# Development of Handwriting Recognition System in Postal Service Sector

E. O. Y. Ngu and S. H. A. Ali
*Faculty of Electrical Engineering, Universiti Tun Hussein Onn Malaysia,*
*86400 Parit Raja, Batu Pahat, Johor*
*aminahh@uthm.edu.my*

***Abstract*—Handwriting recognition is a comparatively popular research due to its diverse applicable environment. It helps to solve complicated problems and at the same time, it reduces manpower consumption. This paper proposes a system for recognizing online handwritten characters by using K-Nearest Neighbor (KNN). General steps of an algorithm are: (1) capturing the postcode and name of district area by using external web camera, (2) performing image processing on the image, (3) creating input data for KNN by extracting vital feature from each character, (4) classifying the dataset using KNN algorithm and performing recognition during the test, and (5) providing result of the recognition. The experiment was carried out in the aspect of text font size, the density of text and light intensity of background text. Experiment results show that training sets, trained inputs and untrained inputs achieved reasonably good result with an accuracy rate of 100%, 87.54% and 75.35% respectively. For processing time, the training sets consumed the lowest processing time which is 195.32ms, followed by trained inputs with 201.30ms and untrained inputs with 204.98ms. Additionally, medium font size, high-density text and optimum intensity of the background text managed to achieve high accuracy rate and low processing time. In this way, the system is able to help the postal services sector to speed up the sorting process as well as reducing manpower consumption in the sorting unit at the same time. Overall, the system has fulfilled the objective of the project, which is to propose high accuracy and short processing time of the handwriting recognition system.**

***Index Terms*—Handwriting Recognition; K-Nearest Neighbor; Postal Service Sector.**

## I. INTRODUCTION

In general, handwriting recognition is classified into two types, which are the off-line and the online handwriting recognition methods. The off-line handwriting recognition involves the automatic conversion of the handwriting written on paper or image into a digital form which then can be edited by a computer and text-processing application. This kind of data is known as a static representation of handwriting. On the other hand, online handwriting recognition involves automatic conversion and real-time processing of text on a special digitizer or personal digital assistant (PDA), where a sensor picks up the pen-tips movement, for example by a pen-based computer screen surface or using images taken by a camera. This kind of data is known as digital representation handwriting [1].

Nowadays, there are a lot of sectors use handwriting recognition systems, such as data entry for business documents like bank check, bank statement, passport, postal letter, invoice and others. Every sector faces the same challenge, which is the involvement of a tremendous increment number of documents. Parcels in the postal service sector are one of the affected sectors that receives millions of parcels every day and they have to be processed and delivered to customers in a short period. According to 2014 Nielsen Global Survey of e-commerce report, Malaysia was ranked number sixth in the top 10 market globally for the use of mobile phone to shop online covering 47% of the market after Philippines (62%), Indonesia (61%), Vietnam (58%) and Thailand (58%) and followed by Singapore (48%). From this statistic, it is known that the online shopping has been driven by courier boom since the past few years [2]. On top of that, courier service is also confronted by growing number of courier service companies that provide faster, newer and higher quality services than the service provided before. By accurately reading postcode and district area on the parcels, it will speed up the sorting process in the postal service sector and be able to meet the challenge and keep abreast with the advance of times.

## II. METHODOLOGY

Figure 1 shows the program flow of the system followed by its brief description. Firstly, the image of postcode and district area was captured through Image Acquisition Module. Then, Image Processing Module was used to process the captured image. The proposed image was sent to the Region of Interest (ROI) Identification Module to identify the selected ROI of the image. Feature Extraction Module extracts a certain feature from the ROI image. Then, the feature from the extracted image was sent to K-Nearest Neighbor (KNN) to perform recognition [3].

### *A. Image Acquisition Module*

Image acquisition is the process of processing the captured image. Web camera and OpenCV VideoCaptur class play an important role in this process. The web camera is used to capture handwritten postcode and name of district area which can be found on the consignment note, while OpenCV VideoCaptur class provides C++ Application Programming Interface (API) for reading video files and image sequences. Therefore, VideoCaptur class provides a platform for web camera to interface with handwriting recognition program coding. The writing is done by using Microsoft Visual Studio 2015 [4].

### *B. Image Processing Module*

Firstly, the captured handwriting image is normalized to a predetermined size and centered in a gray level image with a size of 10 x 10 or with 100 pixels as the features as shown in Figure 2. In order to clean the data, the system undergoes two processes, which are the binarization and the noise removal. In the binarization process, each gray level image is converted into a binary image using a threshold technique. The image then undergoes noise removal process to make sure that the background noise will not affect the recognition accuracy rate [5].

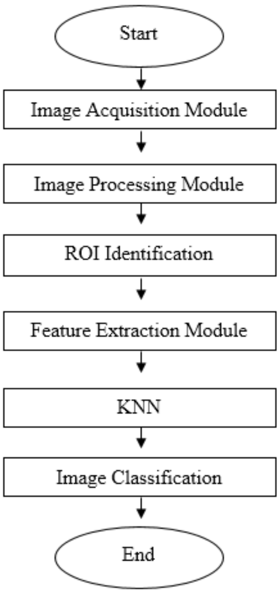


Figure 1: Flowchart of the process

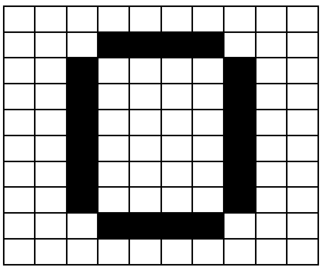

Figure 2: Grey level image of digit ‘0’ with 10x10 pixels size

### *C. ROI Identification Module*

ROI identification is used to determine data to be processed from the captured image. Firstly, an ROI is created on the taken image. Then, recognition process will be performed on a rectangular subset of the image. After recognition process is done, it will reset back the ROI for the next image that will be captured [6].

### *D. Postcode and District Name*

Figure 3 shows the image of SKY NET consignment note. An image consists of postcode and name of district area is captured based on the consignment note as shown in Figure 4. First of all, the image is captured by using a web camera. Then, the user chooses the ROI of postcode using manual point and cut. After the image has been selected, the image is then processed to detect the data inside the boxes. Figure 5 shows the result of the image after preprocessing [7].

### *E. Feature Extraction Module*

In this system, template matching technique is used as a classification method. Each image pixel is used as a feature vector. Basically, the template technique finds the image that matches with the input image by comparing the input image with the training image. The identity of the input character is determined by measuring the similarity between the input characters with a set of training characters. In other words, when a pixel in the input character is identical to the pixel in the training image, the similarity measure will be increased. In contrast, when a pixel in the input character is not identical to the pixel in the training image, the similarity measure will be decreased. After all training sets are compared with the input character image, the character with high pixel match will be assigned to the identity of the input character [8]. Table 1 shows the average similarity of template matching technique for digit ‘0’ towards other digits. Based on similarity score obtained from Table 1, test data ‘0’ is recognized as digit ‘0’.


Figure 3: The captured image of the postcode and name of district area on the consignment note


Figure 4: The cut image of the result

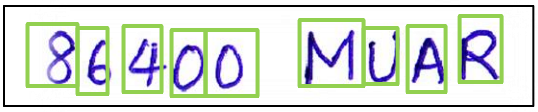


Figure 5: ROI of the postcode and name of district area

Table 1
Average Similarity Score of Digit ‘0’ Towards Other Digit

| Digit | Similarity measure with digit ‘0’ | Digit | Similarity measure with digit ‘0’ |
|---|---|---|---|
| 0 | 98 pixels | 5 | 91 pixels |
| 1 | 82 pixels | 6 | 94 pixels |
| 2 | 92 pixels | 7 | 85 pixels |
| 3 | 93 pixels | 8 | 94 pixels |
| 4 | 83 pixels | 9 | 89 pixels |

### *F. K-Nearest Neighbor*

The KNN plays a major role in this system. For KNN algorithms, a training set and test set are needed. The training set is obtained through OpenCV library. There is a total of 250 numerals (0-9) images, 25 numerals for each digit. In addition, there is a total of 650 capital letter alphabets (A-Z) images, 25 for each alphabet. Each image size is 10 pixels by 10 pixels with each image has a total area of 100 pixels. For test data, there are 200 different sets of handwriting written by different people. The number of K is set to 1 as the lower the number, the higher the recognition accuracy rate. Furthermore, an odd number of K performs better in precision rate than even number [9].

## III. Result and Discussion

This analysis was carried out to determine the effectiveness of the handwriting recognition system. There are three types of test samples, which are Type A, Type B and Type C. Descriptions of Type A, B and C are stated in Table 2.

In the experiment, each type of samples was evaluated in 5 sequences where each sequence was randomly arranged to determine the accuracy and processing time of the system. Each round consisted of 200 sets of test samples. Three different experiments were carried out, which were; (1) the effect of different font size, (2) the effect of text density and (3) the effect of light-density of text background. The examples of text for each experiment is shown in Table 3.

Table 2
Description of Type A, Type B and Type C

| Type of sample | Training sets | A | B | C |
|---|---|---|---|---|
| Group | Group A (consists of 10 people) | Group A (consists of 10 people) | Group B (consists of 100 people) | Group B (consists of 100 people) |
| Data | Capital letter (A-Z) and digits (0-9) | Postcode and district area | Postcode and district area | Postcode and district area |
| Hand-writing pattern | Using their own handwriting pattern | Using their own handwriting pattern | Copying pattern from training sets | Using their own handwriting pattern |

Table 3
Description of Experiments

| Experiment | Type of font or condition | Example |
|---|---|---|
| The effect of different font size | Large font size | 43000 SELANGOR |
| | Medium font size | 43000 SELANGOR |
| | Small font size | 43000 SELANGOR |
| The effect of text density | High-density text | 43000 SELANGOR |
| | Low-density text | 43000 SELANGOR |
| The effect of light density of text background | High intensity of light | Carried out in a bright room (202 lx) |
| | Low intensity of light | Carried out in a dim room (152 lx) |

### *A. The Effect of Different Font Size of Text*

The analysis was carried out in order to show the handwriting recognition performance on the different font size of handwriting. The text occupied less than 30% of the written paper is small font size, the text occupied between 30% to 70% of the written paper is medium font size and the text occupied more than 70% of the written paper is large font size. The average accuracy rate and processing time of different font size of the text are listed in Table 4.

Table 4 shows the medium font size that has the highest accuracy rate for both Type B and Type C with the accuracy rate of 85.60 ± 0.79% and 75.40 ± 0.05% respectively. On the other side, the small font size has the lowest accuracy rate with 65.57 ± 0.02% for Type B and 63.87 ± 0.02% for Type C. These conditions occur because medium characters are better recognized if the resolution of network is high and small characters produce small resolution, which causes the system to generate bad recognition. Large size must be avoided as the characters are frequently treated as images rather than texts during the recognition process.

Based on Table 4, it is obvious to see that the large font size has the highest processing time for both Type B and Type C. In contrast, the small font size utilizes the lowest processing time for both types of test samples. Therefore, larger font size provides better resolution leading to a longer processing time for the system to process it. The S. D reading from Table 4 shows that the system is reasonably stable by looking at the overall S. D value that values less than 1.0.

Table 4
Recognition Accuracy and Processing Time

| Type | Size of font | Accuracy (%) | Processing time (ms) |
|---|---|---|---|
| B | Small | 65.57±0.02 | 197.58±0.07 |
| | Medium | 85.60±0.79 | 201.78±0.07 |
| | Large | 68.76±0.02 | 209.86±0.20 |
| C | Small | 63.87±0.02 | 198.20±0.04 |
| | Medium | 75.40±0.05 | 204.14±0.05 |
| | Large | 64.75±0.01 | 213.36±0.05 |

### *B. The Effect of Text Density*

This analysis was carried out to investigate the handwriting recognition system performance on different density of text. The density of text is categorized into two categories, which are the high-density text and the low-density text. The high-density text refers to the range of the text density exceeding more than 50%. It is resembled by thick and heavy looking handwriting. On the other hand, the low-density text is the text density that is less than 50%. It can be seen as thin and light looking handwriting. The average accuracy rate and processing time of different density of the text are listed in Table 5.

Table 5 shows high-density text for Type B with 87.46 ± 0.03% accuracy while Type C with 75.47 ±0.01%. For low-density case, Type B achieves 63.74 ± 0.01% and 60.72 ± 0.00% for Type C. These values mean that the high-density text has occupied more pixels than the low-density text. In other words, the high-density text consists of high gray value enabling it to produce high-quality output for the system to recognize. As a result, the system recognizes the character with high-density text more accurately than the low-density text.

Table 5 shows that the processing time for both Type B and Type C are approximately between 200ms and 210ms. Since the difference of the processing time between them is small which is only 10ms therefore, it can be concluded that the density of the text does not significantly affect the processing time of the recognition system. The S.D values stated in Table 5 are explicitly small thus proving high stability of the system.

Table 5
Recognition Accuracy and Processing Time of Different Text Density

| Type | Text density | Accuracy (%) | Processing time (ms) |
|---|---|---|---|
| B | High-density text | 87.46±0.03 | 200.02±0.04 |
| | Low-density text | 63.74±0.01 | 205.60±0.11 |
| C | High-density text | 75.47±0.01 | 204.74±0.00 |
| | Low-density text | 60.72±0.00 | 209.20±0.00 |

### C. The Effect of Light Density of Text Background

This analysis provides the handwriting recognition system performance in the different light intensity of the background text. The intensity of the light is divided into two types, which are high light intensity and low light intensity. The background text with high light intensity means that the recognition analysis is done in a bright room (≥70% of the brightness). In contrast, the background text with low light intensity represents recognition analysis that is done in a dim room (≤ 30% of the brightness). The average accuracy rate and processing time of different light intensity of the background text are listed in Table 6.

Table 6 states the high light intensity of the background text achieves 85.60 ± 0.01% for Type B and 75.47 ±0.00% for Type C. This table also shows that the background text with high light intensity performs better than the one with low light intensity. This is due to the fact that higher light intensity of the room causes higher contrastivity to occur between the text and the background making the background noise to be lower thus increasing the precision rate of the system.

The background text with high light intensity consumes low processing time for both Type B and Type C test samples. It is due to the fact that the contrast between the text and background increases and the background noise is very low when the text is recognized in a bright room. Hence, the system takes a shorter time to recognize in the bright room than the dim room.

Certainly, Table 6 shows that the reading results are precise to each other meaning that the overall value of S. D reading is quite slow. It is concluded that the test samples and proposed handwriting recognition system are definitely stable.

Table 6
Recognition Accuracy and Processing Time of Different Light Intensity

| Type | Light intensity | Accuracy (%) | Processing time (ms) |
|---|---|---|---|
| B | High-density of light | 85.60±0.01 | 201.34±0.08 |
| | Low-density of light | 72.34±0.00 | 207.40±0.00 |
| C | High-density of light | 75.47±0.00 | 204.88±0.04 |
| | Low-density of light | 65.88±0.01 | 209.44±0.08 |

### D. Overall Performance

Table 7 shows the accuracy rate of Type A hit the peak which is 100%. Consequently, the system has no problem in reclassifying the training set. In other words, the system has the ability to perform the recognition of the test samples of Type B and Type C.

Based on Table 7, Type B and Type C have lower accuracy rate than Type A. The system recognition rate of Type B is 87.54 ± 0.03% and Type C has the lowest accuracy rate which is 75.35 ± 0.07%. This low rate of accuracy is due to the fact that the network had faced with new data that has never been seen before (Type C). Type B is a test set written by copying the letters exactly the same way as they are printed.

The average processing time of Type A is 195.32 ± 0.04ms followed by Type B with 201.30 ± 0.13ms and Type C with 204.98 ± 0.10ms. This is because Type A samples have previously been used to train the system thus making the response time to be the lowest among the other samples. The processing time for Type C is the highest due to a different style of handwriting in Type C test sample. The handwriting differs very seemingly from the training set. Therefore, it prevents the network to recognize the characters. Users create differences in terms of character size and orientation even though they write the same characters as different people have a different kind of handwriting. As a result, the system of this investigation took the highest processing time to recognize Type C test sample. In addition, the S.D of each type of sample is in the range of 0.0 to 0.2 which is less than 1.0. Therefore, the system is stable in term of accuracy rate, the processing time of test samples and an average of the process.

Table 7
Recognition Accuracy and Processing Time of Different Types of Samples

| | A | B | C |
|---|---|---|---|
| Accuracy (%) | 100.00±0.00 | 87.54±0.03 | 75.35±0.07 |
| Processing time (ms) | 195.32±0.04 | 201.30±0.13 | 204.98±0.10 |

## IV. Conclusions

The objectives of this project are to propose high accuracy rate and short processing time of handwriting recognition system. An application example of the project is to produce a system that is able to help the postal service sector to speed up the sorting process.

Based on the analysis of this research, the KNN approach performance depends greatly on the font size of the handwriting to achieve accurate results. Good results were obtained from the images with high-density text and high contrast between text and background. This is because the system was designed to detect handwriting that was approximately similar to the training set.

In general, the project has successfully proposed handwriting recognition system that provides 100% of accuracy rate with 156.20ms processing time when it was tested on the training set. When the system was tested on the trained inputs which were not used for the training purpose, it generated an accuracy as high as 82.33% with a processing time of 159.40ms. In contrast to the untrained inputs, the accuracy rate was discovered to be 62.78% with the processing time of 162.30ms.

To sum up, the objectives of the project were fulfilled by proposing an online handwriting recognition system based on Microsoft Visual Studio and OpenCV library. The system has managed to recognize numerals (0-9) and capital letter alphabets (A-Z). The system works well with handwriting that is clearly written and shaped together with a good background. Additionally, the processing time of the recognition is short which is within one second. In this way, it is able to help the postal services sector to speed up the sorting process and at the same time reducing the consumption of manpower at the sorting unit.

There are a few important features can be added to improve the performance of the handwriting recognition system. One of the improvements is to include a function to automatically adjust the light intensity of the background text. By having this function, the system will be able to automatically correct the light intensity of the background text to an optimum level so that the accuracy of the handwriting recognition can be increased. The most realistic approach to execute intensity adjustment can be carried out by applying gamma correction [10]. Besides that, adding “diversion image” feature will reduce the number of false detection. Also, it decreases the expense time in setup and detection processes [10].

The precision rate of the system can be increased by utilising more feature extraction techniques like Histogram Orientation Gradient and Modified Alphabet Encoder. Meanwhile, sorting algorithm can be replaced by a more efficient and robust algorithm such as deep learning since a sophisticated and comprehensive handwriting recognition system can be produced by using this kind of algorithm [10].

Last but not least, the web camera can be replaced by a better camera such as camera used by industry. A high resolution and high-speed response camera are able to capture a high-resolution image with low background noise. Hence, the accuracy rate and processing time will be improved.

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