A Feedback Application for Chinese Calligraphy Recognition Using Fuzzy Logic

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Being one of the most spoken and used language in the world, the popularity of the Chinese language, Mandarin in particular, is increasing worldwide. Students of all ages are more interested in learning this foreign language. Since technology and education are two factors that have a huge impact in the society, this research focuses on a handwriting recognition application for writing Chinese characters and words that provides feedback by using an EEG-based device. This application will somehow represent a tutorial program implemented in real-time and after a series of sessions, provide an assessment of the user's cognitive abilities if an improvement has been made at all. Fuzzy Logic is a well-known approach utilized in many pattern recognition problems that uses feature extraction methods to identify the number of strokes, length and its directions. It is used in this research as a means of matching the recognized handwritten input with the sample template saved in a data store. The use of fuzzy inference is advantageous to the study because the expert system is critically smart in recognizing the correctness of the written input. The handwritten characters are extracted by filtering the images and converting the black and white pixels into binary values. The pixel count is used to identify the length of certain strokes. After each Chinese character is fuzzified and categorized in a specific membership, these values will be compared to the original input's stroke length and direction. Thus, stroke accuracies and word accuracies are determined, through the use of the reciprocation of the percentage error formula. In terms of the feedback application, the proponents only used specific brain wave components to determine if the respondent showed signs of improvement in the learning process. After which, the correlation of the brain waves and handwriting accuracies are calculated using Pearson Product-Moment Correlation Coefficient. The results show that there is a -0.081 correlation for Alpha High and -0.045 for the Alpha Low brain waves. In relation to the Beta brain waves, it generated a correlation of -0.034 for High and -0.043 for Low. And for the Theta brain waves, there is a -0.050 correlation. Therefore, with a conclusion that there is a low correlation between writing Chinese Calligraphy in the behavior of a person's brain waves.

General Terms: Chinese Calligraphy, Handwriting Recognition, Brain Computer Interface, Fuzzy Logic
Additional Key Words and Phrases:

1. INTRODUCTION

1.1 Background of the Study

Mandarin Chinese is among the many foreign languages that are widely spoken and used around the world. It has also been discovered that the reason that more people speak Chinese than they do in English is that Chinese is becoming increasingly useful for online communication and can actually increase employment prospects (Te Kete Ipurangi, Inc.).

As well as in Chinese Calligraphy or writing, it has been appreciated as an art form in many different cultures around the world. It has been considered as a form of self-expression and cultivation (Lachman, 2013). However, there are recent sources saying that there are only around 450 teachers in the United States who teach the Mandarin language.

Handwriting recognition is essential to several social and economic activities such as signature verification, mail sorting, and is commonly used in many mobile electronic devices. In this study, a variety of Optical Character Recognition (OCR) devices may be used, including digitizing tablets, screen overlays, or cameras (Watt, 2011). Online recognition, a type of handwriting

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recognition that takes motions and other button presses of an input device, will be implemented in this study because the identification of the input and correction of errors is often regarded as a simple problem.

A theory-based research was established and showed that there are promising results regarding the effectiveness of practicing Chinese calligraphy in causing one's cognitive activation, perceptual sharpening, physiological slowdown, and emotional stability (Xu, et al., n.d.).

In this generation, technology is improving every moment wherein human interaction is less evident. Many computers and devices now are recognized by speech, touch-defined or controlled by artificial intelligence. Now, brain-computer interfaces (BCIs) are vastly increasing in the industry. With the use of BCI, neurofeedback training can be applied to improve and strengthen the respondent's brain waves to the more dominant brain component which is responsible for focus, organization and learning abilities (Webozy Inc., 2011).

A number of approaches about feedback, in general, have already been applied such as Back Propagation Neural Network, Feed-Forward Neural Networks, and Multilayer Perceptron. In addition, the Hidden Markov Model, Artificial Neural Networks and Support Vector Machines were also implemented for handwriting recognition.

On the other hand, our approach will concentrate more on the Fuzzy Logic method to handle the Chinese Calligraphy recognition of every brushstrokes of each word. The said approach will also aid in identifying whether or not the respondent's learning capability has improved or not.

1.2 Problem Statement

The researchers sought to investigate the manner of brushstrokes of the Chinese characters, characteristics of a brain wave, apply feedback to a handwriting recognition system for Chinese Calligraphy using Fuzzy Logic.

Specifically, the study aims to answer the following questions:

- What are the components or parameters needed for the feature extraction of the brain waves and handwriting Chinese characters?
- What method can be used to compare the brain waves?
- How can a Fuzzy Logic approach solve the handwriting recognition problem by identifying handwriting strokes?
- What is the correlation between writing Chinese Calligraphy and brain wave activity?
- Can the measurement of learning be implemented in the problem?

1.3 Research Objectives

The study has the following general objective:

- ➢ To identify the correlation between Chinese Calligraphy and brain wave activity.

The study has the following specific objectives:

- ➢ To identify the different manners of writing Chinese characters.
- ➢ To determine the components and parameters needed for the feature extraction of the brain waves and handwriting Chinese characters.
- ➢ Explain the method on comparing brain waves.
- ➢ Explain the approach on how Fuzzy Logic can solve the handwriting recognition problem and identify how each brush stroke can be obtained.
- ➢ To develop a feedback application for a Chinese handwriting recognition and tutorial system.
- ➢ To be able to verify learning in the respondents within the given amount of time.

1.4 Significance of the Study

The primary goal for this research is to develop an advanced tutorial aid that teaches the proper way of writing Chinese Calligraphy using handwriting recognition, which could be implemented in real-time.

This study will serve as an interactive learning aid in writing Chinese Calligraphy in a way that it will mainly benefit the students and learners of Chinese by presenting a feedback to the user on how the learner has progressed through the course of the sessions.

In addition, this research also presents a feedback application that would help improve memory and cognitive abilities of the user while writing Mandarin characters or words.

Through the innovative and inexpensive brain-computer interfaces developed in the society, identifying the different kinds of brain waves is now easier and faster.

Lastly, this study can serve as a future reference for other researchers who can continue to develop our study in terms of other implementations that are not just centered on handwriting, such as Mathematics, Science, etc.

1.5 Scope and Limitations

The research is conducted by obtaining alpha, beta, theta, delta and gamma waves using Neurosky's MindWave Mobile headset. The device is a single channel EEG-sensing headset which detects waves at the Fp1[1] position near the forehead.

This study is limited to online handwriting recognition and focuses only on the regular or standard style of Chinese Calligraphy. The online recognition shall be implemented in real-time and that system checks for errors every time an input is written. The regular or standard style (also known as Kai Style) is the easiest to recognize and read which implies that it is easier to learn and write than other East Asian scripts. Also, the study will not focus on the stress points of Chinese Calligraphy rather the proponents will only handle brushstrokes and directions of writing.

During testing and evaluation, the proponents will only provide a limited number of words since the system cannot cater to all words of the Mandarin dictionary. In addition, the limitation of this study is that it will only demonstrate Chinese words and not sentences.

Lastly, the study is not intended to develop a fast implementation of the algorithms but it is intended to provide real-time biofeedback to the user in order to monitor the progress of his or her learning abilities.

2. REVIEW OF RELATED LITERATURE AND WORKS

2.1 Chinese Calligraphy

[1] http://www.ebme.co.uk/arts/eegintro/

Calligraphy is the art of writing characters which was vastly developed in China. It has educated thousands by following a series of steps of writing the characters in the correct manner. As each character is written, there is always a proper norm being followed so that it could achieve “beauty” or a good penmanship (White, 2009).

According to Cultural China (2010), Calligraphy does not only involve a proper form or technique for writing Chinese characters, but it also encompasses a way of the expression of Oriental art, and it also involves a branch of learning and discipline as well. There are four major types of Chinese calligraphy: official script, cursive script, regular or standard script, and semi-cursive script.

The stroke order of a character gives the order and direction in which the brush strokes should be written. Stroke order can refer to the numerical order in which the strokes are written and stroke direction refers to the movement of the brush in a particular stroke. These are the two components in the development of stroke order in Chinese Calligraphy (Wertz, 2011).

2.1.1 Existing calligraphy-related studies

There are various studies that have used Chinese Calligraphy as a main topic. However, different approaches were used.

2.1.1.1. Interactive Creation of Chinese Calligraphy with the Application in Calligraphy Education

A semi-automatic creation system of Chinese calligraphy and its application in calligraphy education was proposed. The process of contour tracing and skeleton extraction were performed on the images of original Chinese calligraphy characters, and brushstrokes were extracted interactively. The new Chinese calligraphy characters were compared with the stroke library. The results showed that the created Chinese calligraphy characters look similar to the samples in the structure, however, with different effects (Zhang, et al., 2011).

2.1.1.2. Skeleton-Based Recognition of Chinese Calligraphic Character Image

Since several Chinese calligraphic words are hardly recognized by an optical character recognition (OCR) device, a novel skeletonization algorithm called MFITS (morphology-fused index table skeletonization) and a skeleton-based Chinese calligraphic character recognition method were proposed by the researchers Yu, Wu and Zhuang (2008). The experiments show that MFITS can extract skeletons with only a few deformations and the skeleton-based Chinese calligraphic character image recognition method has a good performance.

2.2. Handwriting Recognition

According to the Center of Excellence for Document Analysis and Recognition (2011), Handwriting Recognition is the technical capability of a computer to identify and interpret handwritten input from a device. It is usually associated with Optical Character Recognition (OCR). However, handwriting recognition also covers proper segmentation of characters to identify each brushstroke.

Mainly, there are two approaches in how handwriting recognition can be implemented. It can be through On-Line or Off-line recognition.

2.2.1. On-Line and Off-Line Handwriting Recognition

Both online and offline handwriting can be used with many handwriting gadgets like PDAs, tablets, mobile phones, etc. On the other hand, the difference between the online and offline cases of handwriting recognition is that the online case deals with the interpretation of the motion, position, acceleration and function of time of the brushstrokes of the characters. While the offline case focuses on the shape of the character and comparing it with a constant source (Plamondon & Srihari, 2000). In this study, online handwriting recognition will be implemented so that the system may be able to check each brushstroke and pen-up performed by the user.

2.2.2. Existing Approaches to Handwriting Recognition

This section provides the approaches used in previous studies that provide a solution for handwriting recognition. Such approaches are dedicated only to recognition algorithms.

2.2.2.1. Hidden Markov Model (HMM) Approach

Using a discrete Hidden Markov Model, researchers Lallican, Viard-Gaudin and Knerr implemented a word recognition system. They used a 54 letter model with a number of states proportional to the average number of observations per letter. The model was trained using the Baum-Welch algorithm wherein the probability of each word can be computed by the forward-backward algorithm.

2.2.2.2. Support Vector Machine (SVM) – A Kernel Approach

The technique used in this study combined dynamic time warping (DTW) and support vector machines (SVMs) by establishing a new SVM kernel. The Gaussian DTW kernel approach has a main advantage over common HMM techniques. Through the use of the UNIPEN handwriting data and incorporate it in the kernel approach, the achieved results were comparable to an HMM-based technique (Bahlmann, et al., 2002).

2.2.2.3. Cognitive-neural Effects of Brush Writing of Chinese Characters: Cortical Excitation of Theta Rhythm

The paper of Xu, et al. is most related to our study because it also involves the interactions within the theory of Chinese handwriting and calligraphy. It is also stated that neurofeedback mechanisms are used for initiation, guidance, and regulation throughout the whole process. However, this paper is only limited to the EEG theta wave as a means of understanding the user’s response, emotions and cognition.

2.2.2.4. A Feature Extraction Technique for Online Handwriting Recognition

The researchers for this study used a feature extraction technique for online handwriting recognition. Their technique incorporated many characteristics of handwritten characters based on size, structural, directional and zoning information. Features were gathered and combined in order to create a single global feature vector without resizing the raw data. This paper used a Neural Network based classifier and UNIPEN benchmark database resulting in recognition rates of 98.2% for digits, 91.2% for uppercase and 91.4% for lowercase (Verma, et al., 2004).

2.2.2.5. A Combined Crisp and Fuzzy Approach for Handwriting Analysis

According to the study of Mogharreban, Rahimi and Sabharwal (2004), an offline handwriting analysis system is used to output the possible personality trait for the writer. Two parameters, the baseline and the slant-angle, are the inputs to a rule-base which implements a crisp algorithm whereas the evaluation of the slant-angle utilizes a fuzzy paradigm. The approaches on geometric feature based segmentation method and the low pass filtering method were evaluated and the outputs were utilized to determine a personality trait.

2.2.2.6. Recent Results of Online Japanese Handwriting Recognitions and Its Applications

This research focuses on online handwritten Japanese text recognition and propose character orientation-free and line direction-free handwritten text recognition and segmentation. Finally, as applications of online handwritten Japanese text recognition, we show segmentation of mixed objects of text, formulas, tables and line drawings, and handwritten text search. Also, the hidden Markov models are also used in this particular context (Nakagawa, et al., 2008).

Based from previous researches, though having almost the same topic as this study, different approaches were implemented. In this paper, handwriting recognition is incorporated with BCI technology which creates a peculiar tandem yet can really contribute to the field of education in the future.

2.2.3. How Handwriting Trains the Brain

An assistant professor of psychology and neuroscience at Indiana University named Dr. Karin Harman James conducted a study on the development of a person's learning capability in writing a new graphically different language, such as Mandarin. In this study, the adults were asked to write using pen-and-paper and typing in a computer keyboard. The results show that those writing by hand had a stronger memory of the characters' proper orientation. This then implies that handwriting differs from typing because it requires executing sequential strokes whereas typing, only involves selecting a specific character or word (Bounds, 2010).

2.3. Brain-Computer Interface (BCI)

2.3.1. Brain Wave Components

Brain waves are described by the (1) amplitude, which is the index of strength or intensity shown by the height of the waves, and the (2) cycles per second measured in Hertz (Hz) (Ulicsak, 2009).

Beta waves **(**12-30Hz**)** are present in all our thinking, logic and critical reasoning, which occur normally in the waking state. Alpha waves (7.5-12Hz) are present in the deep relaxation state when eyes are closed or while daydreaming. Alpha waves increase during the imagination, memory, learning and concentration of a human person. Theta waves (4-7.5Hz) are dominant during deep meditation, light sleep and REM sleep. It is also responsible for the mind's creativity and insights. Delta waves (0.5-4Hz) are the "realm of the unconscious mind". It is present during a deep, dreamless sleep where it transcends the meditation and awareness of a human person (Kotsos, 2011).

2.3.2. Brain Frequencies

According to Synthesis Learning (2008), there are certain frequency values of the brain waves that pertain to specific activities, such as:

In beta waves, 14 Hz represents alertness and concentration. In addition, if the alphas waves go about 11Hz, it suggests that the respondent is relaxed yet still in in awake state. And if it reaches 8-10Hz, it says that the brain is undergoing super learning new information, memorization or comprehension. In relation to our study, these brain frequencies can only give an implication on the user's brain activity during the handwriting recognition process whereas for every stroke, there will be a corresponding brain frequency to show up in every brain wave.

2.3.3. BCI-related works

2.3.3.1. Dynamic Bayesian Networks for Brain-Computer Interface

Shenoy and Rao (2005) describe an approach to building brain-computer interfaces (BCI) based on graphical models for probabilistic inference and learning. The Dynamic Bayesian Network (DBN) is learned directly from observed data and allows measured signals such as EEG to be interpreted in terms of internal states through probability distributions over brain- and body-states during planning and execution of actions.

Unlike traditional classification-based approaches to BCI, the proposed approach (1) allows continuous tracking and prediction of internal states over time, and (2) generates control signals based on an entire probability distribution.

2.3.3.2. EEG Classification with Neural Networks Based on the Levenberg-Marquardt Algorithm

In the study of Chen and Zhang (2012), the Back Propagation (BP) neural network based on error back propagation converges slowly, and has low efficiency in training, limited accuracy in classification of electroencephalography (EEG). To solve these problems, the quick and stable Levenberg-Marquardt algorithm is adopted instead of the BP algorithm to train the neural network. The simulation results show that the accuracy rate of this algorithm is 87.1%, which is superior to 78.2% of the BP algorithm, and it converges better as well. This technology provides an effective way to EEG classification.

2.3.3.3. Analysis of Brainwave characteristic Frequency Bands for Learning

In this research, data is acquired through the use of an EEG to analyze each frequency wave that is related to learning and the researchers formed a learning energy index (LEI) during a time when the respondent is thinking critically or logically. Learning is integrated in this research by not only providing feedback to the learner but also to the teachers to fully understand the capabilities of their student (Kao, Hsieh & Li, 2011).

2.3.3.4. How Brainwave entertainment technology can help you learn a foreign language faster with better results

Rannut (2010) explains in the paper how brainwave entertainment can improve the language learning skills of a human person. However, in his research, he used music as a form of manner to synchronize the brain waves to a complete relaxation state. The brain is manipulated to be put in a correct state of learning, so that information can be stored properly and efficiently.

2.3.3.5. Brain wave states and How to access them

According to Huddleston (2008), when there is a high frequency in the Theta waves, ranging from 5.5Hz - 7.5Hz, the person has activated his/her creative thoughts and has an ease of problem solving. On the other hand, when the Alpha brain waves range from 12Hz – 14Hz, the brain is more active and has increased focus and awareness. Thus, it is good for absorbing information passively. Lastly, when the Beta brain waves range from 13Hz – 27Hz, the brain promotes a more focused attention and conscious thinking.

2.4. Neurofeedback vs. Feedback

Neurofeedback is a kind of brain training that uses an electroencephalography (EEG) or functional magnetic resonance imaging (fMRI) to enable a respondent to improve and strengthen his/her brainwave patterns that would help create better concentration and organization (Webozy Inc., 2011).

However, in this study, neurofeedback is not applied since it does no training to the respondent's brain activity but only presents and shows the brain waves as the proponents will be the ones to interpret the waves.

2.5. Fuzzy Logic

Fuzzy Logic is a statistical approach that uses Boolean logic that handles the concepts of "partial truths" – truth values between completely true (1) and completely false (0) (Rouse, 1996).

2.5.1. Pattern Recognition apparatus and method using Fuzzy Logic

There are a number of pattern recognition methods which can recognize not only standard typewritten characters but also handwritten characters and various styles of fonts. A signal representing the pattern to be recognized is entered and converted into binary signals corresponding to the pattern. The binary signals are compared with the reference pattern. Using Fuzzy Logic, the study results in a certainty factor of the pattern recognition that was calculated from the comparison (Tanaka, 1995).

2.5.2. A Chinese Character Recognition Interface for Mobile Communication devices using Fuzzy Logic and Unit Extraction

Luo and Wu's study (1996) describes a method for on-line handwritten recognition for Chinese characters that is presented with a systematic interpretation of fuzzy logic for characters. A matrix structure, as a fuzzy representation for the characters, is determined by the fuzzy rule base. Since, Chinese characters can be coded in a small set of basic units; a unit extraction module is designed to search the possible units within characters. The input character is recognized by the unit code with the largest fuzzy similarity degree. Results showed a 95% success rate.

2.5.3. Application of Fuzzy Logic to Handwritten Character Recognition

In this study, Cardarilli, et al (n.d.) explains that the segmentation procedure simply consists in a stroke gathering since each character is composed by one or more strokes and each stroke belongs to only one character. The stroke gathering process has been implemented by using a fuzzy logic approach. The researchers also reduced the number of failures in a way that the input fuzzy set can be automatically modified, taking into account the characteristics of the respondent's handwriting. The results showed that 97% correct detection was obtained.

2.5.4. Fuzzy Logic Based Character Recognizer

In the paper of Ravi and Ang (2000), a fuzzy logic-based system is implemented by using an n-tuple recognizer algorithm. Fuzzy Logic is used in this paper because the researchers seek to improve the robustness and flexibility of the algorithm. The original n-tuple method works by matching bunches of n pixels exactly between the test images and the template images. In the researchers' proposed method, new concepts such as 'Importance of Tuple' and 'Degree of

Match' of a tuple are introduced into the matching procedure by generating fuzzy inference systems. The proposed system obtained a high success rate of classification.

2.6. Pearson Product-Moment Correlation Coefficient

The Pearson Correlation Coefficient is a measure of the degree of an association between two variables, and is denoted by r. Basically, the correlation tries to identify the line of best fit through the data, and the coefficient r indicates the how the data points fit in this new line of best fit. This can take a range of values from -1 (negative correlation) to +1 (positive correlation) where 0 indicates no correlation at all between the two variables (Lund Research Ltd., 2013).

2.7. THEORETICAL FRAMEWORK

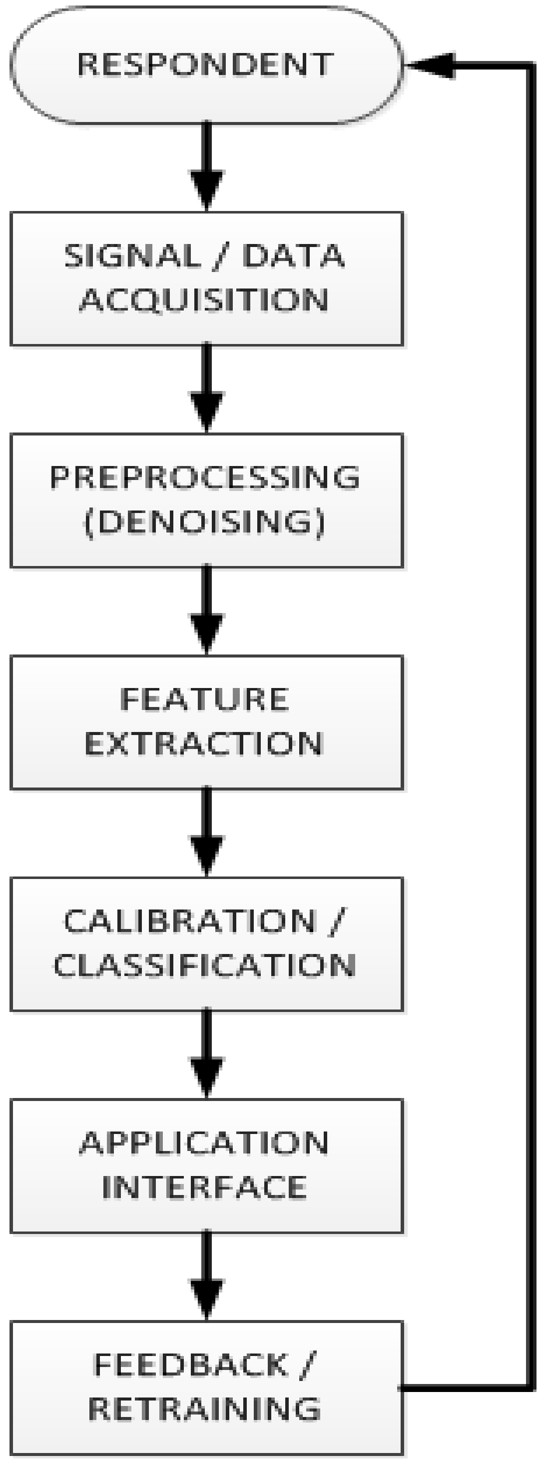


Figure 2.7.a. BCI Framework

2.7.1. Discussion

The figure above shows the step-by-step process in creating a model for machine learning using brain-computer interfaces (Polikar, 2012). Every stage in the theoretical framework is critical in order to accomplish this study. Data, in this case, signals, serves as the most essential piece of information. It is acquired through the use of an EEG-sensing headset called MindWave that captures brain activities. Since an EEG provides several brain waves, it is necessary to remove frequencies that are considered "noise" by filtering or averaging irrelevant information. Feature Extraction is done by determining those components of the signal that are deemed most relevant to the application of the study. These components are the target and non-target stimulus which separate the signal into two parts. In each non-target stimulus, a calibration or classification is made in order to determine what specification should be taken based on the current values of the features. Lastly, a program doesn't exist if doesn't have an application interface which will be implemented through the use of comparing the different brain wave patterns of the respondent's brain. Moreover, feedback and results is returned to the user for further adjustments. This framework will then be incorporated with the framework of handwriting recognition because in the process of writing characters, the respondent's brain activity will be recorded by the device so that the brain waves will be processed and interpreted.

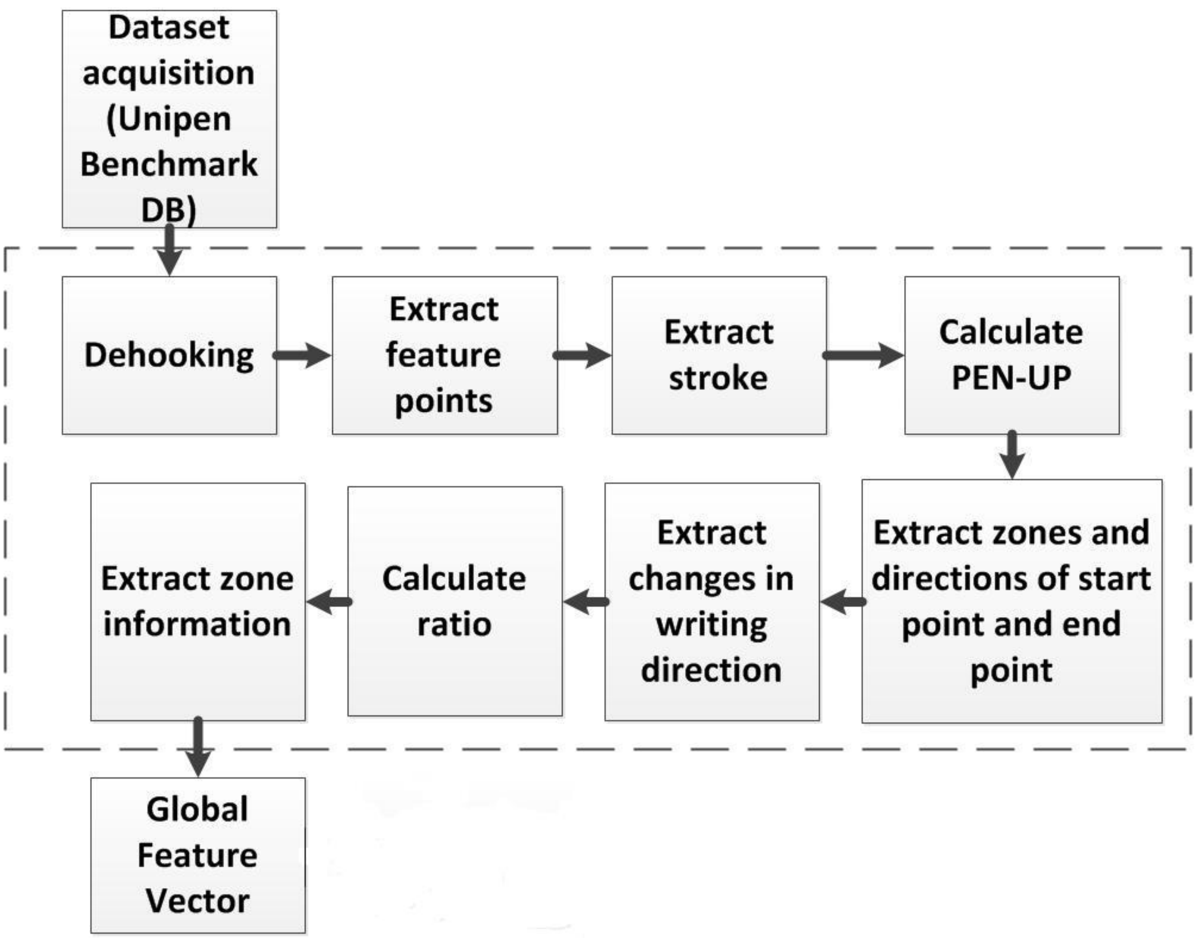


Figure 2.7.2.a. Handwriting Recognition and Fuzzy Logic Framework

2.7.2. Discussion

The Handwriting Recognition and Fuzzy Logic framework above is based on the work of Verma et.al (2004). The following framework will be applied on the same time as the extraction of brain waves from the respondent as stated in the BCI framework. The framework has eight modules for their proposed technique which is almost the same as what the proponents want to accomplish. The researchers used a software called Unipen Benchmark DB that would be used for Data Acquisition. Dehooking is the process of removing hooks. Hooks occur at the beginning and end of the strokes due to inaccuracies in rapid or erratic motion upon placing the stylus on or lifting it off the tablet. In extracting feature points, only the relevant and useful points are acquired. This is done by removing the unwanted characteristics of all points in every character from the database. Strokes are formed by a creating a path from one point to another. To simplify it, the feature can be calculated by counting how many times the pen or stylus is placed on the writing surface occurred in the dataset for every character or digit. Pen-Up is also used as a feature to match the recognized character to the one stored in the database and calculates for the average strokes of a specific character. In finding the areas of start and end points, use the lateral and longitudinal coordinates of the first and second point and with this, the start and end point directions can be calculated. The directions of each brushstroke can be achieved using online handwriting. Also, based on the vector direction, identify the jag points where the brushstroke direction has changed and after getting the coordinates of two jag points, the number of times the direction has changed can be calculated. Calculating the rate of width or height ratio can solve this problem so that a “constant” has been established. Zone information is extracted because it defines the clear boundaries per character or word. The Global Feature Vector is mainly a table that consists of the directions and states of the strokes, and the values will then be forwarded to the Neural Network Classifier as it will be used to recognize handwriting.

3. PROJECT DESIGN AND METHODOLOGY

3.1 Conceptual Framework

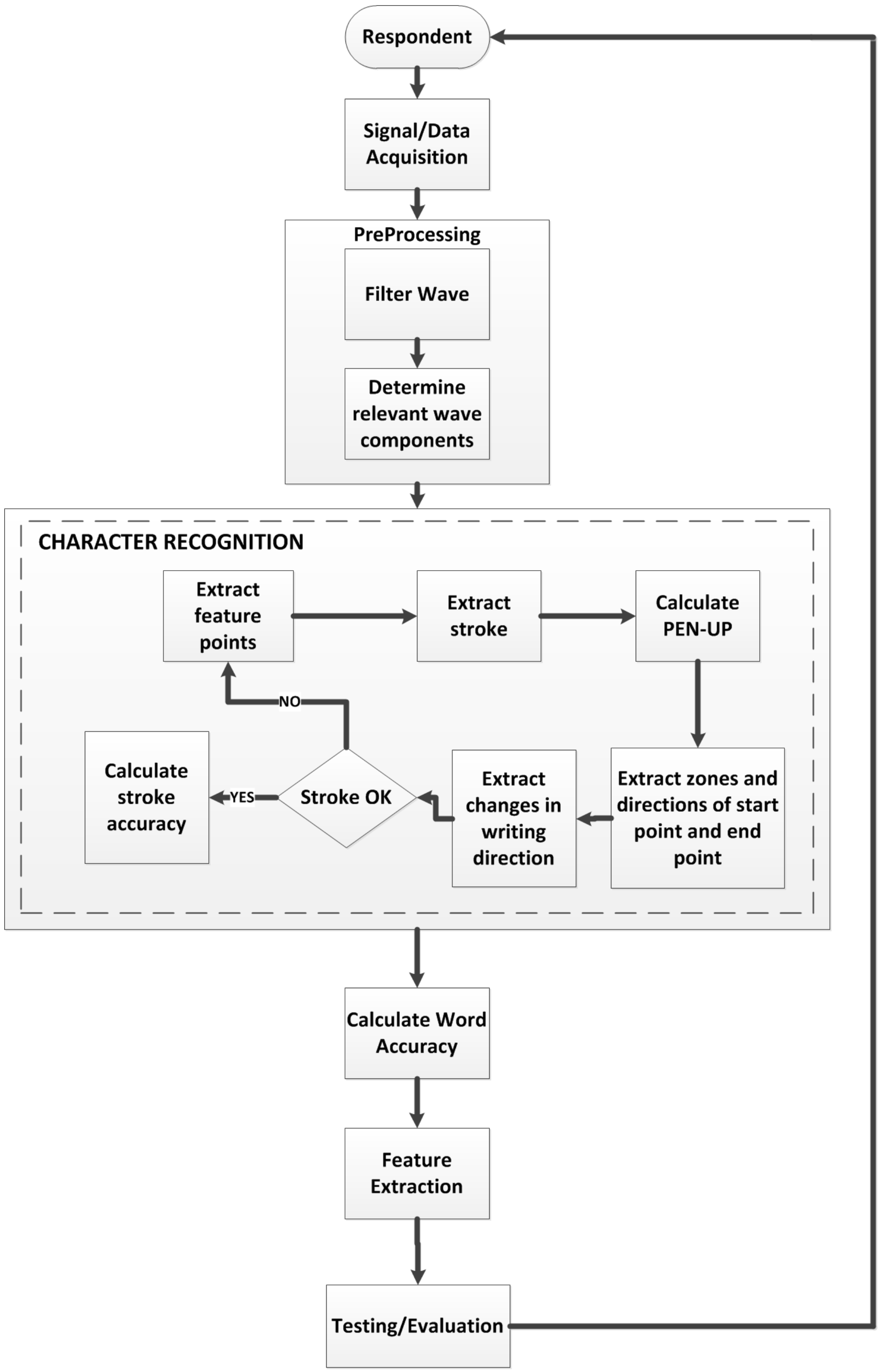


Figure 3.1.a. Conceptual Framework

3.2. METHODOLOGY

In this study on the neurofeedback application for Chinese Calligraphy through Fuzzy Logic, the phases were as follows:

1. Data Acquisition
2. Preprocessing
    2.1. Filter Wave Noise
    2.2. Determine Relevant Wave Components
3. Character Recognition
    3.1 Extract feature points
    3.2 Extract stroke
    3.3 Calculate PEN-UP
    3.4 Extract zones and directions of start point and end point
    3.5 Extract changes in writing direction
    3.6 Calculate stroke accuracy
4. Calculate word accuracy
5. Feature Extraction
6. Testing / Evaluation

3.2.1. Data Acquisition

In this phase, data is acquired through the use of Neurosky's Mind Wave Mobile, a brain-sensing headband that will provide EEG brain waves and frequencies. The variables that are used for this study are the Alpha, Beta, Theta, Delta and Gamma waves.

3.2.2. Preprocessing

Data collected from the said device were preprocessed in order to simplify and remove unnecessary signals.

3.2.2.1. Filter Wave Noise

The raw brain waves were expected to have frequencies or components that are considered as noise. This process is in-charge of filtering these waves through the use of a spatial filter, which is a mathematical formula used to reduce noise from EEG signals.

3.2.2.2. Determine relevant wave components

From the five brain waves gathered, only three shall be used for this study. This process covers the extraction of only the relevant wave components: Alpha, Beta, and Theta.

3.2.3 Character Recognition

In this phase, the respondent starts to rewrite the Chinese characters or words shown to him by following the proper way of the calligraphy. Every brushstroke shall be recorded and checked whether or not correct strokes are performed.

3.2.3.1 Extract feature points

In extracting the feature points of the original image, not all points are useful so only the relevant and useful points are acquired. This is done by extracting the original stroke length and directions of the Chinese characters. It is also in this process that the variables taken for the original image serves as the basis for the comparison of the image in the handwriting recognition. The whole image is also saved as it will be used to calculate for accuracy in the succeeding processes.

3.2.3.2 Extract stroke

Strokes are formed by a creating a path from one point to another, from the moment a pen is placed on the writing surface (“Pen-Down”) to the point when it is lifted up (“Pen-Up”). To simplify it, the “Pen-Down” that occurred in every character will be extracted. This happens every after the respondent writes a stroke of the Chinese character on the writing surface. It is also in this process that the x and y coordinates of the position of the stroke are obtained.

3.2.3.3 Calculate PEN-UP

Pen-Up is also used as a feature to match the character written by the respondent to the one stored in the database and checks for the strokes of a specific character.

3.2.3.4 Extract zones and directions of start point and end point

In this process, checking for the start point and end point of each stroke can be accomplish extracting the lateral and longitudinal coordinates or direction where the respondent began with while writing the Chinese character or word. The length of the strokes is also obtained in this process as the pixels from the start point to the end point are already determined.

3.2.3.5 Extract changes in writing direction

One of the critical parts in checking for the proper way in writing Chinese is in the direction of the brush strokes. By using online handwriting, the change of writing direction and the order of strokes can be obtained. This is also possible by getting the angle where the direction changes. The x and y coordinates of the stroke from the start and end points are also used as they can be calculated to get the angle direction of the written stroke.

3.2.3.6 Calculate Stroke Accuracy

Calculating the stroke accuracy can help distinguish a clearer picture what the respondent is writing. This can aid in the development of the training for the Chinese Calligraphy for the user can understand his/her points for improvement in every trial. The stroke accuracy is calculated by subtracting the original image’s black pixels to the written/experimental image’s black pixels, then dividing it with the original image’s black pixels and the quotient shall be multiplied by 100 to get the percentage accuracy.

3.2.4. Calculate Word Accuracy

Calculating for word accuracy is used after all strokes have been written correctly. This shall be used as to check for the over-all precision of the position, length and direction of the strokes written by the user. This is done by comparing the whole image of the written output with that of the original image. In addition, the word accuracy is calculated by averaging the values for each stroke's accuracy.

3.2.5. Feature Extraction

In one experiment, there will be many subtests or characters that will be presented to the respondent. For every image that appears, as the respondent writes the Chinese characters, his or her brain waves shall be recorded and classified. It is also in this phase that the frequencies of each relevant wave component are determined. The frequency values will then be compared to the frequency in the previous sessions and it will check whether or not the respondent has improved or not.

3.2.6. Testing / Evaluation

After an automatic evaluation for handwriting Chinese calligraphy, several test cases will be generated and documented to show the accuracy of the system. After every word is written by the respondent, the feedback application will suggest or output particular responses or improvement measure.

4. THEORETICAL BACKGROUND

4.1 Chinese Calligraphy

Chinese calligraphy is a practical technique for writing Chinese characters. It has been regarded by many as a unique oriental art of expression involving from the medium of the form, way of handling the brush, presentation and style. It is also the branch of learning and self-discipline that has added personalities to their rules and standards of writing (Li, 2009).

Here are two scripts that were most crucial to the development of Chinese calligraphy. Notice their differences in terms of stroke and ink.

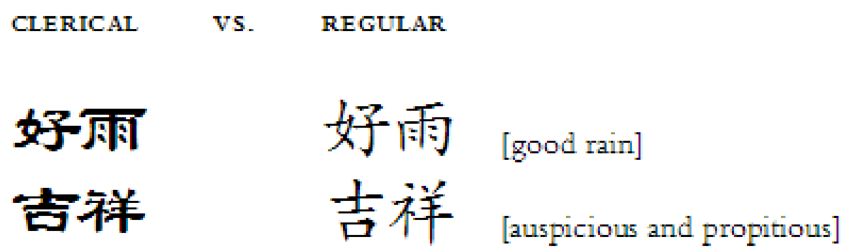


Figure 4.1.a. Clerical and Regular Scripts

In terms of defining the meaning of the characters above, both of the styles are the same. However, there is quite a big difference in comparing the clerical and regular scripts. The most recognizable change is the stress of darkness of the strokes. The clerical script looks compressed and curvier compared to the regular script which looks straightened out and much clearer. They also differ in a way that clerical scripts always contain horizontal lines that have an exception tilting at the end, as compared to regular which is just plain and neat. Also, in the clerical script, there are no “hooks”. Hooks occur at the beginning and end of the strokes due to inaccuracies in rapid or erratic motion upon placing the brush on or lifting it off the paper. It is also apparent that both of these scripts convey different feelings and tastes.

In spite of these differences, the proponents will use the regular script as the style to be used in this study. It has been said that it is the easiest type of script to read and beginners are more comfortable in writing with this style first.

4.2. Handwriting Recognition

A computer is capable of interpreting a comprehensible handwritten character from document papers, photographs and other touch screen devices through what is deemed as Optical Character Recognition (OCR). Handwriting Recognition, as a unique branch of OCR, features system formats, correct integration and locates the plausible words in a given set of texts. This type of input method is becoming common especially for growing areas of pen-input equipment such as palm, Pocket PC-based PDAs and tablet PCs. It has also been applied in various functions like signature verification, bank-check processing, writer recognition and postal-address interpretation (Akiyama et.al, 2003).

Since handwriting recognition needs a device for preprocessing the characters written by a user, the proponents decided to use a Wacom digitizer tablet that is used by many consumers for drawing and editing images.

Handwriting recognition has two methods of identifying the characters. These are the Off-line handwriting recognition and the On-line handwriting recognition.

4.2.1. Off-line Handwriting Recognition

The Off-line Handwriting recognition typically, can only convert machine printed and hand printed text into letter codes that can be used by computer. This method of handwriting only involves the printed types of text because of the fact that people have different handwriting strokes which are more difficult to process. Off-line Handwriting recognition uses OCR engine for machine text and an Intelligent Character Recognition (ICR) engine for hand "printed" (written in capital letters) text.

Here is an example of a diagram (Figure 4.2.1.a) about offline handwriting recognition; the input is a handwritten text. Then, the system recognizes the characters, and the context is then processed or matched with the characters in the common dictionary data store. If an error is detected the system notes the error and saves it to another data store.

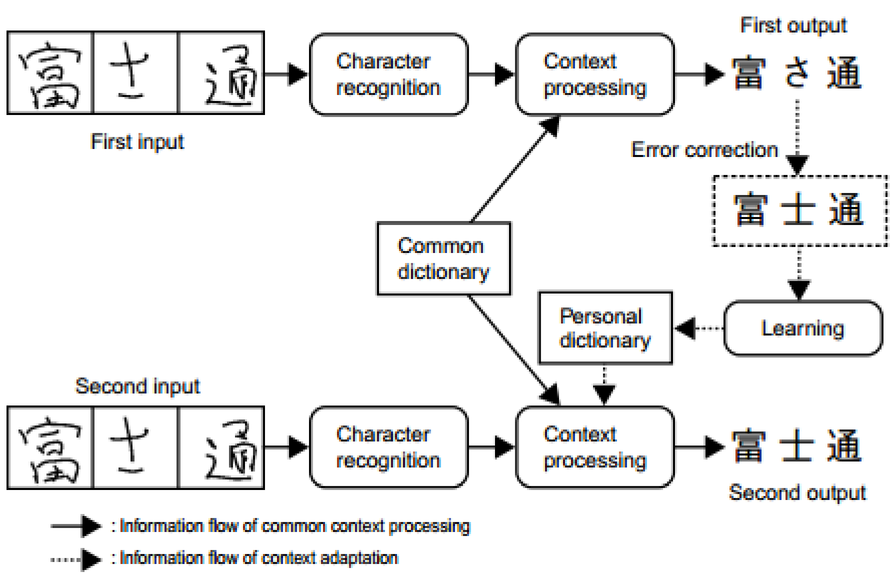


Figure 4.2.1.a – Off-line Handwriting

4.2.2. On-line Handwriting Recognition

In On-line handwriting recognition, you can extract more information and data from the written text such as the starting and end point of the stroke, the speed of the stroke and the direction of the stroke. This uses any touch-based input device to get handwritten texts where the pen-up and pen-down states are calculated.

The figure below shows an example for Online Handwriting recognition, this is just one of those guided handwriting where a user must write in the path provided with the precise stroke.

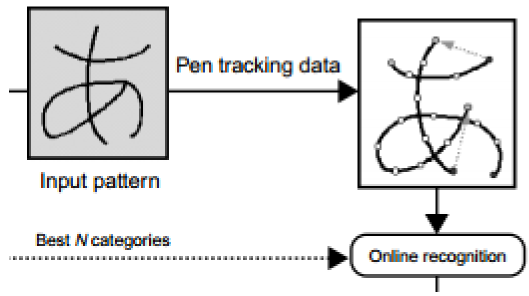
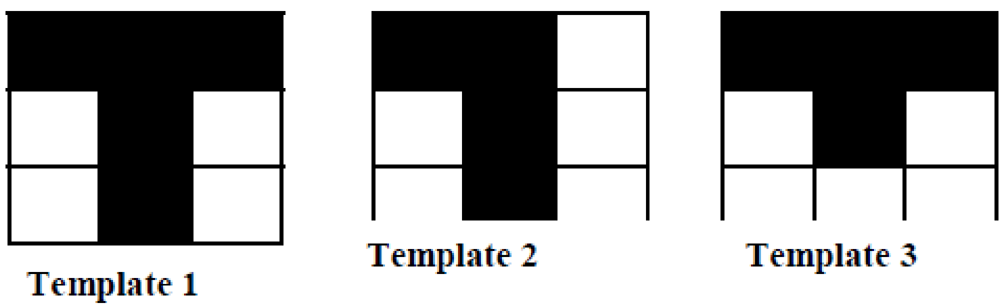


Figure 4.2.2.a-On-line Handwriting

4.3. Fuzzy Logic

Fuzzy Logic concept is a statistical technique that handles reasoning and imprecision degrees of knowledge like 'most probably', 'very', etc. It represents a truth value 1 for true and 0 for false that can be easily processed by a computer. It has also been considered that $F_i = X_i$ if pixel is white $X_i = 1$ and $X_i = 0$ otherwise. Here's an example for our propose approach taken from the study of (Ang et.al, 2000)



Hence, the result shows that in the 3 template shown above, at least two of them are similar for the first row thus the greater the similarity score will be computed then after all computation the template is classified with the maximum score.

4.3.1 Fuzzy Rules

Fuzzy Rules are a series of if-then statements. Fuzzy logic, with fuzzy rules, has the potential to add human-like subjective reasoning capabilities to machine intelligences, which are usually based on bivalent boolean logic. The fuzzy rules that are used in control systems are hand-crafted by the designers of the systems. Rules are usually expressed in the form of:

IF x IS *a* THEN *y* IS *b*,

where x and y are linguistic variables which are determined by fuzzy sets (Pulo, 2000).

4.3.1.1. Membership Function

The membership function describes the classification of the elements of the basis set in the fuzzy set. Functions are often graphed as linear functions, such as triangular, Gaussian or trapezoidal functions. It represents the degree of truth in the evaluation of the functions.

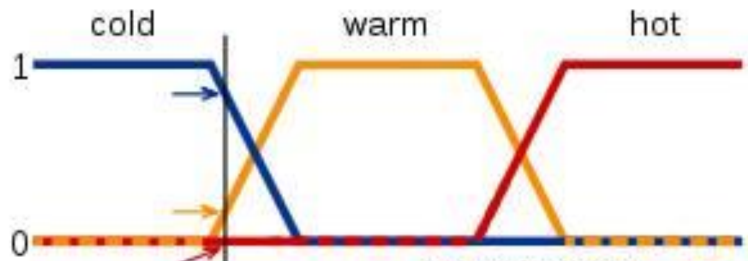


Figure 4.3.1.1.a. Trapezoidal Membership Function Example

In the figure above, the bar drawn between cold and warm indicates that a sample value can be categorized as either 0.2 warm or 0.8 cold, which makes the function uncertain. With fuzzy logic, it can help determine the decision of the correct temperature by simply creating that membership function above and identifying the largest degree of truth accordingly (Schmid, 2005).

4.3.2. Fuzzification

The fuzzification process is the process of transforming crisp or exact values into degrees or grades of membership for some linguistic terms of fuzzy sets. In other words, fuzzification uses a membership function to associate a certain degree or grade to each linguistic variable.

4.3.3. Defuzzification

Defuzzification is a process of reducing the final fuzzy set back to a crisp value through an inferencing method of using the fuzzy rules and associating them with the fuzzified values. This is done by using the Center of Gravity defuzzification, which is the most common method of defuzzification.

5. RESULTS AND DISCUSSION

5.1. Chinese Stroke Dictionary

Chinese characters that were chosen and used in this study were gathered by first searching for available handwriting recognition softwares that would support Chinese characters and training for Chinese calligraphy. A number of softwares were tested and found that some were implemented mainly for the recognition of Chinese words. However, the scope of this research focuses on the stroke order, length and direction of the characters written. Even though there were some softwares that implement stroke order, length and direction, they were not open-source softwares.

The lack of these features in the handwriting recognition softwares resulted in building the recognition software from scratch. This was done by collecting animations of selected characters from trusted websites in Chinese Calligraphy. The different kinds of standard strokes were also gathered from a website and saved in a database so that the strokes will be much easier to identify during the user's input. These data were kept in a for use in the succeeding methods in comparing for the correct stroke order, length and direction.

Stroke direction is analyzed by the use of the animations of the selected characters. It has been indicated that the directions may either be single-stroked or multi-stroked, which can mean that each stroke can contain either one angle or many angles, respectively. After the strokes were analyzed, they were encoded in the database as it is used for the comparison of the original and handwritten output in the next processes.

Stroke Length is analyzed by the number of black pixels of each stroke in the original image. It is also calculated by the position it holds in the original image. The stroke length extraction starts from the pen-down movements to the pen-up movements.

5.2 BCI Data Acquisition

Brain computer interface (BCI) is a system that translates the electrophysiological activity or metabolic rate of a human being's nervous system into such signals that can be interpreted by a mechanical device (Neurosky, Inc., 2012). Neurosky's Mindwave Mobile, is used to acquire the EEG brain wave frequencies and components of the user's brain. Since it is using Bluetooth, in order to link with the program, the device should load all available communication (COM) ports for detection. This is implemented using the ThinkGear connector included with the BCI's software. After the port has been secured or detected, the connection must be made. To connect with the device on the specified COM port, it should also be set in a 57600 baud to maintain stability of the connection.

5.3 Preprocessing

The single sensor on FP1 position of the head provides a high degree of freedom. With this, NeuroSky devices can measure multiple mental states simultaneously (Neurosky, Inc., 2012). The stable connection of the BCI device ensured that the preprocessing of the wave components can be detected and data needed for the study can be collected. There are an abundant number of signals and waves that the BCI device can display. These are Attention, Meditation, Raw waves, Alpha low, Alpha high, Beta low, Beta High, Delta and Theta waves. However, not all the components are relevant in the preprocessing stage, since these are then removed or ignored. In addition, these raw brain waves are converted via Fast Fourier Transform (FFT) so the outputs of the BCI device have relatively large values. With this, the proponents converted these large values into EEG brain wave frequencies in Hertz by dividing the values by 512.

5.3.1. Filter Wave Noise

All of the brain waves contain unnecessary 'noises' that are deemed irrelevant to the processing stage. These waves are filtered to avoid any inconsistencies in the frequency values of the outputs of the device thereafter. Noise filtering is mostly established by the BCI device itself. Part of NeuroSky's device involves noise cancellation. Filtering protocols eliminate known noise frequencies such as muscle, pulse and electrical devices. Notch filters eliminate electrical noise from the grid, which varies from 50Hz to 60Hz, depending on worldwide geography.

5.3.2. Determine Relevant Wave Components

As mentioned above, the device can read several components of the user's brain. Since there are five waves collected from the BCI, there are only 3 waves that are extracted: Alpha, Beta and Theta. The Alpha brain waves are associated with deep relaxation and meditation. This wave is closer to 7.5Hz whenever your brain heightens your imagination, visualization, memory, learning and concentration. The Beta brain waves are also called the waking consciousness and reasoning wave. This is presented with a heightened state of alertness, logic and critical reasoning but at times, they can also translate into stress, anxiety and restlessness. Lastly, the Theta brain waves which are referred to as the Light Meditation and Sleeping Waves are present during the realm of your sub consciousness during sleeping, most especially in a Rapid Eye Movement (REM) dream state. Theta waves are where a person experiences vivid visualizations, great inspiration, profound creativity and exceptional insight (Huddleston, 2008).

According to Huddleston (2008), when there is a high frequency in the Theta waves, ranging from 5.5Hz - 7.5Hz, the person has activated his/her creative thoughts and has ease of problem solving. On the other hand, when the Alpha brain waves range from 12Hz – 14Hz, the brain is more active and has increased focus and awareness. Thus, it is good for absorbing information passively. Lastly, when the Beta brain waves range from 13Hz – 27Hz, the brain promotes a more focused attention and conscious thinking.

These relevant wave components are recorded for the whole duration of the training as their frequency values are used in the later proceedings. The progress of how these waves react or change throughout the experiment is one of the main objectives answered in this research.

5.4. Character Recognition

Character Recognition is defined as the electronic conversion of scanned images of handwritten, typewritten text into machine-encoded text. Chinese calligraphy training starts in this phase wherein the respondent will rewrite the characters correctly as shown in each trial. It is in this process that the program records each stroke written by the user and check whether the stroke order, length and direction are accepted. To recognize each stroke in the written input, the program will need to adjust to the little errors that the user may commit since the exact and perfect character strokes cannot be fully obtained. Through this, Fuzzy Logic is implemented.

5.4.1. Fuzzy Logic

Fuzzy Logic is a statistical approach that uses Boolean logic that handles the concepts of "partial truths" – truth values between completely true (1) and completely false (0) (Rouse, 1996). Through the use of this approach, it is easier to check for the strokes written, as the ranges for the angles, pixel counts, and order of the stroke can be easily detected and acknowledged. With that said, the linguistic variables needed for the fuzzification and defuzzification processes are the angle and the pixel count. These variables contain a series of ranges available so that the consideration for the handwritten inputs can be checked.

5.4.1.1. Fuzzy Sets

The fuzzy sets that are used in this study are the handwritten input for the strokes. With this, the linguistic variables, which are the qualitative expressions for the rules and facts to be used in the fuzzification, are set. They are the pixel count, stroke length, stroke angle and stroke direction. After which, the membership functions, which are the degrees of truth of the certain values, are generated to interpret the input values of the fuzzy set into certain functions to be used in the fuzzification and defuzzification. These values in the membership function are transformed into output values which will then be used as the fuzzified value.

5.4.2. Extract Feature Points

In extracting the feature points from the original image, the stroke's length and direction are acquired. The same goes with the image itself as it will be used to compare the image with the handwritten input and calculate for the accuracy in the succeeding process. This is through the use of image processing wherein the character's pixel counts are obtained. To convert the image into binary values of 1 and 0, C# implements this by calling the different modes for Interpolation. In this study, the proponents have tried different types of interpolation modes to be used to filter the image of the Chinese character. The images below show the filtered image of the word 'love' in Chinese using the different filtering methods.

Figure 5.4.2.a. Bilinear Interpolation mode

Fig rpolation
mo

Figure 5.4.2.c. Bicubic Interpolation mode

Figure 5.4.2.d. High Quality Bilinear Interpolation mode

Figure 5.4.2.e. Nearest Neighbor Interpolation mode

Figure 5.4.2.f. High Quality Bicubic Interpolation mode

In the end, the clearest image that was produced is that of the High Quality Bicubic.

Using System.Drawing.Drawing2D.InterpolationMode.HighQualityBicubic

In order to convert the image to pure black and white pixels and remove gray parts, each pixel will be checked and compared to a threshold lower than 0. If the pixel's threshold is lower than 0, the pixel's color is set to black and if not, it is set to white.

On the other hand, the angle and direction of the original image is determined through the use of the Graphics Interchange Format (GIF) animation obtained from a reliable internet source called cchar.com. With the animation presented in the training, the angles are encoded to the dataset and thus, will be used to compare the direction of the respondent's input after each stroke is written.

It is also in this process that the preliminary data for the selected character is set. For every character selected by the user to be trained, the program will:

Set strokePath location for the ChineseCharacterSelected

Set filename of the ChineseCharacterSelected

Set imgGif of the ChineseCharacterSelected for the Teaching Animation

Set OriginalImgPath or the location of the whole image of the ChineseCharacterSelected

Set Number of Stroke of the ChineseCharacterSelected

Set the integer value of each stroke direction in an array degDir

5.4.3. Extract Stroke

Each character input of the user's handwriting that is recognized is called strokes. Strokes are determined from the "Pen-Down" movement of the stylus to the "Pen-Up" movement when it is lifted up. Strokes are extracted in this program whenever a "Pen-Down" movement is detected. In the same process, the x and y coordinates of the stroke are extracted so that the position of the character displacement can be determined as it will be compared for accuracy in a later process. With the software development program used in this study, C# enables the graphics class and it can easily extract the coordinates after the image is drawn. The x and y coordinates can be obtained by calling the *e.X* and *e.Y* variables from the Mouse Event *e.*

5.4.4. Calculate Pen-Up

After the "Pen-Down" movement has been extracted, the "Pen-Up" movement is obtained. When the "Pen-Up" movement is done by the respondent, it is immediately checked in the Mouse Event of a *Mouse_Up*. This implies that the stroke has been written down and checking for the stroke's correctness will be next.

5.4.5. Extract zones and directions of start point and end point

Since both the "Pen-Down" and "Pen-Up" movements have been obtained, it suggests that both the start and end points of the written input has also been determined. This is done by extracting the lateral and longitudinal coordinates or direction where the respondent began with while writing the Chinese character or word. With this, from the start point drawing out to the end point, a line or curve will be drawn for every pixel it goes by. Through C#'s graphics class, for every Mouse Event *MouseMove,* a graphic of black pixels will fill the rectangle like this:

```
g2.FillRectangle(brush, e.X, e.Y, 10, 10)
```

, where for every x and y coordinate, there will be a 10x10 black pixel drawn on the canvass

5.4.5.1. Fuzzification

The fuzzification process starts by finding the different degrees of membership of the linguistic variables in our study. The input of the handwritten character's stroke will be a basis as the crisp value to be transformed into fuzzified values through the linguistic values of the function. This will then be inference using the fuzzy rules and associate them accordingly to their ranges. In our study, for example, a pixel count of 35 is written by the user. The system will generate a specific truth value from 0 to 1 for that specific input and it will be used in the membership function in the fuzzy rule inferencing. In the fuzzy rule inferencing, the fuzzy rules of fuzzy system will be implemented. The fuzzy rules of this study are indicated in the subsequent sections below. These are the IF and THEN statements which will be associated with the linguistic variables and membership functions. After getting all the fuzzified values of the antecedent of the fuzzy rule (IF statement), the value greater than 0 will be extracted and then determine the consequent (THEN statement).

The length of the strokes is also obtained and checked in this process through the use of Fuzzy Logic. It is obtained through the pixel count which is drawn from the start point until the end point of the handwritten input by the respondent. The length is now checked by the program through the use of the fuzzy rules, fuzzification and defuzzification processes. First, there are 2 membership functions associated with the stroke length: pixel and length. The membership function collection of pixel contains 3 linguistic variables, "few", "many" and "too_many". In the same way, the membership function collection of length contains 3 linguistic variables, "Short", "Long" and "Too_Long". These functions contain different ranges for each linguistic variable as it will serve as the basis for the comparison of the original image's stroke length and the written input's stroke length. The table below explains how the range of the pixels of the written input and the original image will be fuzzified. If the pixel count falls from the minimum to the maximum range, then it will be added to that specific membership function.

Linguistic Variable	Minimum Range	Lower Range	Upper Range	Maximum Range
Few	30	40	75	85
Many	80	90	160	170
Too_Many	165	175	245	255

Table 5.4.5.a. Membership Function Collection for Pixel Count

The table below explains how the membership function of the stroke length is fuzzified. It is much the same with that of the pixel count's table, since it will be associated with it after the fuzzy rules have been determined.

Linguistic Variable	Minimum Range	Lower Range	Upper Range	Maximum Range
Short	0	10	20	30
Long	25	35	45	55
Too_Long	50	60	70	80

Table 5.4.5.b. Membership Function Collection for Stroke Length

After the linguistic variables and membership functions have been set, the fuzzy rules for the collection are established and used to check for the accuracy and precision, in this case, range of the written input. The snippet of code below describes the fuzzy rules for the pixel count and length association.

IF (Pixel IS few) THEN Length IS Short
IF (Pixel IS many) THEN Length IS Long
IF (Pixel IS too_many) THEN Length IS Too_long

After checking for the consequent values, defuzzification process can now begin. Defuzzification is the process by which fuzzy engine outputs a value where the pixel count coincides with the fuzzy rule, and then it shall base the linguistic variable of the length and get the range for the stroke length.

The following figures below show the trapezoidal graphs of the membership functions used in this study. These describe the overlapping ranges that will be used for fuzzification and determination of the consequent values.

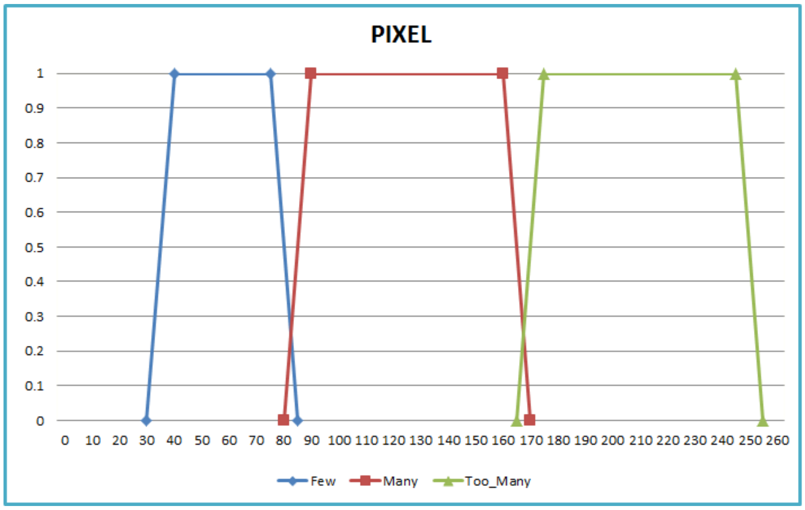


Figure 5.4.5.c. Trapezoidal Membership Function for Pixel Count

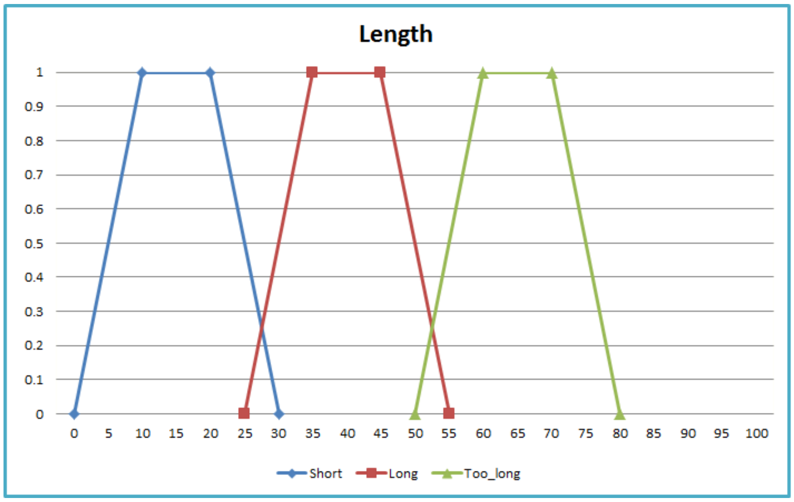
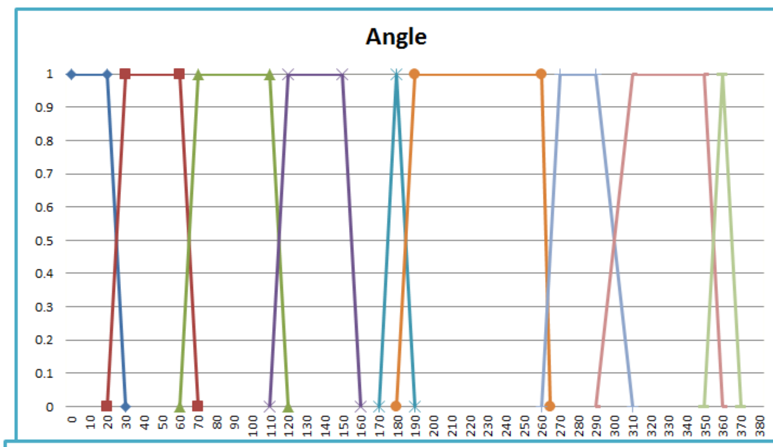


Figure 5.4.5.d. Trapezoidal Membership Function for Length



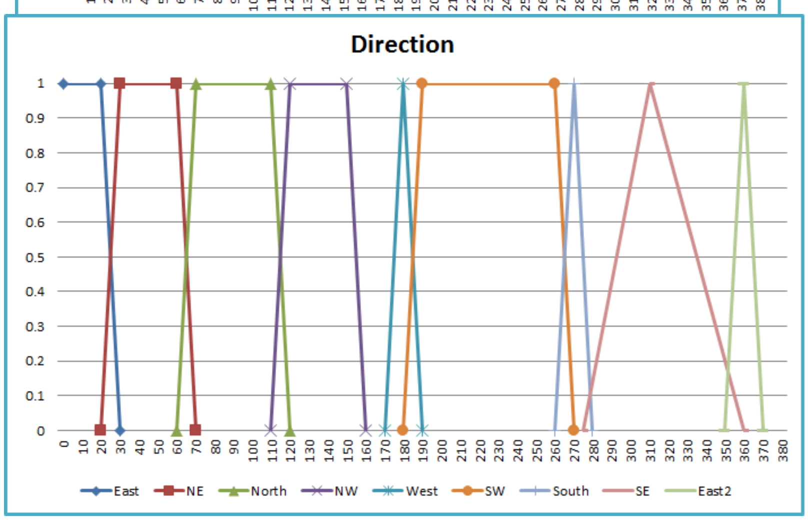


Figure 5.4.5.f. Trapezoidal Membership Function for Direction

5.4.6. Extract changes in writing direction

One of the critical points in Chinese Calligraphy is in the use of the stroke's proper direction. Without having the proper orientation and direction of the Chinese strokes, there would be no art or discipline applied in the attitude of the respondent. By using online handwriting recognition, the change of writing direction and the order of strokes can be obtained.

The direction of the strokes is obtained and checked in this process through the use of Fuzzy Logic. It is obtained through the angle which is drawn from the start point until the end point of the handwritten input by the respondent. The direction is checked by the program through the use of the fuzzy rules, fuzzification and defuzzification processes. Same with the length of the stroke, there are two membership functions associated with the stroke's direction: angle and direction. The angles used in the linguistic variables are according to each positioning in a 360-angle axis.

The membership function collection of angle contains 9 linguistic variables, "0deg", "0deg2", "45deg", "90deg", "135deg", "180deg", "225deg", "270deg" and "315deg". There are 2 angles of 0 since a straight line going right can either be 0 degrees or 360 degrees. In the same way, the membership function collection of direction contains 9 linguistic variables, "North", "East", "East2", "West", "South", "NE", "NW", "SE" and "SW". There are also 2 east directions since two angles of 0 and 360 can be extracted. These functions contain different ranges for each linguistic variable as it will serve as the basis for the comparison of the original image's stroke direction and the written input's stroke direction. The table below explains how the range of the angles of the written input and the original image will be fuzzified. If the angle falls from the minimum to the maximum range, then it will be added to that specific membership function.

Linguistic Variable	Minimum Range	Lower Range	Upper Range	Maximum Range
0deg	-10	0	20	30
45deg	20	30	60	70
90deg	60	70	110	120
135deg	110	120	150	160
180deg	170	180	180	190
225deg	180	190	260	265
270deg	260	270	290	310
315deg	290	310	350	360
0deg2	350	360	360	370

Table 5.4.6.a. Membership Function Collection for Stroke Angle

The table below explains how the membership function of the stroke direction is fuzzified. It is much the same with that of the stroke angle's table, since it will be associated with it after the fuzzy rules have been determined.

Linguistic Variable	Minimum Range	Lower Range	Upper Range	Maximum Range
East	-10	0	20	30
NE	20	30	60	70
North	60	70	110	120
NW	110	120	150	160
West	170	180	180	190
SW	180	190	260	265
South	260	270	270	280

SE	275	310	310	360
East2	350	360	360	370

Table 5.4.5.b. Membership Function Collection for Stroke Direction

After the linguistic variables and membership functions have been set, the fuzzy rules for the collection are established and used to check for the accuracy and precision, in this case, range of the written input. The snippet of code below describes the fuzzy rules for the stroke's angle and direction association.

```
IF (Angle IS 0deg) THEN Direction IS East
IF (Angle IS 0deg2) THEN Direction IS East2
IF (Angle IS 270deg) THEN Direction IS South
IF (Angle IS 45deg) THEN Direction IS NE
IF (Angle IS 135deg) THEN Direction IS NW
IF (Angle IS 225deg) THEN Direction IS SW
IF (Angle IS 315deg) THEN Direction IS SE
IF (Angle IS 180deg) THEN Direction IS West
IF (Angle IS 90deg) THEN Direction IS North
```

After checking for the consequent values, defuzzification process is implemented. Defuzzification is the process wherein the fuzzy engine will now output a value from which the angle coincides with the fuzzy rule, and then it shall base the linguistic variable of the direction and get the range for the stroke length.

5.4.6.1. Defuzzification

After the fuzzy rule inferencing in the fuzzification process, defuzzification will transform the linguistic variables in the consequent into a crisp value or degree of membership to determine the stroke direction and stroke length of the handwritten values, given the pixel counts and stroke angle. This will determine if the stroke direction or length of the handwritten characters are acceptable according to the set ranges.

5.4.7. Calculate Stroke Accuracy

In every stroke written by the respondent, the accuracy is calculated and thus, it can help the respondent distinguish a clearer picture of what he or she is writing. In this way, it can aid in the development of the Chinese Calligraphy for the user can understand his or her points for improvement in every trial. The stroke accuracy can also be used as a point of analysis of the user's progress after the 5 trials. The accuracy can be calculated using the percentage error formula:

$$SA(length) = 100 - \left[\left(\frac{Original - Experiment}{Original}\right) x\ 100\right]$$

$$SA(direction) = \sum_{i=1}^{n} 100 - \left[\left(\frac{Original - Experiment}{Original}\right) x\ 100\right]$$

5.4.8. Calculate Word Accuracy

After all the strokes are written for every word, the accuracy is calculated and this can provide a feedback to the user in the accuracies that he or she has written in every trial. Through this, it can help in the training for writing the Chinese characters so that the user can determine his or her points for improvement in that particular word. The word accuracy can also be used as a point of analysis of the user's progress after the five trials. The accuracy can be calculated using by simply averaging the accuracies for all the strokes of that particular word:

$$WA(length) = \sum_{i=1}^{n} SA(length)$$

$$WA(direction) = \sum_{i=1}^{n} SA(direction)$$

5.4.9. Feature Extraction

In every trial, as the respondent writes the Chinese characters, his or her brain waves shall be recorded and classified. It is also in this phase that the frequencies of each relevant wave component are determined. After the frequency values are converted into EEG brain wave values, the program will output a graph containing the Alpha High, Alpha Low, Beta High, Beta Low and Theta waves and their behavior in every trial. These values that are provided every 1 or 2 seconds are then averaged and the final values will serve as the averaged frequency for every brain wave. These values are combined with the word accuracies and saved into a file that shall be used to determine the correlation in the next process.

5.4.10. Testing / Evaluation

The testing for the program is directed to ten (10) respondents who have no knowledge whatsoever in writing or learning Chinese characters. The respondents in this study are fourth year Computer Science students from the Ateneo de Davao University. The data set used in this study and implemented in the program are ten (10) Chinese characters; these are the numbers one to ten in the Chinese dictionary. However, in the testing process, the proponents chose only five of the ten characters that the respondents will train for. The chosen Chinese characters are one (1), six (6), seven (7), four (4) and five (5), which are done in order in accordance to its difficulty and stroke count.

After an automatic evaluation for handwriting Chinese calligraphy, the proponents have come up with the frequency values for each brain wave and the averaged values for the handwriting accuracies. With these two variables, the correlation can be determined by using Pearson's Correlation Coefficient. The formula for such is:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

Figure 5.4.10.a. Pearson product-moment correlation coefficient formula

But since Microsoft Excel's CORREL() function implements Pearson's Correlation Coefficient, the proponents are going to use that particular platform. After the r value of the correlation is found, a scatter diagram can be created to identify the regression weight and trend line of the data.

Direction Acc	Length Acc	Average	Alpha High	Alpha Low	Beta High	Beta Low	Theta
67.28511999	71.42857143	69.35684571	10.90755177	13.37858105	12.05859375	9.384114	45.39811
53.45445276	78.1512605	65.80285663	3.616736889	4.389573097	2.675330639	3.006911	7.854868
69.11227024	82.35294118	75.73260571	5.043945313	3.491862059	4.122721195	3.98112	13.03548
61.02779558	79.83193277	70.42986418	6.58984375	8.434765816	8.476953506	7.690234	15.42969
62.31745509	74.78991597	68.55368553	8.997265816	17.54570389	7.175976753	9.508594	44.23828
56.12203133	78.1512605	67.13664592	5.055772781	2.206814289	4.538628578	2.401042	15.5319
54.40331934	77.31092437	65.85712186	3.096679688	7.931640625	8.342285156	2.944824	43.8501
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 5.4.10.b Accuracy and Brain Wave and Frequency Values

The average of the direction and length accuracy are each compared to every brain wave, particularly Alpha High, Alpha Low, Beta High, Beta Low and Theta waves. The correlation of each comparison is then computed. The results are combined and it is found that out of the ten (10) respondents, there is an average -0.081 correlation between the stroke accuracy values and the Alpha High brain wave frequencies. Also, it is found that there is a -0.045 correlation with the Alpha Low brain waves, -0.034 correlation with the Beta High brain waves, -0.043 correlation with the Beta Low brain waves and a -0.050 correlation with the Theta brain waves. From these values, we can say that though there are very low correlation values, the negative correlation assumes that there is still no correlation between the user's brain waves and in the activity of writing Chinese characters.

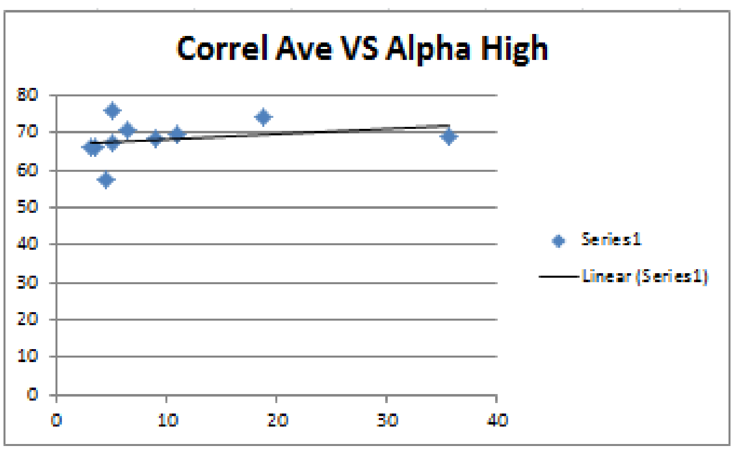


Figure 5.4.10.c. Correlation graph between the Stroke average and Alpha High Brain Waves

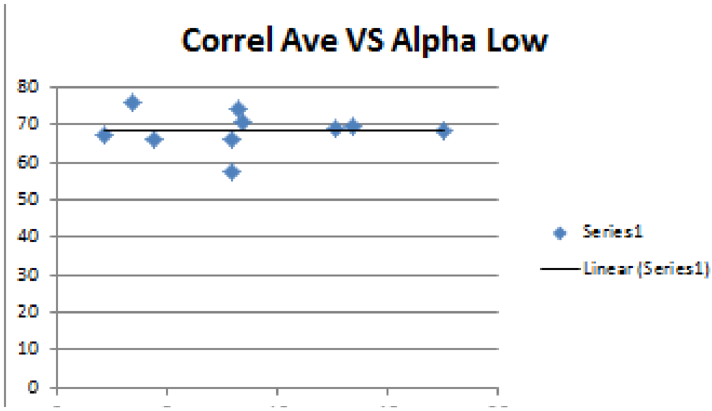
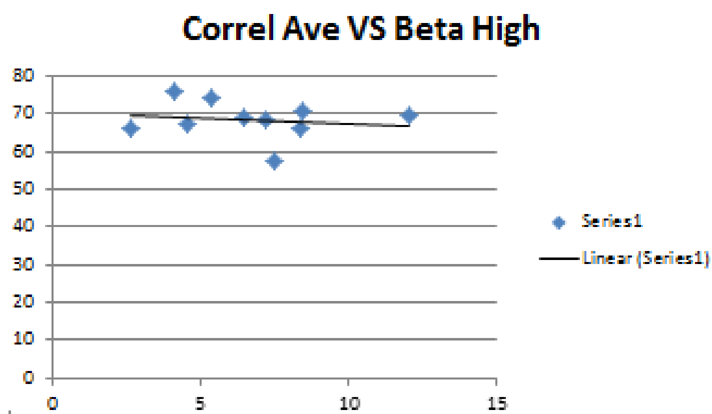


Figure 5.4.10.d. Correlation graph between the Stroke average and Alpha Low Brain Waves



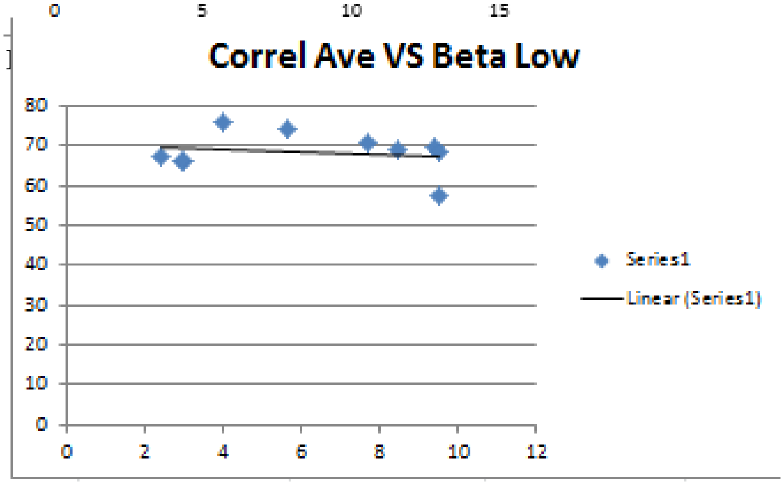


Figure 5.4.10.f. Correlation graph between the Stroke average and Beta Low Brain Waves.

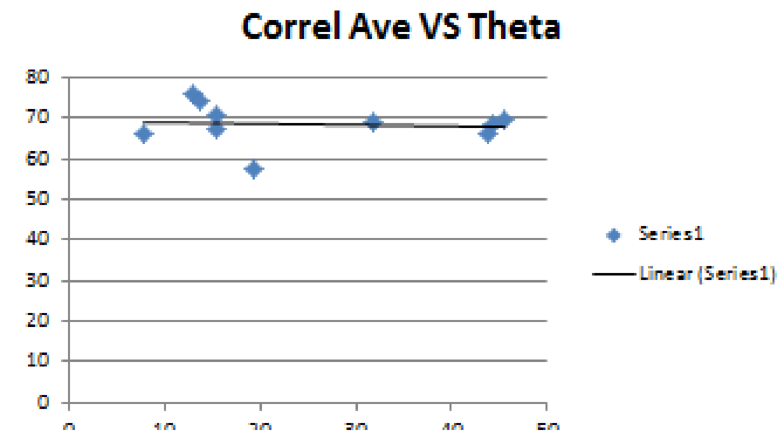


Figure 5.4.10.g. Correlation graph between the Stroke average and Theta Brain Waves.

The figures of the correlation above are taken from the results of a specific respondent. The figures show the regression lines of the values of the stroke accuracies in relation to each of the brain wave components. A diagonal line pointing downwards to the right illustrates that there is a negative correlation between the two variables. Based on graphs above, it is clearly shown that there is an obvious negative correlation however; it is very low based on the inclination of the diagonal lines.

6. CONCLUSIONS AND RECOMMENDATIONS

Based on the study implemented by the proponents, Fuzzy Logic has been very evident in the findings and associations with that of the handwriting recognition. It has been used in comparing the correct usage of length and direction of each Chinese character stroke. The fuzzification process truly evaluated the degrees of ranges for the stroke to be accepted. In addition, the brain waves that are more active in the implementation of Chinese Calligraphy are the Alpha High and Alpha Low brain waves. Thus, it implies that the respondent shows somewhat little attention and conscious thinking in the handwriting activity presented. On the other hand, the Beta High, Beta Low and Theta brain waves show a negative correlation higher than other negative correlation values. This can possibly suggest that there is no relationship between such brain waves with the proper writing of Chinese strokes. This is also supported by Kotsos (2011) that the Theta waves ranging from 4-7.5Hz are dominant during deep meditation, light sleep and REM sleep, which has no relation whatsoever in an active participation of handwriting characters.

The association between the Alpha brain wave and the handwriting stroke over-all accuracy indicate that there is a -0.081 for High and -0.045 for Low. In relation to the Beta brain waves, it generated a correlation of -0.034 for High and -0.043 for Low. And for the Theta brain waves, there is a -0.050 correlation. From the produced results of the study, all of the correlation coefficient values were negative. Hence, the values from each brain wave generated a very low r value and that there is a low or no correlation between the user's brain waves and the handwriting stroke accuracies, generally. There are possible theories to address this supposition are the following:

1. Based on the study of Huddleston (2008), the brain waves frequency values of each frequency band should be around a certain range. This could possibly imply that since some of the respondent's brain activity has not heightened, the concentration of the respondents is low.

2. Brain waves having a negative correlation could not have any effect in the training of Chinese Calligraphy as stated in Kotsos' study and as mentioned above.

3. There is a possible inaccuracy in the Brain Computer Interface device used since it only senses brain waves in the Fp1 position. Therefore, it only accesses brain wave frequencies generated by the prefrontal cortex or forehead part of the brain. In addition, another factor in receiving brain activity is that the raw brain waves are too fast, thus, the program couldn't sense all of the frequency values.

4. The results could show that there is a very low or no correlation between the brain activity and writing Chinese Calligraphy.

5. The dataset used in the study is too simple, since it only caters to the numbers 1 to 10 in the Chinese dictionary. Such level of difficulty could be a reason that the respondents took only a short time in writing the characters. All the same, the number of trials in the exercise for Chinese calligraphy was not enough to establish a proper training for the respondent.

For all the problems encountered and with the results founded in the study, the proponents would recommend the following:

1. Since the program records the brain activity in every trial separately, it is suggested that a continuous recording of the brain waves from the start of the first trial to the end of the tenth trial to ensure the consistency of the brain wave activity.
2. The proponents propose to include the Attention component in the variables of comparing the brain waves. This can be integrated and captured through the use of the BCI device. With this, the Attention component can perhaps increase the probability of having a better correlation.
3. Due to the inefficiencies and constraints of the devices used, the proponents recommend to use a better BCI device that would not only capture the brain waves at the FP1 position, but also other parts of the brain. In addition, the drawing tablet can also be changed to a better one or possibly a touchscreen device, as it may improve the precision of the handwriting recognition.
4. It is also suggested that the depth or the pen pressure of the written characters be implemented and included in the program as it is also a means of having a certain discipline to enhance the Chinese Calligraphy style of writing.

Furthermore, the proponents also recommend more tests to be conducted for it can somehow give a better conclusion and accuracy in the data given by the respondents. It is also suggested to future researchers to engage in the approaches used in this study, particularly of Fuzzy Logic because it can help in decisions or inferences of expert systems. Lastly, it is also suitable to pursue different topics that are related to Brain Computer Interfaces (BCIs) since it is very advanced and it is something worthwhile contributing to in the future.

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