# Automatic Handwriting Recognition Using a Modified Interpolated Kneser-Ney Smoothed Linguistic Post-Processor

Ayla Kangur, s1720120, a.m.a.kangur@rug.nl,

*University of Groningen, Department of Artificial Intelligence*

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## Abstract

**In this paper an automatic handwriting recognition system is discussed which is trained and tested on handwritten historical documents. All implementation decisions from preprocessing to post-processing are elaborated. In a first experiment two separate classifiers are explored, one makes use of Histogram of Oriented Gradients (HOG) features and the other uses pixel count information. Additionally, a third setting is tested in which both these classifiers are combined. Both the classifier using HOG features and the ensemble of classifiers perform significantly better than the classifier using solely pixel count. In a second experiment, the addition of a statistical linguistic post-processor using modified interpolated Kneser-Ney smoothing at a trigram level is analyzed. It is shown that the usage of a linguistic model can significantly improve recognition results given that the post-processor receives a sufficiently small number of words to select from.**

## 1 Introduction

Nowadays, important documents are typically entered into a computer that converts key presses to a standardized font. This makes these documents not only easily readable to anyone who is interested, but the information also becomes easy to access and distribute. However, this is only a very recent development. For centuries after Johannes Gutenberg invented the printing press in 1440, many documents were still written by hand. This means that a large part of our world history is still residing in books written by many different writers, unavailable to a wider public.

A useful approach to make these documents more accessible is the use of automatic handwriting recognition systems that can automatically convert any handwritten document to ascii-code. A possible and common approach for such a system is to segment a page into words and apply preprocessing such as binarization and despeckling to each word image to make sure that purely the ink of the word is left. The system can then extract useful features from the image and learn what makes each unique word different from any other word. From then on, it can classify new unseen data as any of the previously learned words. It should be noted that the recognition does not need to take place at a word-level. A system can also be build by learning the characters within words. A recent review by Rehman and Saba (2011) shows the benefits and drawbacks of each approach. Where word recognition is useful for narrow domains using a limited vocabulary, the problem becomes incomprehensible as the lexicon grows. The approach does not have a way of dealing with unknown words. A character based recognition system on the other hand can be applied to any unfamiliar character sequence. However, this yields new problems when it comes to segmenting a word into separate characters.

As can be seen in the previous paragraph, automatic handwriting recognition systems can differ in many different aspects such as the preprocessing methods used, the features that are extracted and the classifier that compares different sets of features. In this paper, we will explore the effect of using different types of features by testing two sets of features separately and later combining them to see what their joined effect will be. In one feature extraction method, purely the count of the pixels is taken into account. In the second feature set, a more refined method that focuses on the gradients in the words and is called Histogram of Oriented Gradients (HOG) is used. This method was originally used for the task of human detection. However, good results have been found using local HOG features in handwritten word spotting tasks (Rodrìguez and Perronnin, 2008; Terasawa and Tanaka, 2009). We assume this might also perform well in our application of handwriting recognition. HOG has some points in common with Lowe's SIFT key point descriptor (Lowe, 1999), but it differs in the fact that HOG normalizes the histograms in overlapping blocks and makes, as a result, a redundant expression. Also, HOG is computed without scale/orientation normalization and is computed everywhere in the image instead of only around the detected key points.

Over the years much progress has been made using automatic handwriting recognition systems that classify new words according to their features, as can be seen in Plamondon and Srihari (2000). However as Plamondon and Srihari also mention, the addition of a language model is essential in recovering word sequences from a text. This means that we have to go beyond the pixel level and approach the problem from a higher, context related view as well. Automatic handwriting recognition should become a two way street where bottom-up word classification and top-down linguistic models help each other to reach the best possible results. As Bunke (2003) states, $n$-grams are a popular method for incorporating linguistic knowledge. Here $n$ represents any predefined number of words in a word sequence. So instead of the probability of a word depending on all previous words in the text, it is assumed that the probability is only dependent on itself and the previous $n-1$ words. Using $n$-grams, the probability distributions over all possible word sequences can be computed. However, there are a finite number of $n$-grams to be found in any training set whereas our language allows for an infinite combination of words. Therefore, solutions like backing-off (Rosenfield, 2000), interpolation and smoothing (Chen and Goodman, 1999; Jelinek and Mercer, 1980; Ney et al., 1994) can be useful.

In this paper we propose a word recognition method that is tested on extracting different kinds of features. It is hypothesized that HOG, being a more sophisticated method, will outperform the simpler method that uses pixel count. A second hypothesis is that a combination of both feature sets will perform even better because both feature sets focus on different kinds of information. In a second experiment, the recognizer using the best performing feature set will make use of a statistical linguistic post-processor which uses word transition probabilities through $n$-grams. It is hypothesized that this post-processor will indeed improve the recognition results from the classifier. The bottom-up preprocessing, feature extraction and classification stages will be described in sections 2.1 until 2.4 respectively. Section 2.5 focuses on the top-down linguistic model. Section 3 will show the experiments we conducted and the results we obtained are formulated in section 4. The results section also shows how our recognizer performed in a competition held at the University of Groningen, the Netherlands. Here, three teams tested their handwriting recognizer on a secret test set. Conclusively, section 5 will discuss the implications of the experimental results.

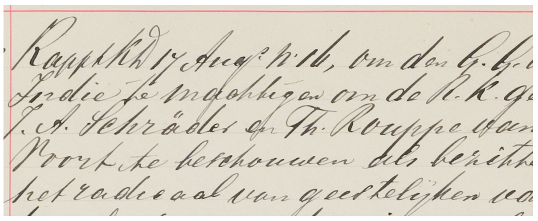
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**Figure 1: A selection of a page from the 'Queen's Cabinet'.**

## 2 Method

To built a robust handwriting recognition system, both bottom-up and top-down information was used. This section first describes the bottom-up pipeline and then focuses on the bridge between these two aspects and the top-down process itself.

### 2.1 Dataset

The handwritten material which was made available for the experiments is historical handwriting from the "Queen's Cabinet" (*Kabinet der Koningin*, stored at the Dutch National Archive, *Nationaal Archief*, Den Haag) as shown in Figure 1. Accompanying every page are the predefined segmentation coordinates with the manually annotated words. Therefore, segmenting pages into separate words is no longer a problem. However, some annotations are not perfect and cover multiple words or even skip words. Therefore, the training and test set contain errors which might weaken the recognition results.

The entire set consists of 66 pages and is made up out of 2323 unique words, 6097 unique bigrams and 8653 unique trigrams. Having so little data to train on results in a sparse data set with 77.4% of the words occuring only one or twice and 95.6% of the words occurring less than 20 times. To obtain a more robust training set, more training samples were created by applying distortions to word images that do not occur frequently. Varga and Bunke (2003) showed that generating synthetic training data can substantially improve the performance of a handwriting recognition system. For every instance that occurred less than 20 times, four additional instances were created. The used distortions were gray scale *erosion*, *dilation*, *opening*, and *closing*.

An extra line transcription file without accompanying word images was available for training the post-processor. Therefore, the linguistic model consists of 10703 unique words, 37100 unique bigrams and 61696 unique trigrams.

## 2.2 Preprocessing

To deal with differing illumination and to get robust features out of a word image, preprocessing methods and normalization were applied to the word images extracted from the pages. In this section, the processes involved in preprocessing and normalization are discussed.

**Conversion to gray scale** A necessary step for the binarization technique we use is to first convert the images to gray scale. As shown in Figure 1, there are some red lines on the page which should be removed. To get rid of these lines and convert the image to gray scale in one step, the green and blue channel of the RGB image were removed. As a result, the red lines become white and because there is only one channel left ranging from 0-255, the gray scale image is obtained. The result is shown in Figure 2(b).

**Deslanting** All words on the pages have a slant angle of 45°. In order to extract robust information from the word images, it is useful to upright the words so that the individual characters overlap as less as possible. To upright the images, a mathematical transformation on the x-coordinate of every pixel was applied, as shown in Equation 2.1:

$$x' = x - (y - height) * -tan(\alpha) \qquad (2.1)$$

with $\alpha = 45$. After this transformation, there are still some parts of the next word in the image. This part of the image was cropped away, leaving only the pixels that belong to the current word. The result is shown in Figure 2(c).

**Binarization** Ntirogiannis et al. (2008) compared different binarization techniques which can be used to obtain a binarized image and showed that Sauvola's method results in high performance. For our proposed method, Sauvola's specialized text binarization method was used (Sauvola and Pietikainen, 2000). It can separate text components from background in bad conditions, caused by uneven illumination or noise. The threshold $t_{(x,y)}$ is computed using the local mean, $m_{(x,y)}$, and local standard deviation, $s_{(x,y)}$, of the pixel intensities in a window centered around the pixel $(x, y)$:

$$t_{(x,y)} = m_{(x,y)} * (1 + k * (\frac{s_{(x,y)}}{R} - 1)) \qquad (2.2)$$

The whole word image was used as window because all the word images are cut from the page beforehand and they are, as a result, already small. Also, the variation in illumination per word is very limited. Two parameters must be defined: $R$, which represents the maximum value of the standard deviation (normally set to 128 for a gray scale document), and $k$, which is a parameter which takes positive values in the range [0.0, 0.5] and controls the value of the threshold in the local window such that the higher the value of $k$, the lower the threshold from the local mean. The local mean $m_{(x,y)}$ and standard deviation $s_{(x,y)}$ adapt the value of the threshold according to the contrast in the local neighborhood of the pixel. To assist Sauvola in this way, contrast stretching was used (Figure 2(c)). Because gray scale images are used, $R$ is set to 128. Even with contrast stretching there is very little contrast in some parts of the words, therefore, $k$ had to be set to a low value. After some experimentation, a value of $k = 0.05$ seemed to be the most optimal. The result is shown in Figure 2(d).

**Unwanted connected components** As shown in Figure 2(d), in some cases there are unwanted connected components at the bottom or top of the image. Connected components were considered unwanted when they touched the bottom or the top of the image and did not cross the vertical center of gravity of the image. The center of gravity, as in physics, can be seen as the point where the mass of the object is equally balanced. In binarized images, this corresponds to the point where there are as many black pixels to the one side as to the other side of the image.

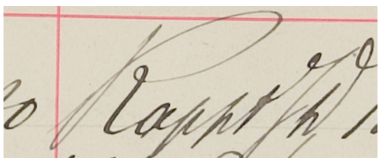
Next to these unwanted connected components, also connected components of size smaller than 10 were considered as unwanted connected components (despeckling). The result is shown in Figure 2(e).

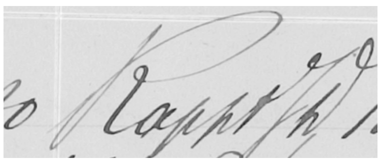
**Centering and resizing** For classification it is very important to have normalized features. To achieve this, some transformations were performed.

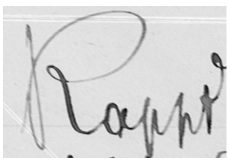
The first transformation was cropping away a certain percentage of the ink on the borders leaving only the core of the image containing the most information. Preliminary experiments resulted in getting the best performance with cropping away 10% of the ink.

The second transformation involved centering the image to the center of gravity. Because most ink situates between the baseline and the corpus line of the words, centering the images to the center of gravity will result in the baseline and corpus line being approximately in the middle of the image. With this, invariance to the position of a word is obtained. The result is shown in Figure 2(f).

The last transformation involved rescaling the word images to a standard size. Every word has a different width and height and this makes is difficult to compare features from these images. Therefore, the images were rescaled using bilinear interpolation to a fixed resolution of $100 \times 50$ pixels ($width \times height$).

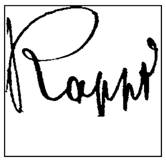

(a) Segmented color image


(b) Conversion to gray scale


(c) Deslanted and contrast stretched

(d) Binarized image using Sauvola's method

(e) Connected components removal


(f) Centered to center of gravity

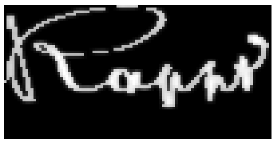

(g) Inverted normalized image used for HOG

**Figure 2: The different stages of preprocessing the word image containing the Dutch abbreviation 'Rappt'. The border around image (g) is for clarification only.**

## 2.3 Feature extraction

According to Suen (1986), there are two types of features: statistical and structural features. Statistical features are derived from statistical distribution of every point in the image such as moments, histograms and zoning. Structural features are based on geometric and topological features of characters such as contours and end points. To use all these features can lead to dimensionality problems commonly known as the curse of dimensionality. Therefore, to overcome this problem, a selection of features must take place.

Two feature sets were constructed to explore which types of features lead to better classification. These sets were constructed with the features stated below.

### 2.3.1 Density histograms

Density histograms give a compact representation of the binary image. They are constructed by the horizontal and vertical projection method (AL-Shatnawi and Omar, 2008). This method works by reducing the 2D array of data to 1D based on the pixels of the image:

$$P(x) = \sum_{y} I(x, y) \tag{2.3}$$

where $P(x)$, in this example, is the horizontal projection of the image for row $x$, and $I(x, y)$ is the pixel intensity in the image at position $(x, y)$, $I(x, y) \in \{0, 1\}$.

### 2.3.2 Radial zones

Radial zones work with the sliding window method (Fig. 3). The window slides on a fixed height from left to right. In our method the window slides on the vertical center of gravity, because this is where the information density is the highest. The window is shaped as a circle and divided into two major components, the outer ring and the inner circle. Both components are further divided into four segments: top right, bottom right, bottom left, and top left. In every segment, the total amount of black pixels is counted and stored. This gives us 8 features per window.

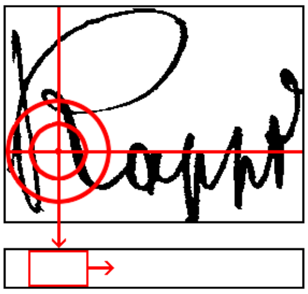


**Figure 3: Radial zones method as a feature for the classifier. A sliding window slides horizontally over the input image and the amounts of black pixels in the 8 different segments are computed.**

Preliminary experiments showed that a suitable measure for the diameter of the inner circle is defined as the height of the image divided by 8, whereas the diameter of the outer ring is determined as the height of the image divided by 4. The inner circle covers the core of the letters, surrounding the vertical center of gravity. The outer ring covers the top and bottom of the lowercase letters and pieces of the ascenders and descenders.

Density histograms and radial zones formed the first feature set, focused on the pixel count of the image.

### 2.3.3 Histogram of Oriented Gradients

The second feature set does not focus on the pixels of the image in particular, but on the orientations of the gradients in the image. The image $I(x, y)$ was divided into $M \times N$ cells, with each cell having height $H$ and width $W$. The cells do not overlap. Then, for each cell the HOG was computed. The gradients were assigned to the closest orientation given a number $T$ of regularly spaced orientations. One can choose to use the entire range ($2\pi$) or use only half ($\pi$).

**Computing the gradient histogram** HOG can be computed on both binarized or gray scale images. Some preliminary experiments were conducted and better performance was observed using the gray scale images. For using gray scale images, the background pixels had to be removed. The background of the image does not contain any relevant information and can thus be subtracted without any loss of information. The gray scale image, $J$, was obtained by leaving only the pixels in the original gray scale image which were detected as foreground pixels by Sauvola's Text Binarization Method.

To facilitate the succeeding feature extraction method, the image was inverted such that the background has intensity 0 and foreground has a new intensity of 255 minus the original intensity. The obtained gray scale images have variable foreground gray levels over different samples. Because HOG is dependent on these gray levels, each image was smoothed and normalized such that the foreground pixels of each image had a standard mean of 210 and a standard deviation of 20, as was done in Liu and Suen (2008). The result is shown in Figure 2(g).

The gradient can be calculated using different operators such as Roberts and Sobel. Roberts and Sobel operators calculate two gradient components, $\mathrm{g}_x$ and $\mathrm{g}_y$, in orthogonal directions. A study by Liu and Suen (2008) showed that Sobel slightly outperforms the Roberts operator. Therefore, a $3 \times 3$ Sobel mask was used to calculate the gradient. At a pixel $J(x, y)$, the Sobal gradient $\mathbf{g} = (\mathrm{g}_x, \mathrm{g}_y)^{\mathrm{T}}$ is calculated by

$$\begin{aligned} \mathrm{g}_x(x,y) &= J(x+1,y-1) + 2J(x+1,y) \qquad (2.4)\\ &\quad +J(x+1,y+1) - J(x-1,y-1)\\ &\quad -2J(x-1,y) - J(x-1,y+1),\\ \mathrm{g}_y(x,y) &= J(x-1,y+1) + 2J(x,y+1) \qquad (2.5)\\ &\quad +J(x+1,y+1) - J(x-1,y-1)\\ &\quad -2J(x,y-1) - J(x+1,y-1) \end{aligned}$$

The gradient magnitude $m$ and direction $\theta$ were then obtained for a pixel at position $(x, y)$ as

$$m(x,y) = \sqrt{\mathrm{g}_x^2 + \mathrm{g}_y^2} \qquad (2.6)$$

and

$$\theta(x,y) = \angle(\mathrm{g}_x, \mathrm{g}_y), \qquad (2.7)$$

where $\angle$ is a function that returns the direction of the Sobel gradient $\mathbf{g}$ in the range $[-\pi, \pi]$.

Next, the orientation bin which is the closest to $\theta(x, y)$ was computed and $m(x, y)$ was added to the corresponding bin. As assigning gradients to the closest orientation may result in aliasing noise, the gradient magnitude of a pixel can be shared between the two closest bins, as determined by a linear interpolation in the angle domain. Let $\alpha$ denote the angle between the pixel and the closest bin, then the distance to the second closest bin becomes $\frac{2\pi}{T} - \alpha$. Then the contribution of this pixel to the closest and second closest bin becomes respectively:

$$m(x,y)[1 - \frac{T\alpha}{2\pi}], \text{ and } m(x,y)\frac{T\alpha}{2\pi}. \qquad (2.8)$$

To avoid boundary effects, it was assumed that outside the image the pixel values are 0.

**Block normalization** After obtaining the histograms for each cell, normalization was performed in overlapping blocks to obtain a redundant expression. A block was defined as a group of $h \times w$ cells. The block slides inside the window image, that means that $(N - h + 1) \times (M - w + 1)$ unique blocks exist. Each block is normalized such that their components sum to 1. The HOG descriptor is a concatenation of the normalized block descriptors. Each block has a dimensionality of $hwT$, resulting in HOG having $(N - h + 1)(M - w + 1)hwT$ dimensionalities.

**Parameter estimation** In the above algorithm, some parameters remained undecided. The number of cells ($M \times N$), the number of orientations $T$, and the number of cells in a block ($h \times w$).

For estimating optimal parameters, some preliminary experiments were conducted. Experiments with the number $T$ and the range resulted in the best settings for our system being $T = 9$ and a range of $2\pi$.

Using the study of Terasawa and Tanaka (2009) as a guideline, preliminary experiments were conducted with the number of cells and the number of cells in a block. The obtained settings were $M = 5$ and $N = 20$, which corresponds to a cell with dimensions $10 \times 5$ pixels ($height \times width$). For the blocks, $2 \times 2$ cells were used, which was also found to be the most optimal in Terasawa and Tanaka (2009).

## 2.4 Bottom-up classification

For both feature sets, $k$-nearest neighbor ($k$-NN) was used for classification. Both the classifier and how distances can be mapped to probabilities, which is needed for the linguistic post-processor, are described in this section.

**$k$-NN** Simple nearest neighbor ($k = 1$) was used for our testing method. This means that the input is assigned to the class of the nearest pattern. As distance metric Euclidean distance was used.

Before classification, the mean word length and mean standard deviation were used to prune word classes that are much shorter or longer than the word that is currently being classified. For example, when it is known that the current instance has a word length of 300 pixels and the standard deviation over all training samples is 50, all word classes smaller than, say, 150 and larger than, say, 450 pixels are very unlikely to be correct. The word length of every training instance was extracted just before resizing and centering the images to the center of gravity, which gives us per class a mean word length and standard deviation. For classes containing only one instance, the mean standard deviation of all classes containing more than one instance was used as standard deviation. A class was considered a possible candidate if the instance to be classified fell in between the bottom and upper limit given by:

$$len(c) - 3 * sd(c) < len(i) < len(c) + 3 * sd(c), \quad (2.9)$$

where $len(c)$ denotes the mean word length of the current class $c$, $len(i)$ the word length of instance $i$ to be classified, and $sd(c)$ denotes the word length standard deviation of class $c$. The word length of the instance thus had to fall inside three times the word length standard deviation of the class, which covers roughly 99% of all instances in that class. Outliers are in this way left out.

A list of $N$ candidates was constructed for the post-processor. The post-processor will then decide from these candidates what the final output for this word instance will be (Section 2.5). When both sets of feature vectors are combined (one set for radial zone and density histogram features and one set for the HOG features), two simple nearest neighbor classifiers are used. In this case, both of these classifiers will thus propose a list of the $N$ most likely candidate(s) for each word.

**Statistical probabilities** The linguistic post-processor combines contextual probabilities with the probabilities from the bottom-up classifier. Because the classifier only returns distances, these distances need to be transformed to statistical probabilities first.

Two frequency maps were constructed of the possible distances, one for same class samples, and one for different class samples. These maps were constructed by calculating the distance, $d$, of every training sample to every other training sample. If the two training samples had the same class, the same class frequency map for distance $d$ was incremented. If, on the other hand, the two training samples had different classes, the different class frequency map for the distance $d$ was incremented. Combining both maps and given a distance, the number of samples that will be classified correctly (or incorrectly) can be estimated.

The problem of having a small training set is that both frequency maps have to be interpolated on missing distances. For example, when a distance of, say, $d = 10$ and $d = 12$ both occur 100 times, and $d = 11$ does not occur, the problem arises of giving wrong probabilities to this last distance. To avoid this, smoothing could be applied, but with larger gaps in the data this problem is not solved. Instead, the frequencies were accumulated. The same class frequency map was accumulated from right to left (largest distance to smallest distance), the different class frequency map from left to right. As a result, two sigmoid graphs were obtained. The probability of classifying an instance correctly, given a distance $d$, becomes

$$P(d) = \frac{F_{same}(d)}{F_{same}(d) + F_{diff}(d)}, \quad (2.10)$$

where $F_{same}$ is the accumulated frequency of the same class map and $F_{diff}$ is the accumulated frequency of the different class map.

## 2.5 Top-down selection

Although the bottom-up pipeline already proposes the most likely word for each word-image, only the pixel information of the words is used to come to this conclusion. This process does not take into account any linguistic knowledge such as the appearance of previous words. Therefore, our method also proposes a top-down post-processor, specifically focusing on linguistic information and clues which can be derived from the interplay between words.

Instead of only receiving the most likely word for each segment in the text, each classifier provides the post-processor with $N$ possible candidates, each with its own probability. From this list of candidates the post-processor then selects the most likely word using $n$-gram probabilities.

In the case where both classifiers are combined and they both suggest the same candidate, only the highest probability for this candidate is used. However, the classifier that proposes the lowest probability is not allowed to provide a new replacement candidate, leaving this classifier with only $N - 1$ candidates to suggest. This way, the candidate that is proposed by both classifiers has an even higher probability of being selected due to lesser competition through other candidates.

**Probabilities of n-grams** All words, bigrams and trigrams are extracted from the manually annotated training data. Typically, the probability $P$ of a unigram $w_i$ is approximated by dividing the count $C$ of $w_i$ by the count of all words $w$ in the training data, so $P_{uni}(w_i) \approx \frac{C(w_i)}{C(w)}$. The probability of an $n$-gram in the training data is calculated by dividing the number of times a specific $n$-gram occurs by the times the preceding word(s) occur. For trigrams, when $P(w_i)$ is approximated given the previous two words $w_{i-2}$ and $w_{i-1}$, the result will be $P_{tri}(w_i|w_{i-2}w_{i-1}) \approx \frac{C(w_{i-2}w_{i-1}w_i)}{C(w_{i-2}w_{i-1})}$.

Note that this way, due to the non-exhaustive nature of the training data, many possible word combinations will not be assigned a probability at all. For this reason, when the probability of a candidate is calculated, an interpolated model is used where the trigram, bigram and single word probabilities are combined. Consequently, when running into a novel word sequence where the highest order $n$-gram will result in a zero probability, information from lower order $n$-grams is also taken into account.

However, this does not solve all problems. For instance, the word sequence 'trouwen in Rotterdam' might not be in the training vocabulary while the sequence 'trouwen in Amsterdam' is. Therefore, it would be senseless to give this first sequence a probability of zero at the trigram level and rely only on lower order $n$-grams. Also, if a sequence like 'trouwen in Amsterdam' occurred only once in our small set of training data, it is very likely that it just showed up by chance and that its probability will be highly overestimated. Smoothing techniques try to overcome these difficulties by adding a small probability to word sequences that have not been encountered before and removing a bit of probability (a discount factor, $D$) from sequences that have. Different smoothing techniques have been proposed, such as Katz smoothing (Katz, 1987) and Jelinek and Mercer (Jelinek and Mercer, 1980). However, as Chen and Goodman (1999) found, a modified version of interpolated Kneser-Ney outperforms all previous techniques.

**Modified interpolated Kneser-Ney smoothing** The basic idea behind Kneser-Ney smoothing (Ney et al., 1994) is that some words appear in less contexts than others and should therefore be assigned a smaller probability in a new context. For instance, in our training data the word 'KD' occurs frequently, but only directly after the word 'Rappt'. Therefore without smoothing, the probability $\frac{C(\text{'KD'})}{C(w)}$ will be very high when running into a new context. Kneser-Ney smoothing on the other hand uses a modified probability distribution for lower-order $n$-grams, based on the number of contexts each word occurs in. This way, 'KD' will receive a relatively low probability when encountered in a novel word sequence where it does not follow the word 'Rappt'. The full set of formula used to make up interpolated Kneser-Ney smoothing is shown in equations 2.11 until 2.13.

$$P_{KN}(w_i|w_{i-2}w_{i-1}) = \frac{C(w_{i-2}w_{i-1}w_i) - D_{tri}}{C(w_{i-2}w_{i-1})} + \lambda(w_{i-2}w_{i-1})P_{KN-bi}(w_i|w_{i-1}) \tag{2.11}$$

$$P_{KN-bi}(w_i|w_{i-1}) = \frac{|\{v|C(vw_{i-1}w_i) > 0\}| - D_{bi}}{\textit{unique-trigrams}} + \lambda(w_{i-1})P_{KN-uni}(w_i) \tag{2.12}$$

$$P_{KN-uni}(w_i) = \frac{|\{v|C(vw_i) > 0\}| - D_{uni}}{\textit{unique-bigrams}} + \lambda\frac{1}{C(w)} \tag{2.13}$$

Here, *unique-trigrams* and *unique-bigrams* represent the total number of unique trigrams and bigrams in the vocabulary respectively. $|\{v|C(vw_i) > 0\}|$ gives the total number of unique word types that precede $w_i$ in the training data. The same holds for $|\{v|C(vw_{i-1}w_i) > 0\}|$, which denotes the total number of word types that precede the bigram $w_{i-1}w_i$. $\lambda$ is a normalization constant such that the probabilities sum to one.

Each $n$-gram order uses a different discount constant $D$. The modification to interpolated Kneser-Ney that Chen and Goodman (1999) propose is that a different discount constant should also be estimated for word (sequences) that occur once, twice or more than twice. This is done according to formula 2.14 until 2.17 where $C_k$ stands for the number of $n$-grams that occur $k$ times.

$$Y = \frac{C_1}{C_1 + 2C_2} \tag{2.14}$$

$$D_{1count} = 1 - 2Y\frac{C_2}{C_1} \tag{2.15}$$

$$D_{2count} = 2 - 3Y\frac{C_3}{C_2} \tag{2.16}$$

$$D_{2+count} = 3 - 4Y\frac{C_4}{C_3} \tag{2.17}$$

Notice that this full set of discount constants is thus estimated for each of the three used $n$-gram orders.

**Viterbi's algorithm** Using the modified version of interpolated Kneser-Ney smoothing on trigrams, the probability of each candidate proposed by the classifiers can be estimated taking into account all other candidates that were proposed earlier. However, this would lead to an exponential time complexity of $O(N^T)$ per classifier, where $N$ stands for the number of candidates proposed for one word and $T$ represents the total number of words in the text. To reduce this complexity, Viterbi's algorithm (Forney, 1973) is used for finding the most likely sequence of words given the sets of possible candidates. This method has successfully been used before in the field of handwriting recognition (Hu et al., 1996; Senior, 1998). In order to obtain more flexible trigram probabilities, Vitberi's algorithm was implemented on a trigram scale in which an extra depth of candidates is being tracked. This increases the time complexity of the algorithm from $O(N^2 * T)$ to $O(N^3 * T)$ which is acceptable and as preliminary experiments showed, it increased performance. The formula that make up Viterbi's algorithm on this third order level are given by:

$$V_{1,k} = P(w_{1,k}|I_1) * \pi_k \tag{2.18}$$

$$V_{2,l,k} = P(w_{2,k}|I_2) * P_{KN}(k|l) * V_{1,l} \tag{2.19}$$

$$V_{t,l,k} = P(w_{t,k}|I_t) * \max_{x \in S_{t-2}} (P_{KN}(k|x,l) * V_{t-1,x,l}) \tag{2.20}$$

Here, $\pi_k$ states the initial probability of a candidate $k$. A set of candidates at word position $t$ is contained in state $S_t$. Therefore, in $w_{t,k}$, $t$ denotes the position of a word $w$ and $k$ denotes a candidate at position $t$, so $w_{2,3}$ indicates candidate three at word position two in a text. A candidate at position $t-1$ is denoted by $l$. $P(w_{t,k}|I_t)$ is the probability that the classifier gave to a candidate, given the word image at the corresponding position. Finally, $V_{t,l,k}$ is the probability of the most likely path (the 'Viterbi path') through the sequence of candidate lists, ending at the bigram $w_{t-1,l}, w_{t,k}$. By using back pointers that remember which candidate is used in the second equation, the Viterbi path $x_1, ..., x_T$ can be found:

$$x_{T-1}, x_T = \underset{l \in S_{T-1}, k \in S_T}{\arg\max} (V_{T,l,k}) \tag{2.21}$$

$$x_{t-1} = Tr(t, x_t) \tag{2.22}$$

$Tr(t,x)$ is a traceback function that returns the value of $x$ which was used to compute $V_{t,l,k}$ in equation 2.20 if $t > 1$. When $t = 1$, the function simply returns the candidate $k$ which maximized the probability of the Viterbi path.

## 3 Experiments

To test the performance of the handwriting recognizer, two experiments were conducted. In the first experiment, three different experimental setups were used to test how the different types of features perform separately and combined. In the first setting only pixel count information from radial zones and density histograms were extracted, while in the second setting solely HOG features were used. These setups shall be referred to as *PC* and *HOG* respectively. In the third setup (*ALL*), both feature sets were combined. In order to decide which proposed candidate to use, simply the candidate with the highest probability from any of the two classifiers was selected. Although no linguistic post-processing followed the classification in any of these settings, the number of proposed candidates $N$ was set to 10 in order to explore the difference between proposed words.

In the second experiment, the *ALL*-setup was compared against a setup in which linguistic post-processing was added. This setting will be referred to as *ALL_PP*. In this setting, a number of different configurations for $N$ were tested in order to explore the effects of the post-processor. The configurations that were chosen are $N = 10$, $N = 2$, $N = 1$.

$k$-fold cross-validation was used to find a reliable estimation of the predictive performance of the different setups. Due to the size of the data set which consists of 66 pages, $k$ was set to 11. From each fold, we obtained the classification results of the six pages within that fold.

## 4 Results

The results of the two experiments are described below. For clarity, the results of all experimental conditions are put together in Table 1.

### 4.1 Experiment 1

One-way ANOVA was conducted to compare the effect of the type of feature on the percentage of correctly classified words on a page in *HOG*, *PC* and *ALL* conditions. There was a significant effect of the feature set on classification performance at the $p < 0.05$ level for the three conditions ($F$(2,195)=4.32, $p$=.01). A Tukey's post-hoc test revealed that the percentage of correctly classified words was significantly higher in the *HOG* condition (M=55.94, 95% CI[54.43,57.46], $p < .01$) and the *ALL* condition (M=55.51, 95% CI[53.99,57.03], $p < .05$) compared to the *PC* condition (M=52.99, 95% CI[51.47,54.50]). There were no statistically significant differences between *HOG* and *ALL* ($p$=.94). These results indicate that both a single classifier using solely HOG features and the combination of two classifiers using both types of features outperform a single classifier which uses solely pixel count features. However, there is no indication that HOG or the combination of features perform better than one another.

To analyze the possibilities that each condition offers

**Table 1: Results experiments 1 and 2**

| | % Correct | % Correct in c-list | % Correct known words | % Correct known words in c-list |
|---|---|---|---|---|
| $\mathrm{HOG}_{\mathrm{N=10}}$ | 55.94 | 70.99 | 64.46 | 81.72 |
| $\mathrm{PC}_{\mathrm{N=10}}$ | 52.99 | 69.35 | 61.04 | 79.88 |
| $\mathrm{ALL}_{\mathrm{N=10}}$ | 55.51 | **73.99** | 64.30 | **85.63** |
| $\mathrm{ALL\_PP}_{\mathrm{N=10}}$ | 51.30 | **73.99** | 59.15 | **85.63** |
| $\mathrm{ALL\_PP}_{\mathrm{N=2}}$ | 57.07 | 67.57 | 65.99 | 78.20 |
| $\mathrm{ALL\_PP}_{\mathrm{N=1}}$ | **58.80** | 62.26 | **67.49** | 72.10 |

Results of the different experimental setups put together. The first two columns show the overall classification performance and the percentage of correct words occurring in the candidate list. The third column shows the percentage of correct words when only the words that were encountered in the training data are taken into account. The last column displays the percentage of previously encountered correct words in the candidate list. The highest scoring setup(s) are displayed in bold.

for the post-processor, it is also necessary to look at the percentage of correct words that can be found in the candidate lists. This percentage gives the upper-limit that the post-processor could eventually reach, because words that are not in the candidate list will never be found otherwise. A one-way ANOVA compared the effect of the feature type on the percentage of correctly classified words present in the candidate lists in *HOG*, *PC* and *ALL* conditions. There was a significant effect of the feature set on this percentage at the $p < .05$ level for the three conditions ($F(2{,}195)=7.92$, $p < .001$). A Tukey's post-hoc test showed that the percentage of correct words in the proposed candidate lists was statistically significantly higher in the *ALL* condition (M=73.99, 95% CI[72.34, 75.63]) when compared to the *HOG* condition (M=70.99, 95% CI[69.34, 72.68], $p$=.01) and the *PC* condition (M=69.35, 95% CI[67.70, 71.00], $p < .001$). There were no significant differences between *HOG* and *PC* ($p$=.17). These results show that the combination of the candidates proposed by each classifier contains significantly more correct words than the lists of candidates proposed by each classifier individually. In other words, the candidates proposed using HOG features differ from the candidates proposed using pixel count features, although both feature sets propose about the same number of correct instances. By combining these two candidate lists, the possibility of having the correct word in the final candidate list increases. For this reason, the *ALL* setting seems to offer more possibilities for the post-processor.

## 4.2 Experiment 2

Experiment 1 showed that the *ALL* condition proposed significantly more correct words in its candidate list when $N = 10$ than the other two conditions. We therefore compared the *ALL* condition to the *ALL_PP* condition with $N = 10$ in order to see how post-processing would affect the number of correctly classified words. Barlett's test showed a violation of homogeneity of variances ($X^1$=9.3, $p < .05$), therefore a two-sample t-test assuming unequal variance was used to compare the effect of post-processing on the percentage of correctly classified words on a page in *ALL* and *ALL_PP* conditions with $N = 10$. There was a significant difference in classification performance for post-processing with 10 candidates (M=51.30, SD=9.06) and no post-processing (M=55.51, SD=6.16) conditions; $t(130)=3.12$, $p < 0.01$. This implies that linguistic post-processing makes performance of our classifier significantly worse when the number of candidates the post-processor may choose from is set to 10. These results did not seem very promising, however two more tests were conducted in which $N$ was set to 1 and 2 respectively.

Bartlett's test showed that variances of the percentage of correct words in *ALL*, $ALL\_PP_{N=2}$ and $ALL\_PP_{N=1}$ conditions were homogeneous ($X^1$=3.3, $p$=.19). Therefore a one-way ANOVA was carried out which indicated a significant effect at the $p < .05$ level for the three conditions ($F(2{,}195)=3.85$, $p < .01$). A post-hoc Tukey's test revealed a significantly higher percentage of correct words in the $ALL\_PP_{N=1}$ condition (M=58.80, 95% CI[57.15, 60.46], $p < .01$) when compared to the *ALL* condition (M=55.51, 95% CI[53.85, 57.17]). No significant effect was found between the $ALL\_PP_{N=2}$ condition (M=57.07, 95% CI[55.41, 58.72]) compared to the $ALL\_PP_{N=1}$ condition ($p$=.14) or to the *ALL* condition ($p$=.19). These results indicate that post-processing can significantly improve the performance of the bottom-up classification, but only when the number of candidates the linguistic model may choose from is set to at the most 1 per classifier.

## 4.3 Competition

In a small competition, our automatic handwriting recognizer using the $ALL\_PP_{N=1}$ setup competed against two other teams from the University of Groningen, the

**Table 2: Results of the competition**

| Team | Avg. edit dist. | % Correct |
|---|---|---|
| Team 2 | 1.77 | 65.62 |
| Our team | 2.01 | 55.53 |
| Team 1 | 2.14 | 51.47 |

Netherlands, on a secret test set of 71 pages. These results are shown in Table 2. Our recognizer outperforms Team 1 which made use of holistic features such as the number of ascenders and descenders in a word. This team also focused on the contour of a word using Fourier descriptors. However, our system is outperformed by the recognizer of Team 2 in which HOG features with different parameter values were combined with multi zoning, a different method for pixel count.

## 4.4 Error analysis

To better understand the errors the proposed system makes, an analysis was performed on the output of the system using the $ALL\_PP$ setting with $N = 1$. The number of encountered training instances for correct and incorrect words were recorded and analyzed. Only the incorrect words that could have been correct, words that occur in the training data, were taken into consideration. The results are shown in Figure 4.

A data point is considered a potential outlier, indicated by a circle, if the point exceeds $< Q1-1.5*IQR$, or $> Q3 + 1.5 * IQR$, where $Q1$ is the lower quartile, $Q3$ the upper quartile, and $IQR$ is the inter-quartile range. Extreme outliers are highlighted with a solid dot ($< Q1 - 3 * IQR$, or $> Q3 + 3 * IQR$).

The original scores were ranked ordered and a Mann-Whitney $U$-test was used to compare the ranks for the $n = 7923$ words that were correctly classified and the $n = 3816$ words that were incorrectly classified and occur in the training set. The results indicate a significant difference between these two types of words regarding the number of instances per word, $U = 5953565$, $p < 0.001$, with the sum of the ranks equal to 55671529 for correctly classified words and 13236401 for incorrectly classified words. This indicates that, in general, the incorrectly classified words (median = 11) are encountered less often in the training data than the correctly classified words (median = 159), as shown in Figure 4.

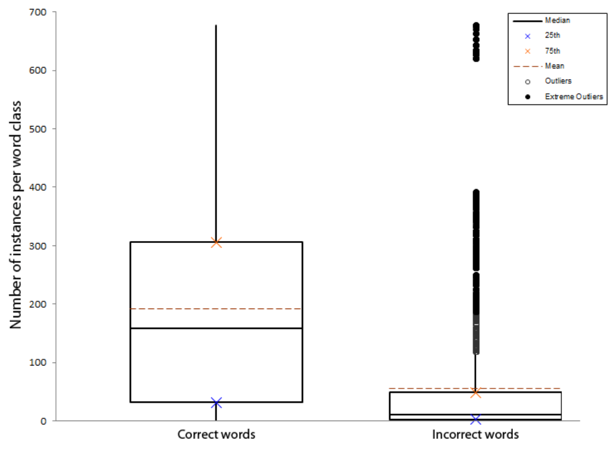


**Figure 4: The number of encountered training instances for correctly and incorrectly classified words. Only the words that could have been correct are shown here.**

# 5 Discussion

In this paper we evaluated an automatic handwriting recognizer which was trained and tested on historical documents. Different types of features were compared and the addition of a statistical linguistic post-processor using modified interpolated Kneser-Ney smoothing was analyzed. The results show that by using pixel count features, performance is significantly worse than by using solely HOG features or a combination of both. This conforms our hypothesis and it shows that HOG or a combination of the two classifiers are expected to be equally useful when the recognizer performs merely bottom-up. However, it should be noted that a different university team performed better using other parameter values for HOG. Therefore, it could be possible that further fine tuning of these parameters will lead to even better results in the future.

The combination of classifiers results in significantly more correct words in the candidate list compared to either classifier separately. This signifies that the two classifiers individually propose very different candidates and that by combining these candidates, improvements can be made. It should be noted that in this system a specific way of combining the classifiers was chosen, it might be possible that a different combination method would lead to even better results. Since the candidate list functions as an upper-limit for the linguistic post-processor, the combination of classifiers is favored above the other two conditions when the linguistic model is incorporated.

When post-processing is added, performance significantly drops from 55.51% to 51.30% when the number of candidates proposed by each classifier is set to 10. However, when less candidates are taken into account and this number is set to 2, the performance after post-processing becomes better than the performance of the bottom-up pipeline on its own. This improvement over the no post-processing setting eventually becomes significantly better when the number of candidates per classifier is set to 1. In this case, both classifiers propose only the single word that got assigned the highest probability. If these words are equal, only this one word is proposed. The post-processor thus has at the most only 2 candidates to choose from. This greatly reduces the freedom of the post-processor which might be one of the reasons why this setup performs better. We conclude from this that in our case, linguistic post-processing has the ability to improve recognition results from a bottom-up pipeline, but only when it is not given too much flexibility by having the luxery of choosing between many possible candidates.

One of the reasons for this finding could be that the bottom-up probabilities given by the classifiers are not accurate enough. In that case, the post-processor might not be able to distinguish which candidates are more likely than others given the feature information from the images. It would be fruitful to test other methods that convert classification distances to probabilities. For instance, probabilities could be computed per word class instead of over all word classes at the same time. Also, different methods for combining the bottom-up and top-down probabilities could be tested. In our method they were simply multiplied, but a neural network might be able to learn specific weights for each part. A final explanation for the lower post-processing recognition results using a greater number of candidates could be that the language model is not trained on enough data. However, preliminary tests showed that performance did not particularly increase after a text file containing almost 100.000 extra words was added. It is therefore plausible that the problem is not just sparse data on the side of the post-processor, but that insufficient data on the side of the bottom-up classifier should also be taken into account.

Indeed, our error analysis shows that there is a significant difference between the words that were classified correctly and incorrectly. The latter ones have been encountered less frequently in the word image training samples, with half of the incorrectly classified words occurring 11 times or less in the training data. Therefore, increasing the training data by adding more training pages and different types of word distortions has the potential of considerably improving performance. Also, due to the nature of the training data which contains many places, personal names and initials, it might be useful to explore the performance of a recognition system that is character based instead of word based.

For future research on improving the linguistic model, a few techniques described by Goodman (2001) might be useful. Two techniques in particular sound promising. In clustering, words are grouped together and their probabilities are put under one 'label'. This can be beneficial in sequences where a certain word group such as digits always follow a particular word. However, it may also lead to further problems because the linguistic probability of a cluster will likely be stronger than the individual probabilities of its members. Therefore, this method puts more control in the hands of the post-processor and thereby reduces the chance of unseen sequences. In caching, words that were encountered before receive a higher probability of being selected in the near future. This is a reasonable approach since generally words tend to pop up multiple times within the same context. However, it is questionable whether this method would work on our data set in which pages are divided into small individual paragraphs of approximately five or six lines. Also, more problems arise when a word is first classified incorrectly and then subsequently has a higher probability of being selected again.

To conclude, we found that HOG features indeed outperform a feature set based on sole pixel count. Combining pixel count and HOG features does not lead to significantly better results, but it does offer more possibilities for a linguistic post-processor. We also found that statistical linguistic post-processing improves mere bottom-up classification, but only when the candidates which the post-processor may choose from are well selected and do not provide the linguistic model with too much freedom. Therefore, many improvements can still be made on the post-processor in order to make it more reliable in the future.

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