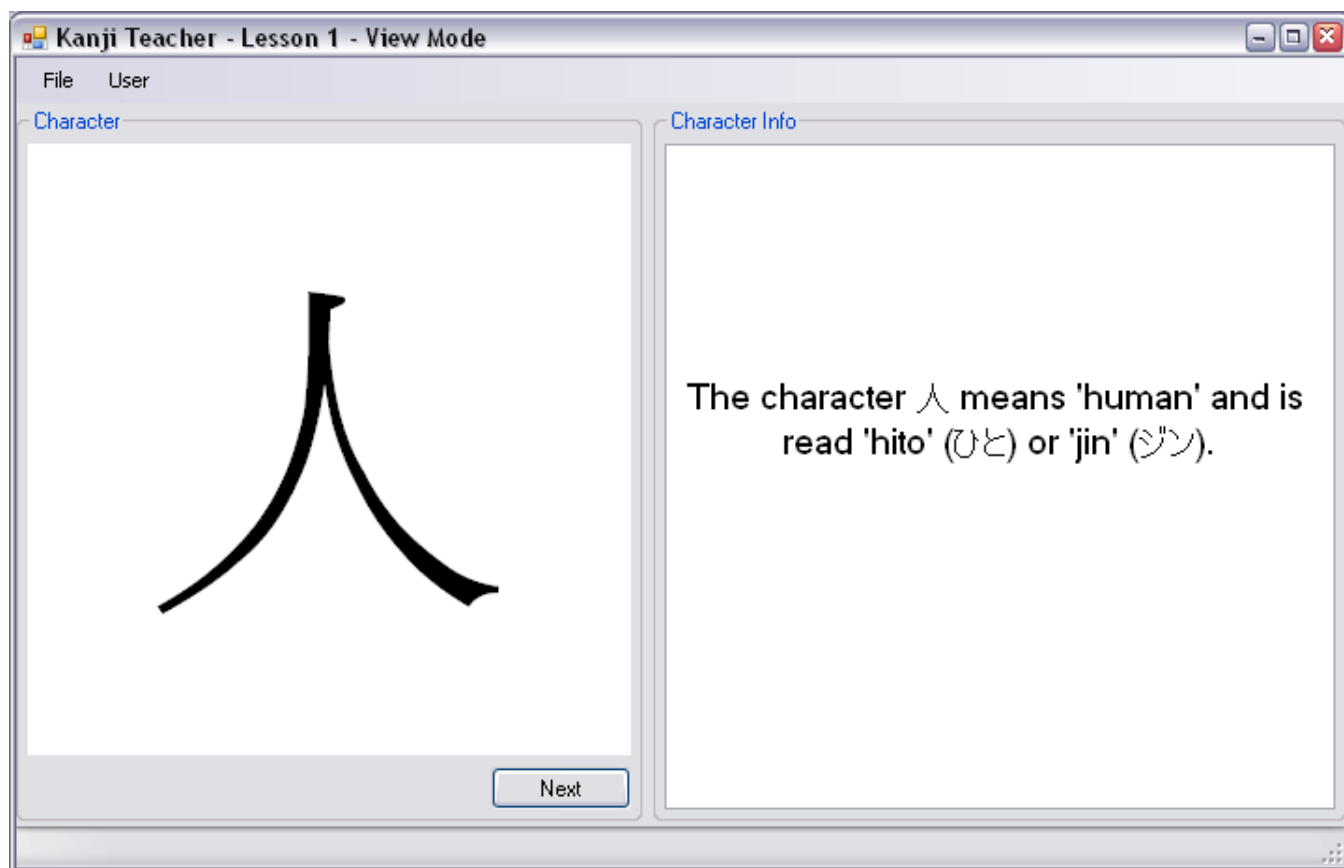


Figure 5.7: Character view mode

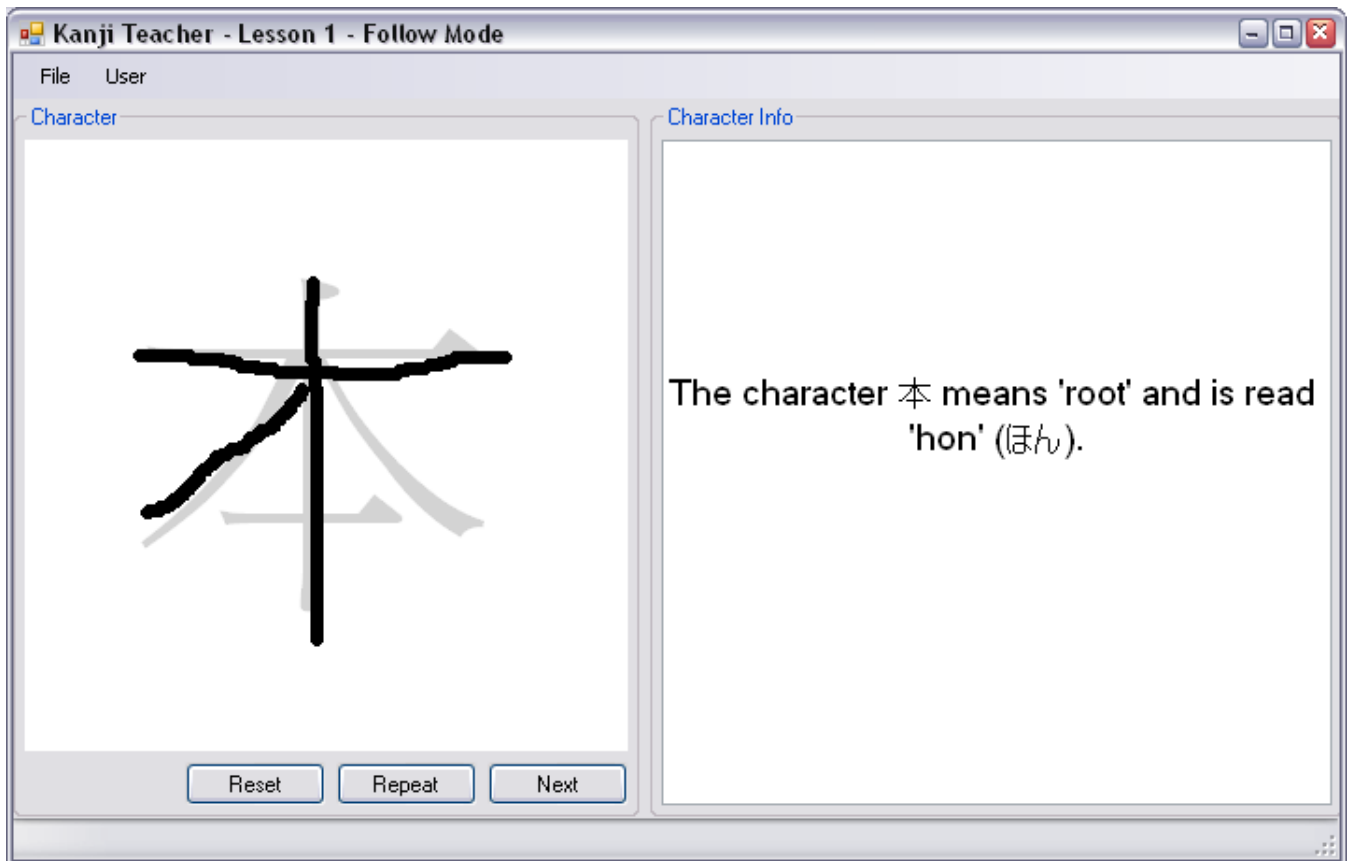


Figure 5.8: Follow mode for drawing new characters

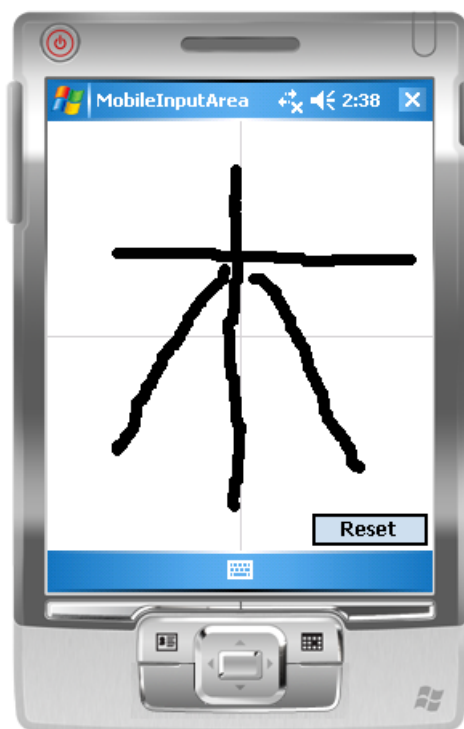


Figure 5.9: Mobile device character input

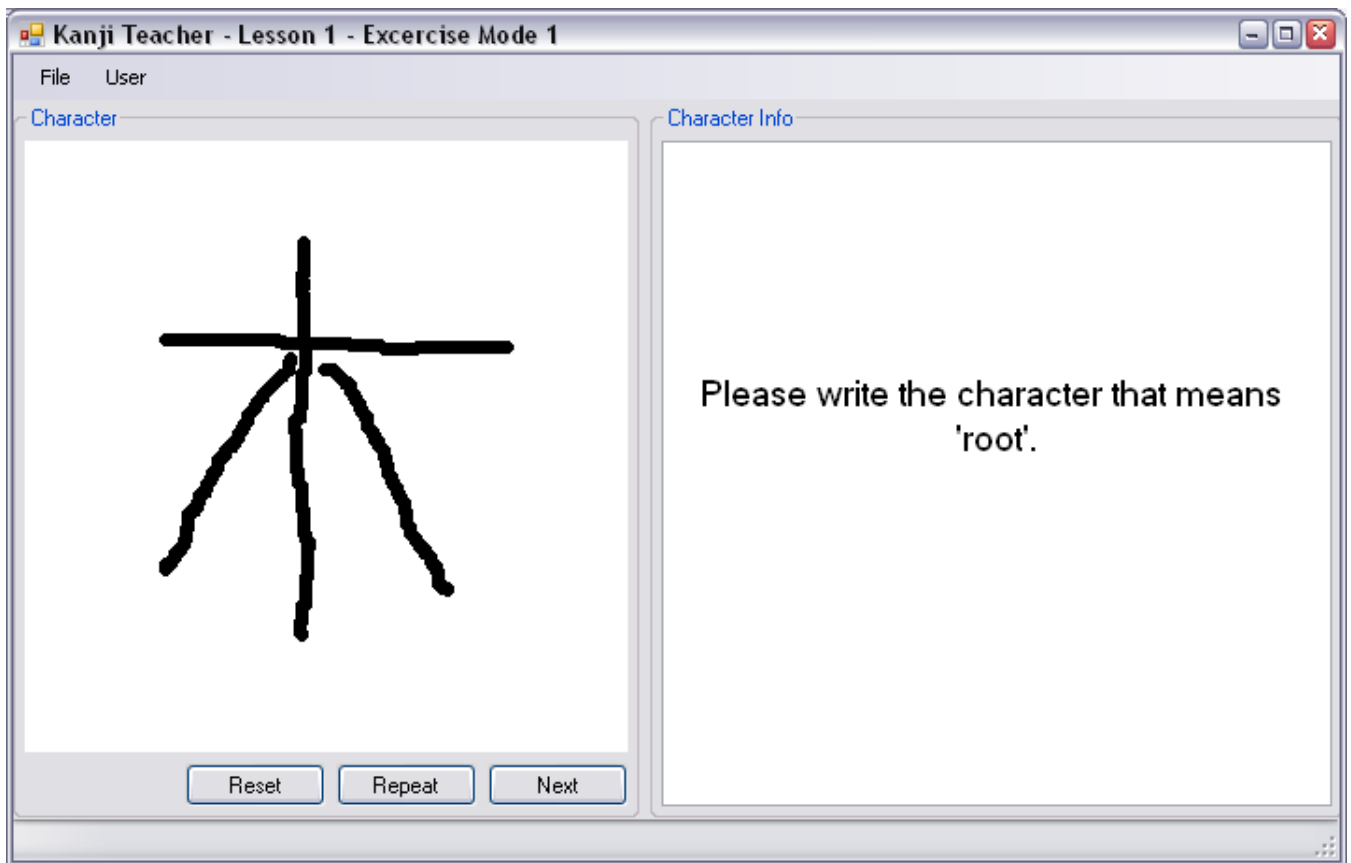


Figure 5.10: Exercise mode 1 for input of Kanji from English source

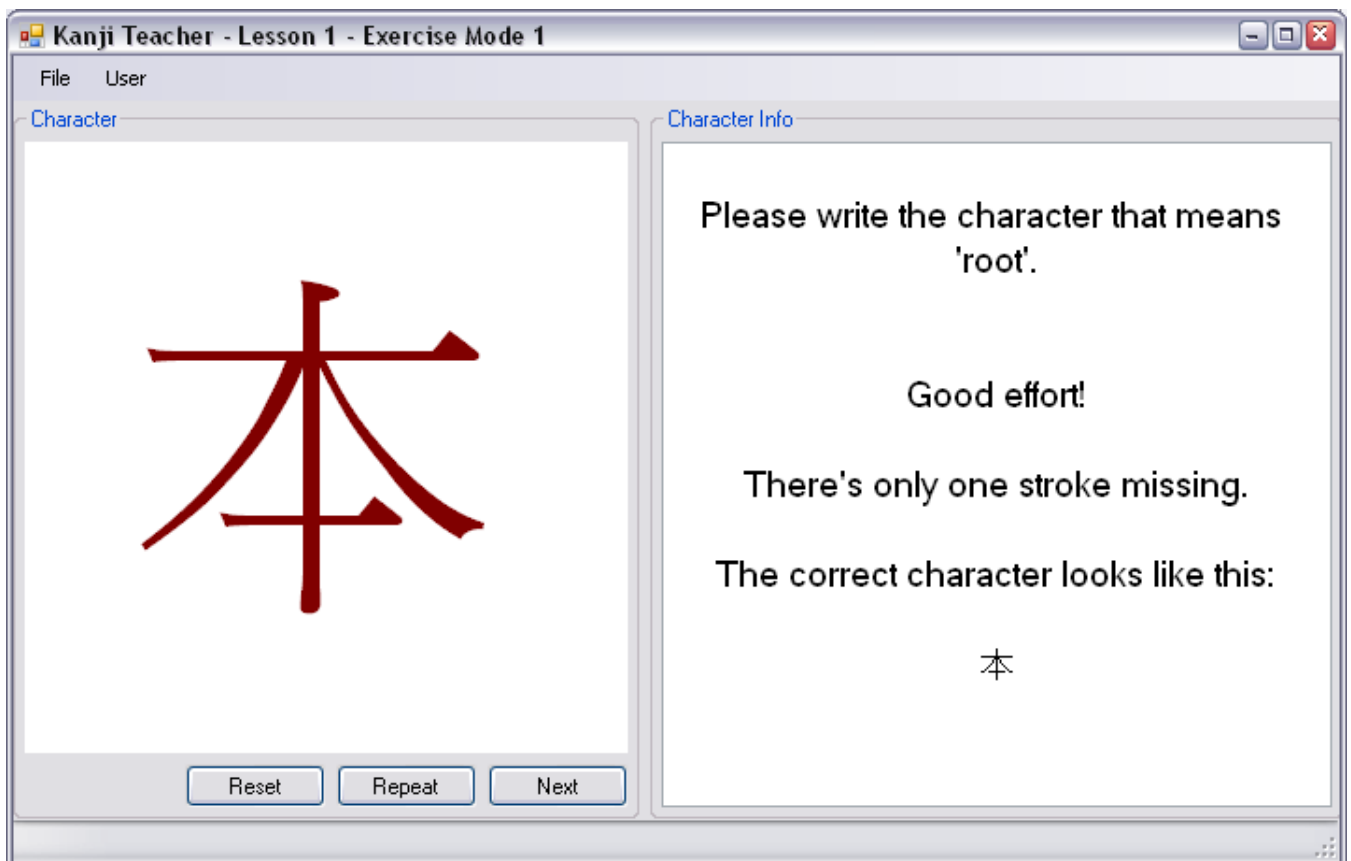


Figure 5.11: Exercise mode 1 after user entered almost correct character

Chapter 6

Technical Design of the Application

The focus of this chapter is on the general architectural choices made during the development of the system. In this chapter, the technical design aspects of the application are described. The general system architecture is laid out in section 6.1. It contains the global view on the software architecture in section 6.1.1, the data flow in within the system in section 6.1.2 and describes the design of the individual modules in section 6.1.3. Section 6.2 describes the technical set-up and framework choices. However, the handwriting recognition engine is described in detail in a separate section.¹

6.1 System Architecture

The system architecture of the Kanji Coach follows the requirements of an e-learning environment dealing with the specific difficulties for learners of the Japanese script (see chapter 2) and those of an on-line handwriting recognition. Techniques of handwriting recognition are reviewed in chapter 3. The general requirements of an e-learning application are presented in chapter 4. The resulting specific conceptual design choices have been laid out in chapter 5. This section deals with the technical aspects of the system design.

6.1.1 Global Architecture

The global architecture of the application follows the Model-View-Controller (MVC) design pattern. This paradigm is used as a general model, however, it is not designed the strict way proposed by (Krasner and Pope 1988). Figure 6.1 shows the general set-up of the MVC design pattern after (Krasner and Pope 1988) the graphic is borrowed from (Schatten et al. 2010). In the MVC paradigm the *model* is a domain-specific software, an implementation of the central structure of the system. It can be a simple integer, representing a counter or it could be a highly complex object structure, even a whole software module. The *view* represents anything graphical. It requests data from the model and displays the result. The *controller* is the interface between the model and the view. It controls and schedules the interaction between the input devices, the model and the view (Krasner and Pope 1988). A global overview of the system architecture is shown in figure 6.2. There are two main architecture areas and two devices:

- The mobile input device with the input module.
- The desktop application including the main modules for learning and character recognition.

The

6.1.2 System Data Flow

The system data flow is shown in figure 6.3. The controller lies in the centre of the application, it runs on the stationary device. It contains a web service that is used as an interface to receive data from the handwriting input data view. The desktop view is the main interaction point for the user. The model contains the logic, while the data access layer provides a reusable interface for storing data. The details of figure 6.3 are described in subsequent sections 6.1.2.2 and 6.1.2.3.

¹See chapter 7.

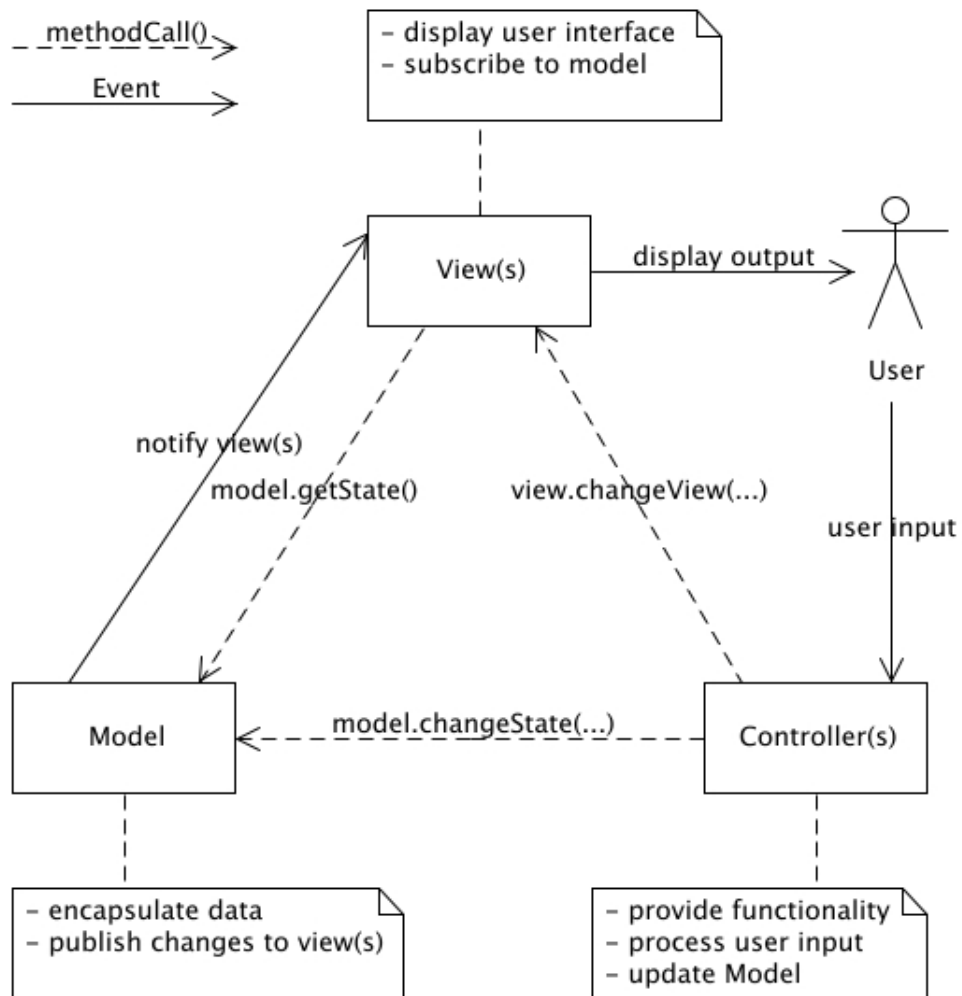


Figure 6.1: The Model-View-Controller paradigm

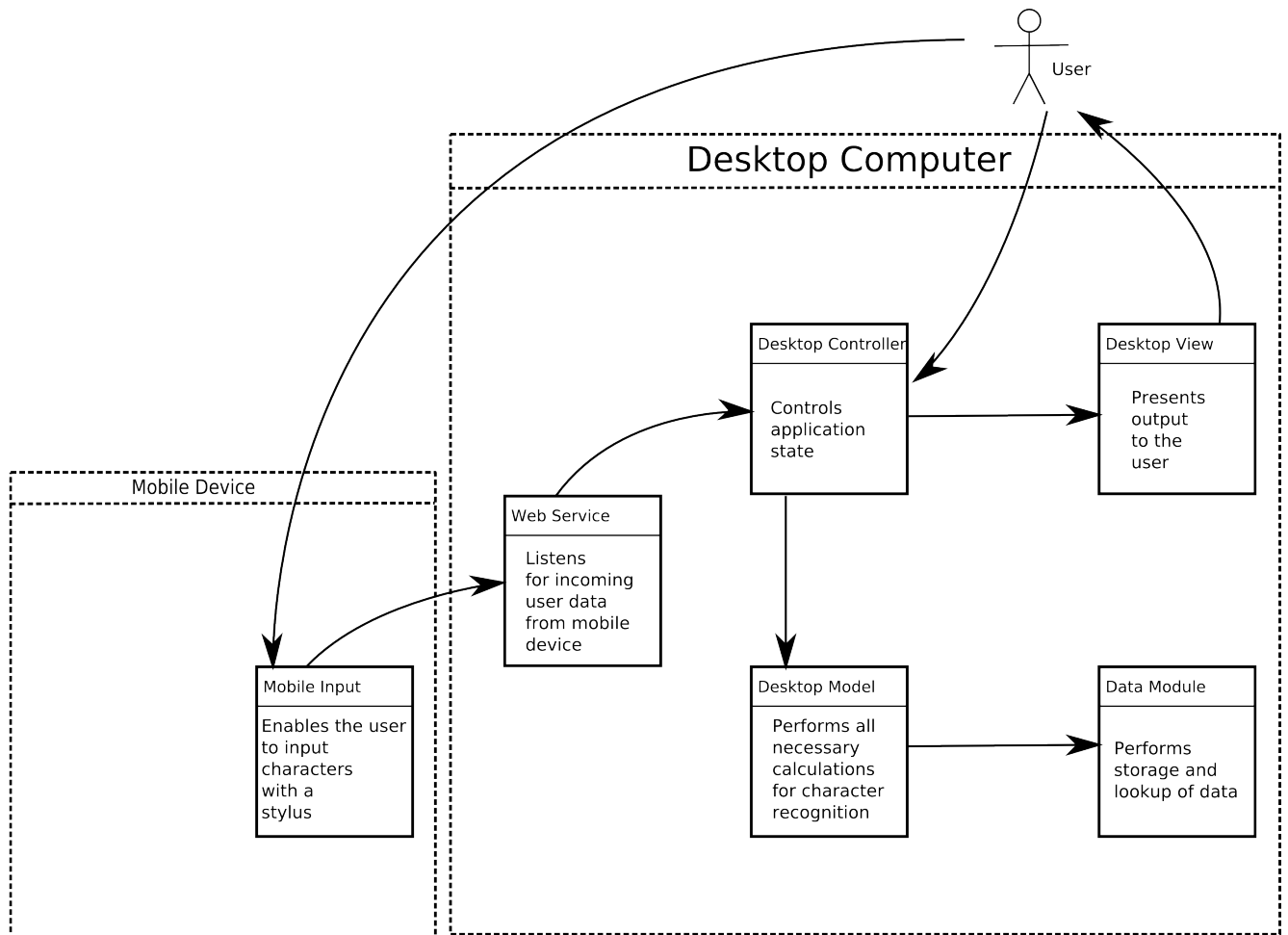


Figure 6.2: The global architecture of the software system

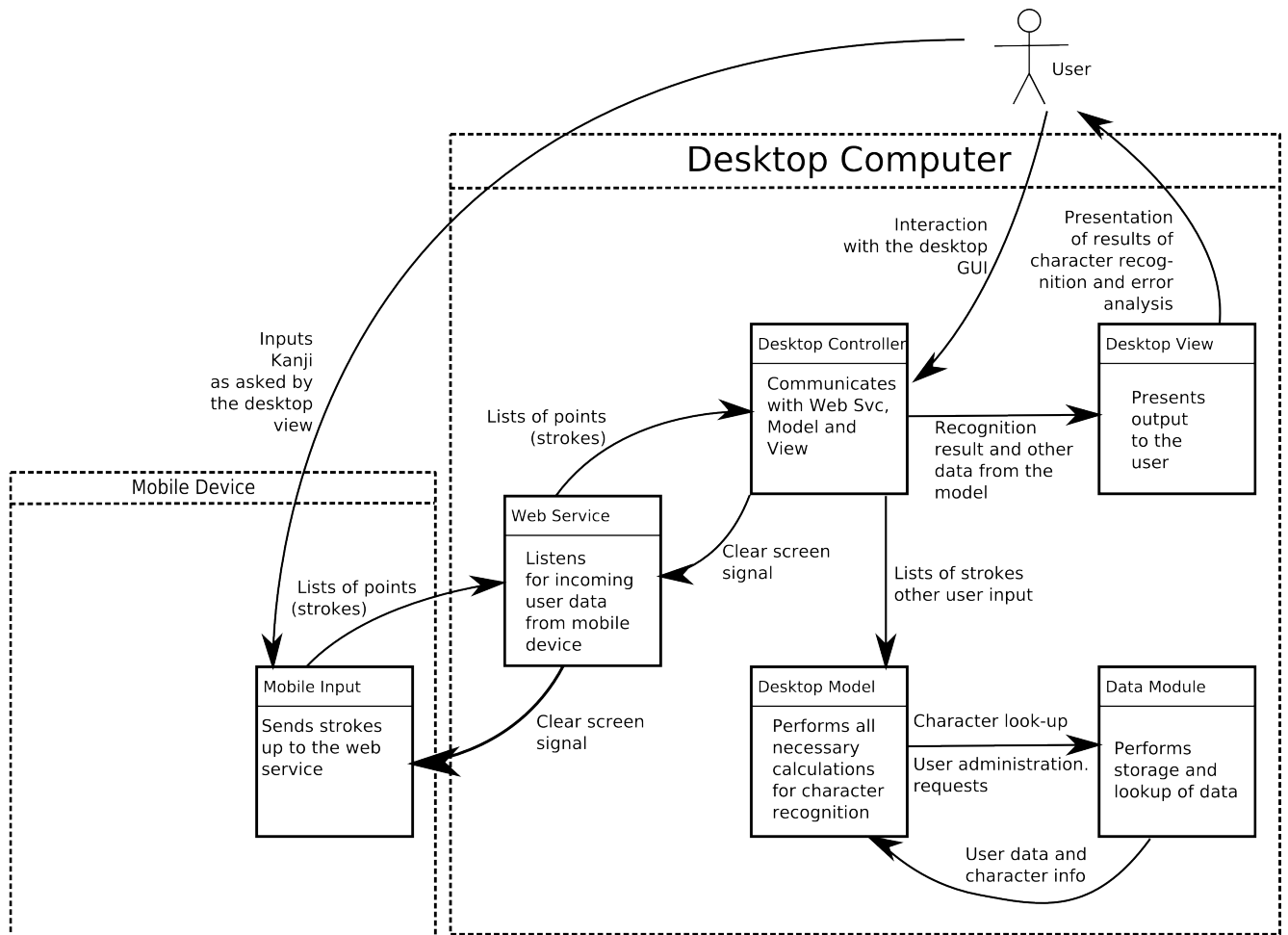


Figure 6.3: The data flow within the software system

6.1.2.1 Communication

The communication between the different parts of the application is realised in two independent and distinct ways. The communication between the modules running under the same process is realised via a messaging system. The communication between the modules that run on different devices or at least as a separate process is realised via a web service.

Loose coupling is used here as a term to emphasize that different modules in a larger system are only loosely connected and do not depend largely on each other. *Coupling* can be understood as the degree of knowledge a module or class have of each another. The lesser the knowledge of each other the software modules can manage with, the more loose the coupling.

In the course of the design and development cycles of the Kanji Coach, it became apparent that it has to be possible to attach different views, input devices and data storage systems to the controller. This is due to the distributed nature of the application. In order to ensure that the handwriting data input view, which currently runs on a mobile device, can run on a different device, it had to be loosely coupled to the main controller. Therefore, the communication between the handwriting input data view and the main controller is realised via a web service. Because of this communication structure, it is possible to exchange the handwriting data input view with a different one, for instance when running the application on a device like a tablet PC. The design of the communication structure within the web service is described in greater detail in section 6.1.3.3.

The messaging system that forms the communication structure between the software modules running as the same process is realised with a message class that can be manipulated by the modules using these messages. Technically, the web service and the controller both run as a subprocess of the main desktop view. When the web service receives a request and accompanying data from the handwriting input data view, both request and data are bundled into an encapsulated message and passed to the controller. A similar type of message is used for requests from the controller to the model, for instance a recognition task that needs be performed.

6.1.2.2 Recognition Data Flow

The recognition data flow is simply the flow of data occurring in a recognition scenario. It can be described in 6 steps as depicted in figure 6.3.

1. Clearing the input GUI screen [Controller \Rightarrow Web service \Rightarrow Handwriting data input view]
2. Transmitting user input data to the web service [Handwriting data input view \Rightarrow Web service]
3. Encapsulating data into a message and passing it to the controller [Web service \Rightarrow Controller]
4. Requesting recognition [Controller \Rightarrow Model]
5. Returning recognition result [Model \Rightarrow Controller]
6. Displaying recognition result [Controller \Rightarrow Desktop view]

When the desktop application requests the use to input a Kanji character, it sends a message to the web service advising the handwriting data input view to clear the screen step 1. The handwriting data input view receives the information by polling the web service. When the user starts drawing on the surface of the handwriting data input view, the data is captured and transmitted to the web service step 2. Each stroke is captured and sent individually in order to ensure a faster recognition. That way, the recognition process is initiated before the user finishes writing a character. The web service receives the data and creates an encapsulated message. That message is passed to the controller step 3. The controller initiates a request to the model, containing all strokes subsequent to the last clear screen event step 4. The model performs the recognition of the set of strokes and returns the result or partial result to the controller step 5. The controller advises the desktop view to display the resulting character step 6.

6.1.2.3 Learning Data Flow

The learning data flow is the data flow between the learning module of the application, the recognition process and the user interaction. The learning data flow design can be summed up in 5 steps.

1. In learning mode or test mode: Asking user to draw a character, based on the current lesson data. The controller sends a display request to the desktop view. [Controller \Rightarrow Desktop view]
2. After recognition process: Request storing recognised character in learning profile. [Controller \Rightarrow Model]
3. Calculation of error points for a character (creation of new data) and storage. [Model \Rightarrow Data access layer]

4. Returning learning state of character [Model \Rightarrow Controller]
5. Displaying learning state [Controller \Rightarrow Desktop view]

The learning data flow is described in the middle of a user interaction with the learning application as it illustrates a typical data flow most appropriately as shown in figure 6.3.

In step 1 of the learning data flow, the controller sends a message to the desktop view with a request to display an invitation to the user to draw a specific character. That step is a part of the general messaging system design that manages the communication between the controller and the other modules. When the recognition process is finished, the character needs to be stored. The controller requests the model to store the character (step 2). The logic layer then creates new data, namely the error points of a character that naturally become a part of the data flow. Both the character recognition result and the error points are stored using the data access layer (step 3). The resulting learning state defines which character will be displayed next. This calculation result is transmitted from the model to the controller after storage in the penultimate step (step 4). The last step in the learning data flow is the display of the resulting learning state to the user in the desktop view (step 5).

6.1.3 Software Modules

6.1.3.1 Handwriting Data Input View

The handwriting data input view is a graphical user interface. It is designed for simplicity and usability. It's main task is data capturing. It contains only an input area, with a cross in order for the user to better locate the strokes of the character. This follows a common practice in Kanji teaching - a cross depicts the writing area in four areas.

There is no *commit* or *finish* button on the handwriting data input GUI, since the end of a stroke sequence is handled with a time out in the learning module. When the user needs too long to input a character there is a problem and help should be offered. Therefore, it is sufficient to only display a reset button on the writing area. Whenever the reset button is pressed, the controller is notified of that event. The current drawing will be removed from the screen. The next user input will be treated as a new character

In the background of the handwriting data input view the user input is sent to the controller module. Besides that, a polling mechanism ensures that any messages from the controller to the handwriting input data view are received. Whenever the user finishes a stroke, the module sends a message via a web service² to the controller.

6.1.3.2 Main View

The main view of the system is a graphical user interface. It contains a simple learning environment, a display area for the characters that have been drawn in the handwriting input area an information area that displays additional information about a character. In a configuration area the user can choose between the different lessons the system offers and between a training mode and a test mode.

6.1.3.3 Web Service

The main communication module between the handwriting data input view and the controller is a web service that runs on the main part of the application as a subprocess of the controller. When the desktop application requests the user to input a Kanji character, it sends a message to the web service advising the handwriting data input view to clear the screen. The handwriting data input view receives the information by polling the web service. However, the main task of the web service is to receive data from the handwriting input data view and forward that data to the controller of the system.

A web service is a standard means of interoperation between different software systems, possibly running on different platforms and frameworks. The web service as such is an abstract definition of an interface, it must be implemented by a concrete agent. The agent itself then must be a software that sends and receives messages (Booth et al. 2004). The web service in the Kanji Coach system is not a web service in the strict sense as intended by the Booth et al. (2004). It does not provide a service as such. The calling client does not receive a reply to a request, just an acknowledge message stating that the data has been received. A reply with more information is not necessary, since the handwriting data input view does not display any information to the user. In summary, the web service design for the Kanji Coach system is a web service in the technical sense, but not in the conceptual sense, as there is no real crosswise interaction between server and client. The concrete implementation of the web service is realised with the *Windows Communication Foundation* (WCF) (Smith 2007). The WCF uses a *SOAP protocol* (originally: *Simple Object Access Protocol*) internally, but the functionality can be accessed from within the .NET framework, the concrete SOAP XML messages will

²See section 6.1.3.3.

be created and unpacked into instances of *Common Language Runtime* (CLR) objects automatically by the WCF framework (Kennedy and Syme 2001; Gudgin et al. 2007; Smith 2007).

6.1.3.4 Recognition Module

As a part of the model within the MVC paradigm the recognition module plays a crucial role. From an abstract viewpoint it functions as a black box. A set of pen trajectories is passed to the recogniser and a set of characters is returned as a result, sorted by their matching value. Additionally, an intended character can be passed to the recognition engine, such that the recognising module can generate an error analysis based on the intended character. If no intended character is given, the recogniser is designed to use the best result as a basis for an error analysis, with lower confidence values attached. The detailed design and implementation choices of the handwriting recognition engine are described in chapter 7.

6.1.3.5 Learning Module

The learning module is designed as a basic module, mainly for the purpose of demonstration. It performs user and character administration tasks. Each user has a personalised character set, containing the lessons that have been studied and the error points of each character. The application is therefore not a vocabulary teaching application, but rather a Kanji teaching application. The error point system is rather simple, the more error points a character has, the more often it will be repeated. Similarly, the character repetition depends on a vocabulary training method, that is employed in a systematic fashion. For details see section 10.0.1.1.

6.2 Framework and Devices

In this section the choices for framework and devices are reviewed briefly. The decision of which framework to use depends on the operating system.

6.2.1 Operating System

Despite the quasi-religious views of which operating system (OS) to use, the choice for the Kanji Coach system was simply user oriented. The user group 'students of Japanese' consists mainly of non-technical people. They usually use a version of the MS Windows operating system. Therefore, even when attempting to provide for cross-platform usability, the windows platform is chosen as the basis for the implementation. Neither the author nor the application seek to convince anyone of using one or the other operating system, therefore it is a logical choice to provide software for a system that most people use.

6.2.2 Framework

The framework to run the system had to fulfill a few criteria.

- It should provide an easy-to-use graphical user interface.
- It should mirror the natural look-and-feel of the operating system it runs on.
- It should be cross-platform if possible and not be bound to native OS-specific code.
- It should provide cross-device communication.
- It should provide a modern high-level programming language

Even though native code that runs directly on the operating system may provide for speed and natural look-and-feel, any efforts to port the system to a different platform become laborious tasks. That rules out the choice of *C++*. Generally, the design ideas and framework criteria seem to apply well to both the Java platform and the .NET framework. Both provide functionality for an easy-to-use GUI. .NET does not mirror the natural look-and-feel of the windows operating system, it *is* the natural look-and-feel on Windows. Java has the ability to adopt the look-and-feel of different systems it runs on, MS Windows as well. The Java virtual machine has long been known to run on different platforms, most importantly Linux and Windows, while the .NET framework has been implemented for X-Systems by Novell and is called *Mono*. The two differences that gave the .NET framework a slight advantage over Java was the comfort and ease the Windows Communication Foundation offers. The web service functions can be called exactly the way as if they were methods of a local software module. The integration of the different parts of the system, namely the handwriting data input view and the controller does not require much additional effort. Another advantage of the .NET framework is the programming language *C#* that combines many features of the Java with some of *C++*. Additionally, *C#*

offers a smoother handling of generic lists, which is useful when dealing with lists of mouse coordinates, lists of strokes that are lists of mouse coordinates and ultimately lists of characters. With the CLR, which is an ECMA standard like C#, it is also possible to easily integrate with other languages available for the .NET environment. Lastly, despite the ease of integration with a .NET client, the WCF also allows for other systems to connect to a webservice. Since it uses SOAP internally, it is possible to communicate with a WCF web service even without .NET, using so called *POX* (Plain Old XML) messages that can be generated in any programming language on any framework and operating system.

6.2.3 Desktop Computer

The choice for a stationary computing device is driven by the kind of user the learning application is aimed at. A notebook computer the way it can be bought in any computer store is the closest match to what a user of the system most probably will be running. The learning system is a standard desktop application with a standard MS Windows forms GUI. Therefore, this kind of system is most suitable for the designed system. Nevertheless, it is possible to run both the handwriting data input view and the desktop application on the same PC - for example a tablet PC. The integration could stay exactly the same.

6.2.4 Pen Input Device

The pen input device has been chosen to be a *Personal Digital Assistant* computer (PDA). The reason for that design choice is simple. At the time of drawing the user should be able to see what he is drawing on the writing surface. At the same time the data should be available to the controller in real-time, i.e. after a pen-up movement. The main decision had to be made between a graphics tablet and PDA. The option of mouse input of characters was ruled out from the beginning, because the mouse is not a useful device to enter handwritten characters. Graphics tablets like a Wacom tablet are cheaper than a PDA, however, their distribution on the market and therefore among potential users is small. The solution with a PDA leaves room to exchange the device that runs the input area with any mobile device that has the ability to connect to a wireless LAN, e.g. an iPhone. Another possibility would be pens that write on paper and also transmit data to a PC. Those, however, either do not perform the transmission in real-time, or do not come as plain mouse coordinates but bitmaps or can not connect to custom made software at all, but only to their OEM software.

Chapter 7

Handwriting Recognition Engine

7.1 Data Capturing

Each handwriting recognition process begins with the data capturing. The user's handwriting must be captured and fed into the system. The data capturing is therefore a crucial part of the whole process. In this system a GUI is used for the capturing of the pen movements on a writing surface.

7.1.1 Writing Surface

The writing surface module, the view is split into two parts. The writing surface GUI and the writing surface background module. The technical design of the data input GUI is described in section 6.1.3.1.

7.1.1.1 Writing Surface GUI

The GUI works with pen-down and pen-up events. It has a cross in the middle in order to partition the writing surface the same way, character practising paper sheets are usually partitioned. The GUI class is listening to *pen-down*, *pen-up* and *pen-move* events. These are the equivalent in the mobile world for regular mouse-down, mouse-up and mouse-move events. However, there is one difference - the pen-move event can only be captured between a pen-down and a pen-up event. An earlier conceptual idea for the HWR engine included using the mouse-move events during the input of a character between the strokes. This could not be realised, however, because the series of pen-move events can only be captured when there has been a previous pen-down event and no pen-up event yet. The GUI captures the events and passes the point coordinates on to the background class.

7.1.1.2 Writing Surfaces Background Module

When a pen-down event is detected, the background class of the GUI starts listening for the pen movement. All point coordinates and the time of their capturing are stored in two separate lists with the same indices. An alternative solution would have been to store a number of instances of a custom-made encapsulated Point class including the time stamp in one list only, however, using two separate lists resulted in increased speed. Therefore, the point coordinates are stored in the frameworks Point class that does not account for time stamps. Therefore a separate list is used for the timestamps only.

The background module of the writing surface mainly administrates the capturing of the pen trajectory and sends it to the recognition module as soon as a stroke is finished. Therefore the system does not receive a separate signal indicating that the drawing of the character is finished. That design creates a segmentation problem that is solved with the *clear* button and the *clear* message. The segmentation of characters is left undetermined - only the beginning of it is determined through the *clear* message that is sent to the mobile view from the controller - or the clear message that is sent to the controller because the user clicked the *reset* button. After a stroke is finished the according point and timestamp sequences are passed to the main part of the HWR engine.

7.2 Data Format

7.2.1 Requirements of the Data Format

The data format for the recognition process underlies a number of requirements. Firstly, it has to be stated that two main data formats are necessary. One for the actual recognition process as a data structure in the RAM.

Secondly, there needs to be a storage format for the data base that represents the handwriting of a character, radical, stroke, point list or simple point. The requirements for both data structures are:

- **Expressiveness:** The data structure should be able to fully represent a complete character and all sub-elements that belong to it. That requirement is due to the structural approach to handwriting recognition that is the basis for the error handling.
- **Well-definedness:** The information structure should be unambiguous, two different characters must have a different structure.

The storage structure has some additional requirements:

- **Accessibility:** The data should be formatted in a way that a human editor can access the data, but it should also be prepared for programmatic access.
- **Well-formedness:** There should be a way to check if the data is well-formed
- **Parsability:** It should be possible to create the run-time data structure from the storage data structure.

The run-time data structure should in addition provide

- **Serialisability:** It must be possible to create the storage data structure from the run-time data structure.

Any combination of two formats used should meet the above requirements, at best in a uniform way. That is, any combination of storage format and run-time format should ideally be compatible without the need of a complex data format converter.

7.2.2 Existing Handwriting Formats

There are some existing formats for the description of handwriting. Their intended use is for handwriting recognition systems. The formats that will be reviewed in this section are the *Microsoft ISF* format in section (7.2.2.1), which is a binary format. The other formats are text based and human-readable. In this short review, the formats will be checked against the requirements defined in section (7.2.1). We will consider *InkML* in section (7.2.2.2), *UNIPEN* in section (7.2.2.3), *hwDataset* in section (7.2.2.4) and *UPX* in section (7.2.2.5). The central question is, if one of these formats meets the above requirements in a sufficient way. This is unclear, because the most of the formats have been originally developed mainly for alphabetic scripts or for usage scenarios different from the one proposed in this chapter.

7.2.2.1 The Microsoft Ink Serialized Format (ISF)

The *Ink Serialized Format* (ISF) format is owned by the Microsoft Corporation. However, it is not a proprietary format, the specification is freely available. Since the format is purely binary, it can not meet one of the requirements for the storage data structure: It is not feasible for a human to read and write files in that format, therefore ISF does not provide the necessary *accessibility* (Microsoft Corporation 2007). The format could still be used as a run-time data structure, if it meets the requested criteria. The requirement of *serialisability* is generally met. A binary format allows for fast and reliable programmatic access to the data, it can be stored in binary files on a data storage medium. The problem that accrues from this type of serialisation is that the storage format, the format used in a file or database, would again not be human-editable and therefore fail to meet the *accessibility* requirement. In order to provide a serialisation that results in a human-readable format, a format converter would be needed. Another problem originates from the ISF format specification:

It accounts only for the description of mouse coordinates or pen trajectories, but does not offer any structures for linguistic information. It fails to meet the ideal, a unified format for linguistic and graphic information, as it is lacking some degree of *expressiveness*.

7.2.2.2 InkML

InkML is a markup language for describing electronic pen trajectories. Hence the name *ink*. *ML* stands for markup language, as is customary for XML-based and SGML-based languages. The specification is currently in a draft status, maintained by the World Wide Web Consortium (W3C) (Chee et al. 2006). Judged from the viewpoint of the defined requirements, InkML is a candidate for the storage format. As an XML format it automatically fulfils the criterion of *well-formedness*: Any piece of InkML code can be evaluated with common techniques, since InkML has a well-defined scheme description.

The main elements in the simplest form of InkML are the `<ink>` and the `<trace>` element. These elements allow for a very simple form of a pen trajectory, basically a flat list of point coordinates. The `<ink>` element is the root element of any InkML code. The `<trace>` element holds point coordinates.

Listing 7.1: Demonstration of the *trace* tag

```
<ink>
  <trace>
    282 45, 281 59, 284 73, 285 87, 287 101, 288 115, 290 129,
    291 143, 294 157, 294 171, 294 185, 296 199, 300 213
  </trace>
</ink>
```

Listing (7.1) covers the general gist of the InkML format. Despite being an XML format, it is a flat format, each value pair, separated by commas, represents one point in a coordinate notation.

It is possible to add *time* information to the trace. In order to do so, a time channel needs to be defined. Listing (7.2) shows the definition and use of a time channel. The example shows a time channel whose values for a given point are the relative to the timestamp referred to by *#ts001* (Chee et al. 2006). Below there are two *timestamp* tags. The first one has the ID *ts001* and is referred to by both the time channel and the second time stamp that defines a time offset to time stamp *ts001* with the *timeOffset* attribute. The possibility to define time channels enables the InkML format to hold information about the time at which a sample point has been taken. This is useful for the recognition mechanism used in this application, because it compares point coordinates as well as time stamps.

Listing 7.2: Demonstration of the *time channel*

```
<channel name="T"
  type="integer"
  units="ms"
  respectTo="#ts001"/>

<timestamp xml:id="ts001"
  time="1265122414000"/>
<timestamp xml:id="ts002"
  timeOffset="600000"
  timestampRef="#ts001"/>
```

The InkML data structure fulfils several of the requirements necessary for a storage data structure. InkML is

- *well-defined*: Any point sequence that has different coordinate values than another point sequence can be distinguished from the other.
- *accessible*: As an XML format it can be handled programmatically, but is also human-readable and can be edited by a human with a simple interface like a text editor.
- *well-formed*: As an XML format it can be validated according to it's specification.
- *parsable*: As an XML format, InkML does not need to be parsed with custom-made methods, since most modern high-level languages offer an access method to XML tree structures.

However, InkML is lacking some *expressiveness*. Only pen trajectories and their time stamps can be expressed in the InkML format. InkML is not designed to hold any of the other information compulsory for the structural handwriting recognition. In the case of character recognition, it needs to be able to account for more than coordinate points and time stamps. There needs to be a way to encode structural information about the characters and sub-elements of the characters. InkML does not to be a sufficient format for the given task.

7.2.2.3 The Standard UNIPEN Format

The standard UNIPEN format specification is a file format definition for a flat text file. It contains tags in dot-notation. For example the tag *.COMMENT* means that the following free text should be ignored, the tag *.KEYWORD* is used to define a new keyword, while the tag *.RESERVED* states that the text that comes after that tag is a reserved word within the UNIPEN format. The format is self-defined with the three keywords above. Any new keyword is defined with *.KEYWORD* (Guyon et al. 1994; Unipen Foundation, International 2010).

As a data structure for the purpose of a handwriting recognition, UNIPEN can serve as a storage format, which is the primary purpose for the existence of the format. The UNIPEN format accounts for both pen trajectories as well as information about the characters that have been written.

Listing 7.3: Demonstration of the *UNIPEN* format

```
.COMMENT #####
```

```
.COORD      X Y

.SEGMENT TEXT 235:0–297:9 OK "Kurosu_Masaaki"
.SEGMENT CHARACTER 235:0–255:9 OK "JISx3975_ 'Kuro' "

.PEN_DOWN
486  –1456
488  –1454
490  –1452
488  –1450
488  –1450
486  –1452
480  –1456
474  –1466
464  –1480
452  –1492
440  –1506
428  –1524
.PEN_UP
406  –1556
394  –1574
384  –1590
374  –1602
.PEN_DOWN
```

Listing (7.3) is an excerpt from a data file created by (Unipen Foundation, International 2010). It shows an example of a UNIPEN data structure. The `.COORD` tag defines the structure of the pen coordinates. The `.SEGMENT` tag with the `TEXT` modifier informs about the full text of the next number of segments. The `.SEGMENT` tag with the `CHARACTER` modifier informs about the character that is represented with the sequence of pen coordinates. The other information given is the start and end position within the file and the character code in JIS encoding. The `.PEN_DOWN` tag can be understood as a flag. All pen coordinates following this tag have been captured as *pen down* coordinates. The tag `.PEN_UP` sets the opposite flag: The coordinates stated after this tag were captured while the pen was not touching the writing surface. The last `.PEN_DOWN` tag is the beginning of a new coordinate sequence for the next stroke. From a requirements point of view the UNIPEN provides a high standard, as it meets a great number of requirements for the storage structure.

The UNIPEN format is:

- **partially expressive:** UNIPEN can represent a complete character and the pen trajectory along with it. It does however, not account for capturing the time information. At a constant sample rate the time stamps of the individual points could theoretically be calculated, if time stamp of the first point is encoded in the meta information. However, that solution is not optimal, because it needs constant sampling, even between a *pen-up* and a *pen-down* event. There are input devices that do not offer those coordinates and the recognition system presented here does not rely on them for that reason. The examples given are encoded in JIS, but it seems possible and feasible to use the format with Unicode encoding.
- **well-defined:** The UNIPEN is unambiguous, two different characters do have a different data structure, because the JIS code can serve as an ID.
- **accessible:** The data resides in flat text files, designed for human editing. It is accessible programmatically, too, but has a weakness on that requirement compared to an XML-based format.
- **parsable:** The flat file format can be parsed easily. Due to its procedural nature it is also possible to create a run-time data structure that is conceptually based on the storage structure and therefore serialisable.

The main weakness of the flat format file is the lack of *well-formedness*. There is no automatic way to check a document against a predefined format specification. It can not be assessed if a file is well-formed. Additionally, the expressive power of the UNIPEN format would be seriously challenged if it should provide for sub-structures of characters. In order to do so, it would be necessary to create new tag definitions for the Radicals of the Kanji. Agrawal et al. (2005) describe some more shortcomings of the UNIPEN format. It can be concluded that the standard UNIPEN format is not suitable for the task given.

7.2.2.4 Handwriting Dataset (*hwDataset*)

The *Handwriting Dataset* (*hwDataset*) is an XML format that is a complement to InkML. It is inspired by the UNIPEN format. The *hwDataset* format attempts to close the gap between pure ink data and the annotations that are needed for handwriting recognition (Bhaskarabhatla and Madhvanath 2004). The format contains three main parts. The *datasetInfo*, the *datasetDefs* and the *hwData*. The *datasetInfo* element holds any metadata, like *name*, *category* and the like. The *datasetDefs* encompasses information about *data sources*, different *writers* and their features like *handedness*, *gender*, *age*. The *hwData* element in the XML code organises the handwriting data hierarchically. Each hierarchy level contains one or more *hwTrace* elements. The *hwTrace* element refers to an InkML file, containing the actual handwriting data. A detailed description of the *hwDataset* format can be found in (Bhaskarabhatla and Madhvanath 2004).

The format provides an XML scheme description and thus meets the *well-formedness* requirement. It is *well-defined*, because it accounts for unique structures. The *parsability* is not an issue for any XML format, since methods for accessing XML trees are provided by modern programming libraries. The *accessibility* is provided, the format has a clearly defined structure that can easily be understood by humans. The *hwDataset* format can structure many desirable information for the handwriting learning system proposed in this chapter. From an *expressiveness* viewpoint it can create substructures for different parts of a sequence of pen trajectories. The *hierarchy level* (H) of a trace accounts for the expressive power necessary. The H(n) elements of the *hwData* elements are designed to hold meaningful names like *PARAGRAPH* or *WORD*. It may be possible to use the format even to denote different parts of the same character. There is no reason why one should not introduce an H(n) definition for *RADICAL* or *GRAPHEME*.

7.2.2.5 The UNIPEN XML Format (*UPX*)

The format *Unipen for XML* (*UPX*) can be seen as an XML version of the UNIPEN format. The UNIPEN standard described in section (7.2.2.3) does not bear any resemblance with the InkML format shown in section (7.2.2.2). Both formats fulfil a number of the requirements presented in section (7.2.1), but both formats fail to fulfil them all. The *hwDataset* format described in section (7.2.2.4) solves many of the problems UNIPEN faces, as it brings together a superset of the expressiveness of UNIPEN with the well-defined InkML format in a uniform way. According to Agrawal et al. (2005) *hwDataset* was designed to support new data collection. The motivation to create another format came about from the fact that existing UNIPEN resources should be made available in a modern XML-based format that unifies InkML and UNIPEN. *hwDataset* comes very close to this aim, but does not necessarily account for a conversion of UNIPEN resources. Agrawal et al. (2005) attempt to create a format that allows for a well-defined conversion from UNIPEN. The UNIPEN foundation considers UPX as the new de facto standard format for storing annotated databases of on-line pen input (Unipen Consortium 2006).

UPX is a multi file format. It resembles *hwDataset* in the way that it comprises both meta information and data annotations as well as pure InkML data in separate files. Within the UPX *hwData* element there can be any number of *hLevel* elements in order to define the hierarchy of the trajectory. Listing (7.4) shows an example after (Unipen Consortium 2006). In the listing, the *hLevel* tag is demonstrated. The word *sexy* is described hierarchically. Firstly, in the outermost *hLevel* tag, the *level* attribute specifies a *WORD*. Then the inner *hLevel* elements specify a lower level of hierarchy, the characters. Note that not all characters are defined individually in this example. The *hwTraces* elements surround a number of *traceView* elements that in turn point to the corresponding positions in an InkML file that holds the pen trajectory. The meta data information that can be stored in UPX has a similar expressive power as the *hwDataset* format. Madhvanath et al. (2006) give a full format description of the UPX format in their technical report.

Listing 7.4: Demonstration of the *hLevel* tag in UPX

```
<hLevel id="WORD_0" level="WORD">
  <label id="WORD_0">
    <alternate rank="1" score="1"/>sexy</alternate>
  </label>
  <hwTraces>
    <inkml:traceView traceRef="w0629.inkml#dataSet_0_traces"
                      from="22"
                      to="24"/>
  </hwTraces>

  <hLevel id="CHAR_0" level="CHAR">
    <label id="CHAR_0">
      <alternate rank="1" score="1"/>e</alternate>
    </label>
```

```

<hwTraces>
  <inkml:traceView traceRef="w0629.inkml#dataSet_0_traces"
                    from="22:91"
                    to="22:161"/>
</hwTraces>
</hLevel>

<hLevel id="CHAR_1" level="CHAR">
  <label id="CHAR_1">
    <alternate rank="1" score="1"/>y</alternate>
  </label>
  <hwTraces>
    <inkml:traceView traceRef="w0629.inkml#dataSet_0_traces"
                      from="24:61"
                      to="24:162"/>
  </hwTraces>
</hLevel>
</hLevel>

```

It seems as if the UPX format was able to fulfil all requirements. The UPX format fulfils the requirements of

- *Well-definedness*: As an XML structure providing IDs and names for each element and substructure, the format is well-defined.
- *Accessibility*: As an XML format it is both human and machine readable and editable.
- *Well-formedness*: As an XML format with a defined scheme it can be validated for its syntactic features.
- *Parsability*: As an XML format it can be easily parsed into a tree structure.
- *Expressiveness*: The format provides the missing link between the standard UNIPEN format and the InkML format. Additionally, it can describe hierarchical structures.

Since any XML format translates directly into a tree structure, the data structure for the run-time does not need to be defined separately. Converting pen trajectories in InkML format into a data stream has been studied (Keshari 2008). These techniques however, are not necessary for the proposed system. The data exchange is provided as technique available within the framework without any conversion (see section 6.1.3.3).

7.2.3 Data Format Description

The data format description could trivially be described with the UPX description. In this case however, UPX needs to be adapted to the special needs. This section describes the adaption of UPX to the requirements of an on-line handwriting recognition for Kanji characters in a learning environment. The section describes both the file format and the run-time data structure.

7.2.3.1 Point Data Format

In UPX, points are not represented directly, but in an outsourced InkML file, where they are part of the InkML standard pen trajectory definition. In InkML files, points are stored in traces as specified in the InkML format description.

Listing 7.5: Definition of the trace format

```

<timestamp xml:id="ts001"
           time="1265122414000"/>
<traceFormat xml:id="KanjiStrokeTrace">
  <channel name="X" type="decimal"/>
  <channel name="Y" type="decimal"/>
  <channel name="T" type="integer"
           units="ms"
           respectTo="#ts001"/>
</traceFormat>

```

Listing (7.5) shows the trace format description as used in the system. The format consists of three channels that are given in ordered sequence. There are no intermittent channels. The first two channels are *X* and *Y* for the pen coordinates. The third channel is *T* for a time stamp. The pen coordinates can be given as *decimal* numbers, while the time stamp (in milliseconds) must be an *integer*. The *respectTo* attribute in the time channel indicates that all values must be interpreted as offsets to the time stamp with the id *ts001*.

An actual trace would then contain three values, each value triple separated by a comma. The trace format definition ensures the correct interpretation of the values.

Listing 7.6: A sample trace

```
<trace id="id123abc">
  45 76 0, 3 5 100, 4 -8 200, 4 -5 300,
  9 -2 400, ...
</trace>
```

Listing (7.6) shows a trace. Given the file contains the trace format definition shown in listing (7.5), the trace in listing (7.6) is interpreted in table (7.1).

Trace	Channel X	Channel Y	Channel T	Comment
45 76 0	45	76	1265122414000	The first trace initialises the values. The time stamp value is read from timestamp <i>ts001</i> .
3 5 100	48	81	1265122414100	The delta values are added to the existing data.
4 -8 200	52	73	1265122414200	The time stamp values are relative to <i>ts001</i> , not to the last time stamp, unlike the pen coordinate deltas that are added to the current value trace by trace.
4 -5 300	56	68	1265122414300	Negative values are treated as regular delta values.
9 -2 400	65	66	1265122414400	The values change as expected.

Table 7.1: Sample trace interpretation

The run-time data structure for a point holds the coordinate values and an integer value for the time stamp. The conversion between the run-time instance and the trace format is trivial and needs no description.

7.2.3.2 Stroke Data Format

There is no explicit format for a stroke in the storage structure. A stroke is simply the trace between a pen-down event and the following pen-up event. All the points captured between form one stroke. Thus, in the InkML file format a stroke is simply a trace. If a greater number of strokes comes together, each one of them will be a trace and they can be grouped together as a *tracegroup* element in InkML. It would be possible to create a separate level for strokes, as demonstrated in listing (). However, since every *hLevel* element for a stroke would contain exactly one *hwTrace* element, it seem redundant to do so. Listing (7.7) shows a potential data structure for a stroke. As stated before, this data structure is redundant in the way, that an *hLevel* definition would contain only exactly one trace. If a trace is interpreted as a stroke, the additional *hLevel* for strokes becomes unnecessary.

Listing 7.7: An example of how a stroke could be represented in UPX

```
<hLevel level="stroke" id="STROKE1">
  <!-- The first stroke in this Radical of handwriting. -->
  <label id="STROKE1label" labelSrcRef="labelref_DW" labelType="truth">
    <alternate>[unicode value]</alternate>
  </label>
  <hwTraces>
    <inkml:traceView traceRef="/example.inkml" from="12" to="12"/>
  </hwTraces>
</hLevel>
```

The run-time data structure for a stroke is generated from a trace. Despite not being represented in the storage structure, the run-time data structure for a stroke plays a crucial part in the recognition process. The actual data within the structure is purely a list of point instances. Any other numerical values are computed from the point list, with algorithms that are described in detail in section (7.5).

7.2.3.3 Radical Data Format

The Radical data format is a data structure that works with the UPX *hLevel* element for hierarchical description. Conceptually, a Radical is a hierarchical element in the composition of a Kanji character. With the UPX format specification in hand it is fairly straightforward to define an appropriate data structure. Listing (7.8) shows a UPX data structure for a Radical. The Radical 本 consists of four strokes. Since strokes are not represented explicitly in the data format, there are four *traceView* elements under the *hwTraces* tag.

Listing 7.8: A Radical representation in UPX

```
<hLevel level="radical" id="RADICAL75">
<!-- The first Radical in this Kanji character of handwriting. -->
  <label id="RADICAL75label" labelSrcRef="labelref_DW" labelType="truth">
    <alternate>U+6728</alternate><-- Unicode value -->
  </label>
  <hwTraces>
    <inkml:traceView traceRef="/example.inkml" from="12" to="12"/>
    <inkml:traceView traceRef="/example.inkml" from="13" to="15"/>
    <inkml:traceView traceRef="/example.inkml" from="16" to="19"/>
    <inkml:traceView traceRef="/example.inkml" from="20" to="23"/>
  </hwTraces>
</hLevel>
```

The run-time data structure of a Radical is a collection stroke instances. All values for recognition of a Radical are computed from the strokes instances by using different permutations of the strokes to match a database entry. A more detailed description of the Radical recognition process will be given in section (7.6).

7.2.3.4 Character Data Format

The character data format is an ordered list of radicals, according to their standard sequence of writing within the character. In listing (7.9) the character 東 is shown. It consists of the radicals 日 and 木. The storage data structure for characters in general is totally straightforward and exploits the advantages of the UPX format. In the concrete example, the outermost *hLevel* element is used for the character and additional descriptions, the two inner *hLevel* elements are used for the two Radicals of that character. Each *traceView* tag within the Radicals represents a stroke. Thus, the data structure implicitly encodes the stroke number of a Radical. Here, both the Radicals 日 and 木 have four strokes each, the Kanji character 東 is comprised of eight strokes in total.

The stroke order of 東 is shown in figure 7.1. Notice, that the Radicals of this Kanji are not drawn one after another. The very first stroke is a part of the 木-Radical, the four following strokes constitute the complete 日-Radical and the last three strokes, again, are part of the 木-Radical. The UPX structure shown in listing (7.9) accounts for that by not specifying a total order of Radicals, but rather a preferred order. The traces are spatialised to their Radical, the order of drawing does effect the InkML traces and ultimately the recognition process, but not the UPX data structure.

Listing 7.9: A character representation in UPX

```
<hLevel level="character" id="CHARACTER71">
<!-- The character 71 consists of the Radicals 72 and 75 -->
  <label id="CHARACTER71label" labelSrcRef="labelref_DW" labelType="truth">
    <alternate>U+6771</alternate><-- Unicode value -->
  </label>

  <hLevel level="radical" id="RADICAL72">
    <!-- The first Radical in this Kanji character of handwriting. -->
    <label id="RADICAL72label"
          labelSrcRef="labelref_DW"
          labelType="truth">
      <alternate>U+65E5</alternate><-- Unicode value -->
    </label>
```

```

<hwTraces>
  <inkml:traceView traceRef="/example.inkml" from="0" to="3"/>
  <inkml:traceView traceRef="/example.inkml" from="4" to="7"/>
  <inkml:traceView traceRef="/example.inkml" from="8" to="9"/>
  <inkml:traceView traceRef="/example.inkml" from="10" to="11"/>
</hwTraces>
</hLevel>

<hLevel level="radical" id="RADICAL75">
  <!-- The second Radical in this Kanji character of handwriting. -->
  <label id="RADICAL75label"
        labelSrcRef="labelref_DW"
        labelType="truth">
    <alternate>U+6728</alternate><!-- Unicode value -->
  </label>
  <hwTraces>
    <inkml:traceView traceRef="/example.inkml" from="12" to="12"/>
    <inkml:traceView traceRef="/example.inkml" from="13" to="15"/>
    <inkml:traceView traceRef="/example.inkml" from="16" to="19"/>
    <inkml:traceView traceRef="/example.inkml" from="20" to="23"/>
  </hwTraces>
</hLevel>
</hLevel>

```



Figure 7.1: Stroke order of the Kanji 東

7.3 Database

7.3.1 Database Organisation

The database used in the system consists of two parts. The first part is centred around handwriting information about characters and their substructures, the second part is concerned with lexical information only. The **handwriting part** is a UPX file structure that holds character descriptions, Kanji character unicode values, as well as Radical descriptions and pointers to InkML files holding pen trajectories representing the data structures given in the UPX file. The **lexical part** is an XML file in a format described by Breen (2004). The XML file contains lexical information about characters, such as their key Radicals, their Readings, and their translation into a number of languages. The handwriting part of the database has been discussed in section (7.2.3). The storage data structure laid out there is the structure used. The lexical part is provided¹ in an XML text file.

Listing (7.10) shows a sample database entry of the multi-index database created by Breen (2004). The *character* element is the root of an entry. The *literal* tag holds the digital form of the character. Under the *codepoint* tag, different code points can be stored, in the current version it is Unicode and JIS0208 (Unicode Consortium 2000; Japanese Industrial Standards Committee 1997). The *radical* element holds the number of the key radical of the character. In the current example for the character 東 the key radical is 木, which is number 75 in the classical Radical index. Miscellaneous information that may help a human finding the character in a paper-based dictionary are stored in the *misc* element. The file format provides room for the character index in different paper-based dictionaries and study books in the *dic.number* element. For example the *dic.ref* with the attribute *dr.type="sh_kk"* holds the character index in (Hadamitzky 1995). This information can be very useful for a learner when referring to study books. The *reading-meaning* element holds information about the pronunciation of the character and translations into a number of different languages. The *nanori* elements describe additional Japanese readings that occur only in person- and place names.

¹KanjiDict2 is freely available from <http://www.csse.monash.edu.au/~jwb/Kanjidic2/>

With this organisational approach it is possible for different parties to work on different information structures simultaneously. These can be accessed, modified and improved separately. This is due to the encapsulation of the different data structures.

Listing 7.10: Sample lexicon entry for lexical data

```
<!-- Entry for Kanji: 東 -->
<character>
  <literal>東</literal>
  <codepoint>
    <cp.value cp.type="ucs">6771</cp.value>
    <cp.value cp.type="jis208">37-76</cp.value>
  </codepoint>
  <radical>
    <rad.value rad.type="classical">75</rad.value>
    <rad.value rad.type="nelson_c">4</rad.value>
  </radical>
  <misc>
    <grade>2</grade>
    <stroke_count>8</stroke_count>
    <freq>37</freq>
    <jlpt>4</jlpt>
  </misc>
  <dic.number>
    <dic.ref dr.type="nelson_c">213</dic.ref>
    <dic.ref dr.type="nelson_n">2596</dic.ref>
    <dic.ref dr.type="halpern_njecd">3568</dic.ref>
    <dic.ref dr.type="halpern_kkld">2221</dic.ref>
    <dic.ref dr.type="heisig">504</dic.ref>
    <dic.ref dr.type="gakken">11</dic.ref>
    <dic.ref dr.type="oneill_names">771</dic.ref>
    <dic.ref dr.type="oneill_kk">27</dic.ref>
    <dic.ref dr.type="moro" m.vol="6" m.page="0172">14499</dic.ref>
    <dic.ref dr.type="henshall">184</dic.ref>
    <dic.ref dr.type="sh_kk">71</dic.ref>
    <dic.ref dr.type="sakade">121</dic.ref>
    <dic.ref dr.type="jf_cards">63</dic.ref>
    <dic.ref dr.type="henshall3">201</dic.ref>
    <dic.ref dr.type="tutt_cards">164</dic.ref>
    <dic.ref dr.type="crowley">108</dic.ref>
    <dic.ref dr.type="kanji_in_context">39</dic.ref>
    <dic.ref dr.type="busy_people">2.10</dic.ref>
    <dic.ref dr.type="kodansha_compact">1053</dic.ref>
    <dic.ref dr.type="maniette">516</dic.ref>
  </dic.number>
  <query.code>
    <q.code qc.type="skip">4-8-3</q.code>
    <q.code qc.type="sh_desc">0a8.9</q.code>
    <q.code qc.type="four_corner">5090.6</q.code>
    <q.code qc.type="deroo">1564</q.code>
  </query.code>
  <reading.meaning>
    <rmgroup>
      <reading r.type="pinyin">dong1</reading>
      <reading r.type="korean_r">dong</reading>
      <reading r.type="korean_h">동</reading>
      <reading r.type="ja_on">トウ</reading>
      <reading r.type="ja_kun">ひがし</reading>
      <meaning>east</meaning>
      <meaning m.lang="fr">Est</meaning>
      <meaning m.lang="es">Este</meaning>
      <meaning m.lang="pt">Oriente</meaning>
    </rmgroup>
  </reading.meaning>
</character>
```



```

    </rmgroup>
    <nanor i>あい</nanor i>
    <nanor i>あがり</nanor i>
    <nanor i>あずま</nanor i>
    <nanor i>あづま</nanor i>
    <nanor i>こ</nanor i>
    <nanor i>さき</nanor i>
    <nanor i>しの</nanor i>
    <nanor i>とお</nanor i>
    <nanor i>はる</nanor i>
    <nanor i>ひが</nanor i>
    <nanor i>もと</nanor i>
  </reading_meaning>
</character>

```

7.3.2 Alternative Database Structures

The structure and organisation of the databases as it is now, seems optimal among several alternatives. The reason for that is that the data is stored in separate and self-contained units. The indexing referencing between the different structures works seamless via the Unicode codepoints. Another advantage of using the available formats. KanjiDict2 is work in progress and updates may be available for other languages or for additional characters. Using the KanjiDict2 the way it is allows for reliability. The same is true for for UPX and InkML: UNIPEN has been the de facto standard for handwriting data exchange for a long time and UPX is considered the official successor of UNIPEN and InkML is a W3C recommendation².

7.3.2.1 A Unified File Format

An alternative solution to the split information approach would be to establish a unified file format for the pen trajectories, the UPX metadata and the lexical information. The advantage of that approach is that all data would be in one single place. However, a number of disadvantages would emerge from that approach, too. The file formats, InkML, UPX and KanjiDict2 already exist. Creating a new file format based on those would on one hand not create much additional value, but on the other hand lead to not using available de facto standards. Every time, a new version of the lexical data is issued or every time one would want to update the gold standard pen trajectory of a character, the formats would have to be linked together.

7.3.2.2 Relational Database

Establishing a relational database to hold the different data structures sounds like a feasible plan. With consideration of the three formats InkML, UPX and KanjiDict2 it should be possible to design a relational database that holds the different information in a structured manner. However, again the same problem arises. Updates and extensions of the formants of the data would create the need for a conversion tool. If the XML specification of one of the formats changes, the table structure in the relational database would have to be adapted, too. Alternatively, the actual XML code could be stored in relational database tables. That approach however seem awkward. XML is a format for structuring data in human readable text files. All three formats, InkML, UPX and KanjiDict2 have been designed to be human-editable and therefore accessible without any special software or tools but a text editor. Storing these XML structures in a relational database would compromise the advantage of a relational database that lies in querying and would also make editing the data a more complex task. Additionally, the application is a desktop application for a single user environment. Depending on what relational database was used that could force shipment of the database software along with the Kanji learning system. The conclusion is that once InkML and UPX have been standardised and are therefore more reliable formats it could be beneficial to design a relational database structure that mirrors these formats. Then, the relational database could be used in an on-line environment, where a server application performs the recognition for a web client. For the time being and the technical equipment given it does not seem useful to employ a relational database.

²However, until the end of 2009 InkML has not been standardised by the W3C and UPX is still in a planning stage concerning standardisation.

7.4 Recognition Architecture

7.5 Stroke Recognition Process

7.5.1 Normalisation

Many handwriting recognition systems perform some kind of normalisation. See section 3.4.2.3 for a review of common techniques. In this system, only size normalisation is performed. Other normalisation techniques reported in literature were often necessary, because the input devices returned insufficient data. With modern input devices many of the normalisation techniques that were used to clean the data from different kinds of noise are not necessary.

In order not to lose any data, the complete list of points is maintained, there is no point reduction. Since the prototype is a learning application and not a pure handwriting recognition, the main issue seems the size of the character. The size normalisation is done in two steps. Each complex that is more complex than a point has a bounding box around that can be used for scaling.

7.5.1.1 Boxing

The term *bounding box* needs not much introduction. It is the smallest box surrounding a graphic object. In this prototype, bounding boxes are rectangles with the same height and width. Rectangles are defined as a 3-tuple of a handle point, a height and a width. $R := \langle \langle x, y \rangle, w, h \rangle$ where the 2-tuple $\langle x, y \rangle$ is a point in the coordinate system with the decimal values x and y as coordinates, h is the y -height of the rectangle and w is the x -width. In order to find an extended square bounding box of any sequence of points, a method finds the four outermost points C_i with the minimal and maximal values for x and y .

$$\begin{aligned} C_{x_{min}} &:= \langle x_{min}, y_1 \rangle \\ C_{x_{max}} &:= \langle x_{max}, y_2 \rangle \\ C_{y_{min}} &:= \langle x_1, y_{min} \rangle \\ C_{y_{max}} &:= \langle x_2, y_{max} \rangle \end{aligned}$$

The intermediate handle point $H_{intermediate}$, the width w and height h of the minimal bounding box B' can be calculated as follows:

$$\begin{aligned} H_{intermediate} &:= \langle x_{min}, y_{min} \rangle \\ w &:= x_{max} - x_{min} \\ h &:= y_{max} - y_{min} \\ s &:= \arg \max(w, h) \end{aligned}$$

Then, the handle point H can be calculated by:

$$H := \begin{cases} \langle x_{min} - \frac{s-w}{2}, y_{min} \rangle & \text{if } s \text{ equals } h \\ \langle x_{min}, y_{min} - \frac{s-h}{2} \rangle & \text{if } s \text{ equals } w \end{cases}$$

The minimal bounding box B' is a rectangle with the following values:

$$B' := \langle H_{intermediate}, w, h \rangle.$$

The extended, square bounding box B is a rectangle with the following values:

$$B := \langle H, s, s \rangle$$

The use of boxing is multi-functional in the prototype. One of the uses is for distortion-free scaling (see section 7.5.1.2). Another use is for the comparison of positions of substructures of a character or Radical (see section 7.6).

7.5.1.2 Scaling

The bounding box of most Kanji is square, in cases where it is not, the space given to a smaller Kanji is still a square of the same size. In order to account for that, scaling is done with respect to the ideal of a square shape of a character. That concept is used for full characters, as well as Radicals and strokes. Before scaling the size of a stroke, a square bounding box is constructed. The handle point of the square bounding box is used as a vanishing point for vectorial projection. In a stroke data structure that consists of a point sequence p_1, \dots, p_n a number of vectors $\vec{v}_1, \dots, \vec{v}_n$ is created. Each vector is defined by the handle point $H = \langle x_h, y_h \rangle$ of a square bounding box and the p_i .

$$\vec{v}_k := p_k - H = \begin{pmatrix} x_{p_k} - x_h \\ y_{p_k} - y_h \end{pmatrix}$$

In order to generate a scaled version of a sequence of points, all the \vec{v}_k are multiplied with a scaling factor.

7.5.2 Recognition of Straight Strokes

7.5.2.1 Identification of a Straight Stroke

The notion of *stroke* essentially means *point sequence* in a technical sense. That is, strokes are not mathematical objects like functions. In order to perform stroke recognition, it is necessary to determine what shape a stroke has. For the identification of a straight stroke, a linear regression line is constructed from the point sequence with the Gaussian method of least squares. The construction is done with the standard method for calculating least squares, as described in literature. The method seeks for the minimal sum of squares of residuals (Marquardt 1963). If the sum of residual squares is below a certain threshold that has been determined empirically, the system assumes that the point sequence generally follows a straight line. In that case, straight stroke matching will be performed. If the line appears to be curved, it will be matched with curve analysis methods as described in section 7.5.3.

7.5.2.2 Straight Stroke Matching

For the matching of a straight stroke there are a number of features that could be considered for a feature vector. In order to describe a straight stroke and then match it with another one, a feature vector is constructed that has the following features:

- **Length:** The total length of the line. Sum of the distances of succeeding points.
- **Initial point:** The coordinates of the initial point
- **Endpoint:** The coordinates of the endpoint
- **Total number of measured points:** The number of sample points that were measured by the input device
- **Velocity:** The velocity with which the stroke was drawn
- **Gradient/Direction:** The slope of the linear regression line that can be constructed for the point sequence, or the general direction of the line, represented as a numerical vector.

However, some of the information seem redundant. In order to match two strokes by their feature vectors F_{db} and F_{exp} , the following values are considered:

$$F := \begin{pmatrix} \text{Length} & l \\ \text{Initial point} & p_I \\ \text{Endpoint} & p_E \\ \text{Velocity} & v \\ \text{Direction vector} & \vec{d} \\ \text{Sum of residual squares} & \sigma \end{pmatrix}$$

The features are used for matching with other straight strokes by comparison of their values. The length l is calculated as the sum of the Euclidean distances d_i between the individual points p_i and p_{i-1} within a sequence of N points.

$$d_i := \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}$$

$$l := \sum_{i=1}^{N-1} d_i$$

In the case of the initial point and endpoint comparison of the two strokes, the Euclidean distance between the original point $P_{I,db}, P_{E,db}$ and the candidate point $P_{I,exp}, P_{E,exp}$ is used as a comparison value. The velocity v is calculated from the time difference δ_T between sampling time of the initial point t_{p_I} and the endpoint t_{p_E} :

$$\delta_T := t_{p_E} - t_{p_I}$$

$$v := \frac{n_p}{\delta_T}$$

The velocities v_{db} and v_{exp} are both real numbers and can be compared directly. The direction vectors of the regression line \vec{d}_{db} and \vec{d}_{exp} are compared by the deviation of their directions. The deviation is expressed as the angle α between the original and the candidate vector.

$$\alpha := \vec{d}_{db} \angle \vec{d}_{exp}$$

The sum of residual squares σ is calculated from the measured point sequence with respect to the regression line of the database point sequence. Given the regression line f_{db} , the sum of the squares of the residuals for the input sequence is:

$$\sigma := \sum_{i=1}^N (f_{db}(x_{i,exp}) - x_{i,exp})^2$$

The smaller σ the closer the measured points to the regression line from the database. This is only done for strokes that have been calculated to be straight, since any set of points can have a regression line, even curved ones. In the case of curved strokes, a linear regression line as it is used here does not seem to bear the potential helping identify a point sequence to be a certain shape.

7.5.3 Curve Handling

7.5.3.1 Detecting Curves in Strokes

Different curve matching techniques are described in section 3.4.3.4. The technique used here refers to is a vector-based technique, that aims at the extraction of features to describe the curved stroke. In this prototype the direction feature plays a crucial role. It is generally following several approaches in on-line handwriting recognition literature. The direction feature as it is used in other applications has been discussed in section 3.4.3.3). The approach for curve recognition used here defines direction vectors.

The general concept is to define a direction vector between a point within the point sequence and a successor point. However, since the measured points are usually very close together, the direction vector is defined between a point and another point that is further away, defined by a dynamic threshold, considering distance, total number of points and the total length of the stroke. If non of these vectors deviates from the general direction of the stroke, a dynamic threshold, considering the total stroke length, the stroke is considered straight. Nevertheless, for matching straight strokes, a feature vector for straight strokes is used. If the slope of the curve changes, i.e. the direction of the vectors changes, a curve has been detected. There is a threshold T_{min} for the minimal size of a *recognisable angle* between two vectors. Any angle smaller than that will be ignored completely. A second threshold T_{max} describes the minimal size for an angle γ that is taken into account. Any angle β_i between T_{min} and T_{max} will be stored. When the sum of the β_i exceeds T_{max} the position will be treated as a curve.

$$\alpha < T_{min} \Rightarrow \alpha \text{ will be ignored}$$

$$T_{min} < \beta_i < T_{max} \Rightarrow \beta_i \text{ will be stored}$$

$$T_{max} < \gamma \Rightarrow \gamma \text{ will be interpreted as an angle in the stroke}$$

$$T_{max} < \sum_{i=k}^l \beta_i \Rightarrow \sum_{i=k}^l \beta_i \text{ will be interpreted as an angle in the stroke}$$

A successful curve detection extracts the key feature of the curve description. The remaining features can be extracted or calculated, by using the detected curves.

7.5.3.2 Feature Extraction for Curved Strokes

The feature vector for curved strokes contains the following elements:

$$F := \begin{pmatrix} \text{Length} & l \\ \text{Initial point} & p_I \\ \text{Endpoint} & p_E \\ \text{Velocity} & v \\ \text{Corner angles} & \gamma_i \quad i := 1, \dots, n \\ \text{Corner points} & c_i \quad i := 1, \dots, n \\ \text{Direction sequence} & \vec{d}_j \quad j := 1, \dots, m \end{pmatrix}$$

The partial feature vector l, p_I, p_E, v is identical to the partial feature vector of the straight strokes with the same elements and needs no further description (see section 7.5.2.2). The corner angles have been calculated. In the case of a summation of angles the point with the greatest angle will be determined as the corner point. In the case of angles that have been observed directly without summation, the corner point is the point where the angular vectors meet. Therefore, the number of corner points m and corner angles is identical. The feature *Corner points* is defined as the sum of Euclidean distances between the corner points from the stored data structure with the candidate data structure.

$$c_p := \sum_{i=1}^n \sqrt{(x_{i,db} - x_{i,exp})^2 + (y_{i,db} - y_{i,exp})^2}$$

The corner angles feature is defined as the sum of the squares of the differences between the angles at the corner points.

$$c_a := \sum_{i=1}^n (\beta_{i,db} - \beta_{i,exp})^2$$

For both c_a and c_p the smaller the value, the closer the more similar the strokes. In fact, if c_a or c_p are equal to 0, the point analysed point sequence was identical with the stored point sequence. The *direction sequence* feature takes into account all the direction changes, as opposed to the corner angles that use only the most significant ones. The direction sequence feature uses the angle of each line segment regarding the X-axis of the coordinate system. The angles are then matched against the time they were produced in.

7.5.4 Dynamic Time Warping

The technique of *dynamic time warping* (DTW) has been used for stroke matching by several studies and systems (see sections ?? and 3.5.4.2). It is an elastic matching technique that seeks an optimal path through a matrix of point distances. Details of the algorithm have been described in literature.

7.5.4.1 Standard DTW

Following Vuori et al. (2001) and Niels and Vuurpijl (2005), the DTW technique is implemented for two pen trajectories, namely the trajectory stored in the database $P_{db} = (p_{1,db} \dots, p_{n,db})$ and the input trajectory generated by the user's drawing $P_{exp} = (q_{1,exp}, \dots, q_{m,exp})$. Any point pair $p_{i,db}$ and $p_{j,exp}$ matches if one of two constraints is met:

1. **Boundary condition:** The points $p_{i,db}$ and $p_{j,exp}$ match, if one of the following boundary conditions is fulfilled:
 - $p_{i,db}$ equals the initial point $p_{I,db}$ and $p_{j,exp}$ equals the initial point $p_{I,exp}$ of their respective point sequences P_{db} or P_{exp}
 - $p_{i,db}$ equals the endpoint $p_{E,db}$ and $p_{j,exp}$ equals the endpoint $p_{E,exp}$ of their respective point sequences P_{db} or P_{exp}
2. **Continuity condition:** The points $p_{i,db}$ and $p_{j,exp}$ match, if the following equation is fulfilled

$$\frac{M}{N}i - cM \leq j \leq \frac{M}{N}i + cM$$

c is a constant between 0 and 1, indicating the strictness of the condition.

7.5.4.2 3-Dimensional DTW

In addition to the standard DTW algorithm, a second DTW classifier performs a 3-dimensional distance calculation. That is, a point sequence $P = (p_1 \dots, p_n)$ is considered 3-dimensional in the way that it contains the relative time (in ms) from the beginning of the stroke as a third dimension. The point distance calculations are Euclidean, ignoring the fact that the third dimension is a different type of coordinate.

$$d_i := \sqrt{(x_{i,db} - x_{i,exp})^2 + (y_{i,db} - y_{i,exp})^2 + (z_{i,db} - z_{i,exp})^2}$$

$\langle x_i, y_i \rangle$ are the regular 2-dimensional point coordinates, while the z_i are the relative times from the beginning of the stroke. The actual DTW algorithm works exactly the same, the difference lies in the distance calculation. This version of the algorithm has been conducted as an experiment. The direct comparison with the regular DTW is reported in section 8.2.2.

7.5.5 Stroke Matching Summary

Four different classifiers have been implemented. The straight stroke matching via regression lines, the curve matching classifier with direction sequences and two variants of the dynamic time warping algorithm, a regular DTW algorithm and the three-dimensional variant DTW. The stroke matching occurs in NUMBER parts. Firstly, the straight stroke recogniser attempts to establish if a stroke is straight or not. Then the straight stroke matcher analyses if the input stroke and the database stroke are equal. Secondly, if the stroke is regarded as being curved, the curve detector performs a search for the significant points and angles in both sequences. After that, the curved stroke matcher compares the features of the curved strokes. If both recognisers fail to recognise the expected stroke, dynamic time warping is used as a fall-back option.

7.6 Radical Recognition Process

7.6.1 Radical Recognition Features

The recognition of a Radical is a search process. The data format of Radicals is described in section 7.2.3.3. Essentially, a Radical is an ordered collection of strokes. In order to recognise a radical, the sequence of strokes from the database is compared to an input sequence. The measure of similarity is a feature vector that consists of the number of strokes and the similarities between them. Furthermore, permutations of the stroke sequence will be penalised. In order to match two radicals by their feature vectors F_{db} and F_{exp} , the following values are considered:

$$F := \begin{pmatrix} \text{Total number of strokes} & n_s \\ \text{Position of bounding box} & P \\ \text{Size of bounding box} & S \\ \text{Stroke matching values} & m_{i,j} \\ \text{Stroke sequence} & < s_1, \dots, s_n > \end{pmatrix}$$

Some of the features need little explanation. The total number of strokes n_s is an integer. In the matching process - if the $n_{s,db}$ and $n_{s,exp}$ differ, the confidence value of the radical recognition value will be lowered. The position of the bounding box P is determined by the handle point of the box. The Euclidean distance between the P_{db} and P_{exp} serves as a distance measure. The size of the bounding box S can support or refute assumptions about the general shape and size of a radical.

7.6.2 Exploitation of the Stroke Recognition Process

Stroke matching forms the core of the Radical recognition process. Each input stroke is matched against all the strokes of the Radical. A matrix of matching values will be generated by comparing each input stroke to each database stroke for a Radical. The confidence values in the stroke matching matrix M are used to analyse if the input stroke sequence signifies the currently analysed Radical.

$$M_{m,n} = \begin{pmatrix} \mu_{1,1} & \mu_{1,2} & \cdots & \mu_{1,n} \\ \mu_{2,1} & \mu_{2,2} & \cdots & \mu_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{m,1} & \mu_{m,2} & \cdots & \mu_{m,n} \end{pmatrix}$$

The matrix M forms the basis of the Radical recognition. The maximal confidence value for a Radical will be achieved if

- $m = n$
- the maximal matching value $\mu_{i,j}$ for each stroke is above a threshold in order to conclude that it matched with its corresponding stored stroke from the database.
- the maximal matching values $\mu_{i,j}$ for all strokes form a diagonal path through the matrix, with $i = j$ for each maximal matching value, starting at $\mu_{1,1}$, ending at $\mu_{n,n}$ (and $m = n$).

If two identical stroke sequences are analysed, the ideal is fulfilled. Any deviance from these constraints will be penalised and leads to a lower confidence value for the Radical match. The matrix is the source for both the features of the stroke matching values $m_{i,j}$ and the stroke sequence $< s_1, \dots, s_n >$. A deviance from the diagonal path means deviance from the ideal stroke sequence.

7.7 Character Recognition Process

The character recognition process relies on the Radical recognition process. Each character is comprised of a set of Radicals the position of their bounding boxes. In order to determine if a stroke sequence represents a certain character, firstly the individual Radicals are recognised. For character matching, the recognised Radicals are compared with the Radicals of the character. If they match with a confidence values above the threshold and their position within the character is correct and the character is recognised correctly. Generally, the confidence value of a character depends on the confidence values of the individual radicals and the distance and position of the bounding boxes to the database entry. A feature vector F here is defined as:

$$F := \begin{pmatrix} \text{Number of Radicals} & n_r \\ \text{Position of Radical bounding boxes} & P_i \quad i = 1, \dots, n_r \\ \text{Radical confidence values} & c_i \quad i = 1, \dots, n_r \end{pmatrix}$$

The $n_{r,db}$ and $n_{r,exp}$ are compared numerically, as they are real numbers. The positions of the Radical bounding boxes $P_{i,db}$ and $P_{i,exp}$ are compared by their Euclidean distance. The Radical confidence values c_i are averaged. The confidence value C for a character is calculated in several steps. The confidence value C_n for the number of Radicals is computed as follows:

$$C_n := \begin{cases} \frac{n_{r,db}}{n_{r,exp}} & \text{if } n_{r,db} \leq n_{r,exp} \\ \frac{n_{r,exp}}{n_{r,db}} & \text{if } n_{r,db} > n_{r,exp} \end{cases}$$

The confidence value C_p for the Radical positions is extracted from a matrix of Euclidean distances between the Radical handles $P_{i,db} = \langle x_{i,db}, y_{i,db} \rangle$ and $P_{i,exp} = \langle x_{i,exp}, y_{i,exp} \rangle$. All the distance values $\mu_{i,j}$ are computed first to generate a Matrix of Radical position distances $M_{m,n}$, where $n = n_{r,db}$ and $m = n_{r,exp}$.

$$\mu_{i,j} := \sqrt{(x_{i,db} - x_{j,exp})^2 + (y_{i,db} - y_{j,exp})^2}$$

$$M_{m,n} = \begin{pmatrix} \mu_{1,1} & \mu_{1,2} & \cdots & \mu_{1,n} \\ \mu_{2,1} & \mu_{2,2} & \cdots & \mu_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{m,1} & \mu_{m,2} & \cdots & \mu_{m,n} \end{pmatrix}$$

The minimal value ξ_m of each line or column is chosen. f_p is a constant factor for scaling the confidence value.

$$C_p := \begin{cases} f_p * \sum_{i=1}^{n_{r,db}} \xi_i & \text{if } n \geq m \\ f_p * \sum_{i=1}^{n_{r,exp}} \xi_i & \text{if } n < m \end{cases}$$

The confidence value C is the averaged sum of the other confidence values. The sum consists of the confidence values for the number of characters C_n , for the position of the Radical bounding boxes C_p and the averaged sum of the Radical confidence values. All partial confidence values are weighted with the w_i constants.

$$C := \frac{1}{3} (w_n * C_n + w_p * C_p + \frac{w_c}{n_{r,exp}} \sum_{i=1}^{n_{r,exp}} c_i)$$

7.8 Error Handling

Error handling is a crucial part of the handwriting recognition engine. It provides the information needed in order to give informed feedback to the user, when he has drawn a character. The general motivation for error handling has been discussed in section 5.4.1 typical sources of error have been described in section 5.4.2. The focus in this section lies on the technical aspects of error handling.

7.8.1 Error Detection

Error detection is fully integrated into the character recognition process. Concerning abstract module structure it is not an individual model, but rather an integral part of the recognition module. There is a logical explanation for that matter. The error detection in this prototype is a structural error analysis. The achievement of a structural error analysis the main cause for the character recognition process to be structural. The task of error detection is not trivial, since there can be recognition errors as well. However, in the case presented here, the error detection uses the confidence value calculations for strokes, radicals and characters in order to find out if there were errors. Additionally, the confidence values for the structural elements define what type of error has been detected.

7.8.1.1 Direction of Error Detection

Error detection is performed when the learning system asks the user to enter a certain character. Depending on the confidence value for the recognition of character substructures, error detection determines why and where the recognition failed. Error detection works in two directions: From *inside out* and from *outside in*. The direction of error detection refers to the hierarchical nature of the character structure as well as the character recognition process.

Inside out error detection occurs if the confidence value of a terminal element in the hierarchy was low during its recognition. If a stroke has been recognised as the correct stroke, but has a significant deviation from the corresponding stroke in the database, the deviation and certain information connected to it is stored as a minor error. For example, if a straight stroke has been detected with the correct position and the correct direction, but incorrect length, the fact that the stroke did not have the correct length will be stored. Inside out error detection is performed during the recognition process focuses on detecting minor errors.

Outside in error detection occurs if the confidence value of a character was below the threshold. The cause of the low confidence value will be ascertained top down, checking the confidence values of the substructures. If a character recognition failed because of a low confidence value of a specific Radical, that Radical will be examined further. Outside in error detection is performed after the recognition process is completed and focuses on detecting the major errors.

7.8.2 Error Processing

After the error detection and localisation, a feedback is generated depending on the primary source of the errors. Major errors contain incorrect characters and incorrect Radicals within characters. Missing or additional strokes within Radicals are regarded as intermediate errors. Minor errors are strokes that are recognisable but vary in shape from the database standard. The error location and type are returned together with the recognition result. In case a character is incorrect and no error could be recognised, a standard character recognition process is performed. In analogy to that, if a Radical within a character was deemed incorrect by the system, the substructure undergoes a new recognition process. In case of incorrect strokes the system generates an error description based on the shape of the stroke.

Chapter 8

Implementation and Evaluation

see: (Chua and Dyson 2004) and: Lanzilotti_eLSE_Methodology_aSystematicApproach_to_the_Evaluation_of_e-Learning_Systems.pdf
find references - not in bibtex yet.

- Why this section? The purpose of this section is It would be off purpose, if - What goes into this section? The main content of this section is * if describing a problem: why is the problem relevant. * if describing a solution to a problem: what alternatives were there to solve it, why was this solution chosen? what made it the best choice? was it the optimal solution? - How will this section be structured and organised? The organisational structure of the section - In what style will it be written? The style of writing will be - Next action - what to write first? The next part to write is

8.1 Implementation Details

Pointer auf CD und auf Appendix mit Beispielinteraktionen (diese mit Foto). Screenshots. Zahlen zur Erkennung - z.B. wie lange dauert es, ein zeichen zu erkennen?

wie wurden einzelne dinge realisiert, z.b. vectorielle funktionen? was war neu? klassen wie box / bounding box, technisch, alles was in HWREngine nicht behandelt wurde.

abschnitt ueber optimierung. optimierungszyklus inklusive ausprobieren beschreiben. s. 51 rueckseite

s 49 rueckseite: interface-optimierung entscheidungen herausstellen.

s 27,28 vectorschnitt

s.11 iPhone - port of input app. checked out objective C and stuff!

see section 7.1.1.1. describe what was difficult concerning the lists and bloody point objects. performance issues! optimisation with try and error!

ISF - see section 7.2.2.1

dead end of data format description: how I first developed my own format and then found that UPX was better.

in 7.3 there is an undiscussed point: 3. Description of the production of the lexicon. it was not just taken from j.b. but it was intervowen?! (verflochten) with the trajectories. where did I get these from? how many chars are in the two dictionaries

in section 5.1.3.1 I claim that I am taking the ISO something 'installability' into account. this should happen somewhere here. from section 5.1.3.1

which is defined in ISO9126 as *installability* as well (Chua and Dyson 2004). The ISO9126 type of installability will be taken into account during the software evaluation, which is reported in chapter 8.

8.2 Evaluation of the HWR

8.2.1 Evaluation Metrics

evaluation method: counting precision and recall section about precision and recall - the odd numbers. how can that be done honest and useful? how can I get meaningful numbers at all?

s. 12 beachten: WICHTIG: eval kurz und qualitativ.

8.2.2 DTW vs. 3-D DTW

This section al

8.3 Evaluation of E-Learning Application with Integrated HWR

qualitative auswertung, keine zahlen, sondern fragebogen. fuehlt der lerner sich unterstuetzt? glaubt er, dass es schneller geht als ohne HWR? besser als auf papier?

8.4 Evaluation of the Error Hints

use cases, inwieweit helfen die fehlerhinweise? geht das lernen dann wirklich schneller? wie laesst sich der mehrwert bewerten? system kann sagen: wo liegt die verwechslung? warum war das falsch?

Chapter 9

Conclusions

In the history of Computational Linguistics there have been a several attempts to integrate natural language processing techniques with existing technologies. That task is complex in many aspects, depending on what is aimed at exactly.

In this study, I will attempt to create a handwriting recognition for Japanese Kanji. That seems interesting because Kanji the characters form a morphemic writing system with a large number of characters. Thus, handwriting recognition (HWR) of Kanji follows different patterns than in alphabetical writing systems like Latin script. The overall methodology of HWR system is similar to systems for Latin characters, but the details of analysis vary strongly.

Studying Japanese language is a complex task, because a new learner has to get used to a new vocabulary that - coming from a European language - has very little in common with the vocabulary of his mother tongue, unlike in European languages where quite often there are several intersections. The learner also needs to learn a new grammar system. Broadly speaking, most of the central European languages follow a subject-verb-object (SVO) structure. Japanese follows a subject-object-verb (SOV) structure. These create additional difficulty, comparable with German reversed subclause structures that are a source of error for many learners of German. Yet, the most notable difference for a language learner with a central European mother tongue is of course the writing system. The Japanese writing system uses three different scripts. The so-called *Kana* scripts *Hiragana* and *Katakana* are syllabic, each character represents a syllable. Each syllable consists of either a vowel, a consonant and a vowel, or a consonant cluster and a vowel. The syllables are called *open*. Hiragana and Katakana represent roughly the same inventory of syllables and both have around 40-50 characters that can be modified with diacritics in order to yield additional syllable representations. Therefore, these scripts are a hurdle for a learner, but relatively unproblematic, due to their limited number of characters. Besides, the two sets of Kana characters look quite distinct, so the problem of confusing one character with another is limited to a relatively short learning period of those two scripts.

The Kanji, on the contrary, form the largest part of a writing system that has around 3,000 characters, which are built up of around 200 subunits called *Radicals*. One part of the complexity lies in the number of characters. The other part lies in the general method of representing an idea or concept with a character instead of attempting to represent the sounds with graphemes in connection with language specific pronunciation rules. Another difficulty lies in cognitively connecting the characters with their pronunciations. Most characters have multiple pronunciations and for a language learner, studying Japanese vocabulary takes at least twice as much effort compared to languages using a Latin or at least some kind of alphabetic writing system. The two tasks of learning the Kanji and studying the vocabulary together can epitomise a very high learning curve. A connected subordinated problem lies in the fact that quite often subjectively 'simple' vocabulary comes with complex Kanji. Some e-learning applications have taken on that issue by creating a learning environment in which a learner can connect learning vocabulary with studying the Kanji characters.

9.0.1 Integrating NLP and E-Learning

In this project, the main focus lies on the creation of an analytical handwriting recognition engine for Kanji. The advantages of such an engine can be applied to e-learning applications. This is exemplified with a sample e-learning application that includes specialised exercises for handwritten input. The novelty about it is a handwriting recognition that gives the learner the ability to actually practise writing the Kanji and get a feedback, instead of the rather limited multiple choice recognition that most other applications use.

The integration of NLP and e-learning relies on the analytical handwriting recognition. Since characters are split into sub units, the generated feedback about the input correctness can guide a user of the e-learning application precisely to the error. This is an advantage over a binary statement *correct* or *incorrect* that is directly based on recognition success.

Chapter 10

Outlook

- Why this section? The purpose of this section is It would be off purpose, if - What goes into this section? The main content of this section is * if describing a problem: why is the problem relevant. * if describing a solution to a problem: what alternatives were there to solve it, why was this solution chosen? what made it the best choice? was it the optimal solution? - How will this section be structured and organised? The organisational structure of the section - In what style will it be written? The style of writing will be - Next action - what to write first? The next part to write is

What can we do for other languages, using similar character sets? This HWR as a service for other applications?

What can be done with future devices? With a multi-touch device? With a pressure-sensitive device?

Idea: Port auf iPhone. Wieviel aufwand?

See source of section 3.4.1 for this paragraph here: xxx: The reason for not using pressure intensity as a recognition feature might be that it is plausible to assume that pressure intensity is even more individual to the writer than the shape of the drawn characters. Therefore, featuring pressure intensity in a HWR application could add more noise to the data. However, the differences in pressure intensity between different characters drawn by the same writer should be analysed. [xxx put the speculation about pressure intensity into outlook chapter? something along the lines of progress in device technology, subsection pressure intensity of tablets? Or maybe refer from here to outlook chapter?] :xxx

ISF - see section 7.2.2.1 and section in implementation chapter.

10.0.1.1 Character Repetition

In section 4.5 the pure repetition of grammatical structures as a learning method has been criticised. The system should account for that by not just forcing the user to reproduce fixed structures. In fact, it should leave room for creativity. The system does not provide a free-drawing module in order to allow for total creativity. But, creativity is given through the use of the Handwriting input as such. A user can practice his own writing style. The tolerance thresholds given by the character recognition allow for a interpretation of the character shape, rather than a pure repetition.

Appendix A

Japanese Language

A.1 Kana かな

A.1.1 Hiragana ひらがな

Hiragana is a syllabic script. For a description of use and structure of Hiragana see section 2.2.1.1. A full table of the Hiragana script can be found in table (A.1). Table (A.1) is adapted from (Hadamitzky 1995).

	a	i	u	e	o	n
∅	あ	い	う	え	お	ん
k	か	き	く	け	こ	
s	さ	し	す	せ	そ	
t	た	ち	つ	て	と	
n	な	に	ぬ	ね	の	
h	は	ひ	ふ	へ	ほ	
m	ま	み	む	め	も	
y	や		ゆ		よ	
r	ら	り	る	れ	ろ	
w	わ				を	

Table A.1: The full set of Hiragana characters

A.1.2 Katakana カタカナ

Katakana is the second syllabic script in use in the Japanese language. For a more detailed description of what it is used for, see section 2.2.1.2. A full table of the Katakana script is depicted in table (A.2). Table (A.2) is adapted from (Hadamitzky 1995).

	a	i	u	e	o	n
∅	ア	イ	ウ	エ	オ	ン
k	カ	キ	ク	ケ	コ	
s	サ	シ	ス	セ	ソ	
t	タ	チ	ツ	テ	ト	
n	ナ	ニ	ヌ	ネ	ノ	
h	ハ	ヒ	フ	ヘ	ホ	
y	ヤ		ユ		ヨ	
r	ラ	リ	ル	レ	ロ	
w	ワ				ヲ	

Table A.2: The full set of Katakana characters

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