Thai Online Handwriting System Using Neural Networks and Fuzzy Logic

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ABSTRACT

In this paper, an on-line handwriting recognition system is proposed. Such a system combines the advantages of neural network and fuzzy logic algorithms. In this approach, Thai input-character is normalized in the preprocessing process. Then, the generic and specific features are extracted. Only a few generic features are fed to the neural network model so that the computational time of the training phase is minimized. After that, if the neural network yields a lower probability, then the fuzzy logic model is needed. In this case, the set of simple fuzzy rules are set up by means of the specific features. In this way, the experimental results illustrate that the proposed system can accurately recognize up to 86.28%.

KEYWORD : online handwriting, neural network, fuzzy logic, corpus, character recognition

1. INTRODUCTION

Thai character recognition plays an important role in today's computer literature, because it can identify the symbolic from an image to characters. In general, the character recognition can be categorized into two main schemes : offline recognition and online recognition. The offline recognition differs from the online recognition in that the input of the offline system is document an image while the input of online system is a signal captured from electronic devices, such as a mouse and an electronic pen. Although many online recognition methods have been proposed [3], [6], [8], these methods cannot be applied directly to Thai language. This is because its structure is very complicated when compared with European language. Thai characters are composed of several features, such as, circles, zigzags, curves, heads, tails, and levels. Furthermore, the absent of a space between words makes the character segmentation difficult. This leads to a challenge field of research.

In this field of research, many character recognition approaches were proposed. Almost approaches were based on neural networks [1], [10], [11], [13] and fuzzy logic [2], [4], [7], [15]. However, neural networks and fuzzy logic models still have disadvantages. That is, neural networks require many input-features and take long computational time in training process. On the other hand, fuzzy logic also has difficulty of defining fuzzy rules so as to cover all feasible solutions. Therefore, in order to overcome these disadvantages and to improve Thai character recognition system, the combination of neural networks and fuzzy logic is proposed. In this method, the features of Thai characters are divided into two types: generic and specific features. The generic features are comprised of distance and directional change of successive points and are fed to the neural network model. On the other hand, the specific features are composed of a size ratio, beginning and ending positions, stroke-and-level, heads, loops, heads and loop directions, and a main angle. These features are fed to the fuzzy logic model. At this point, we can summarize that the input features of neural networks are reduced whereas fuzzy rules of fuzzy logic are simple. For this reason, the disadvantages of neural networks and fuzzy logic are overcome.

2. PROPOSED APPROACH

In the proposed method, the system consists of three processes: preprocessing, feature extraction, and recognition. The overall system is shown in Fig. 1 and all processes are described as follows.

2.1 Preprocessing

Preprocessing is a first step to normalize signals acquired from an electronics pen and to remove noises occurred during the signal captured. In practice, an electronics pen or a mouse captures the signals containing temporal sequence of points. these signals are made up by the following procedures:

- *Resizing* is a procedure for making the signal size acquired from the electronics pen identical and for deleting all redundant or adjacent points. In addition, it also translates the coordinate points to the same reference.
- *Dehooking* is a procedure for cutting all hook shape characteristics that may cause troubles for extracting features of a character. Fig. 2 shows a hook-shape in the characters.
- *Interpolation* is a procedure for fulfilling the coordinate character. In this work, the linear interpolation is applied to create a new coordinate between two successive points that are too far apart.
- *Down-sampling* is a procedure for reducing the number of points in signals to be equal. Furthermore, it also removes the redundant or adjacent points.
- *Smoothing* is a procedure for adjusting coordinate points in signals caused by noise during the capturing process. To do this, each coordinate point is replaced by an average of the neighboring coordinates. Fig. 3 shows an example of smoothing character.

2.2 Feature Extraction

In this subsection, we consider and classify the features of Thai character into two types: generic and specific features. The generic features are basic features of characters that can be found in any character signals, such as the distance of points and the direction of handwriting. On the other hand, the specific features are occurred with only Thai characters, such as,

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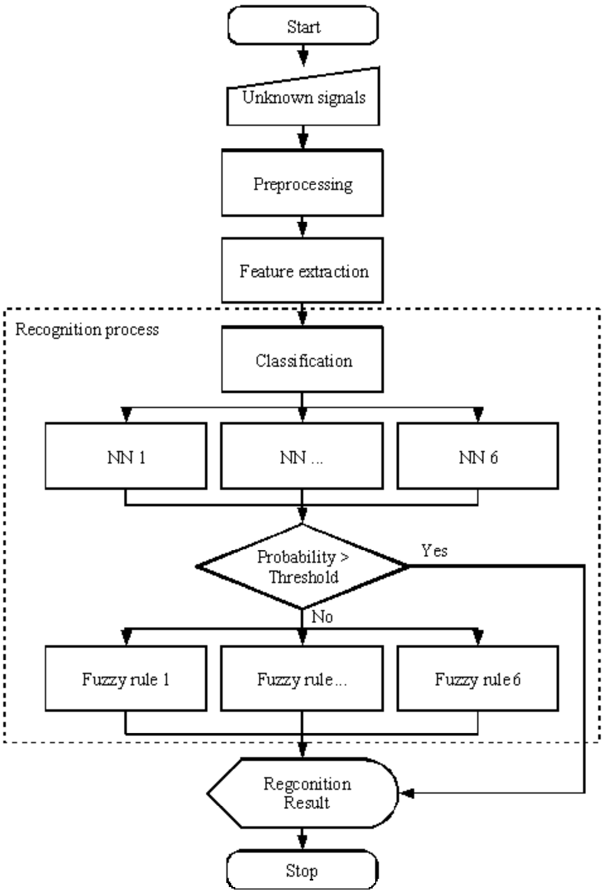


Fig. 1. Flow chart of recognition system

heads, loops, and levels. Therefore, for classification the generic features are fed to the neural network while the specific features are fed to the fuzzy logic system so as to gain up the accuracy of recognition. The following subsections describe techniques and procedures of feature extractions.

2.2.1 Generic Feature Extraction

- Directional change feature : This feature is determined by detecting the changing angle of each successive point as depicted in Fig. 4.
- Distance between successive points : This feature is the distance between two successive points as shown in Fig. 4.

2.2.2 Specific Feature Extraction

Typically, specific features of character signals are occurred in different locations. To specify the locations of different features, the character signal is split into sub-regions. In this work, each character signal is separated into 3x3 sub-regions. These sub-regions are used for reference in the following procedures.

- *Size ratio* : The size ratio is the proportion between width and height of each character signal. It can be calculated from width by height of the character signal.
- *Beginning and ending positions*: The beginning point is the first point of stroke and the ending point is the last point of stroke. The positions of beginning and ending of

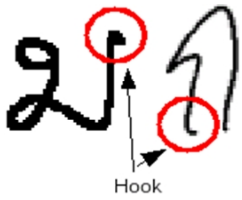


Fig. 2. Hook-shape in characters

Fig. 3. Smoothing character

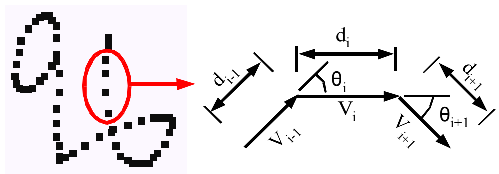


Fig. 4. Distance and angle between successive points

stroke are mapped to the sub-regions as illustrated in Fig.5.

- *Stroke and level*: Stroke is a written signal occurred between two pen-lifts. Commonly, a character can be composed of one or more strokes as shown in Fig. 6. Level is the writing area split into base, above-vowel, and below-vowel sub-areas as depicted in Fig. 7. These specific features are very important since they can be used to classify the character groups.
- *Head detection*: Head is a circle or an oval shape occurring at the beginning of the stroke, i.e., from the stroke of the beginning point and turns around to the beginning point again as shown in Fig. 8. To detect this feature, the distance between the beginning point and each coordinate point is computed as shown in Fig. 9. Then, the outcomes are graphically plotted as illustrated in Fig. 10. The lowest curve is called a "valley point". This valley point contains rich information indicated

the nearest beginning point. In this case, if the distance computed at the valley point is lower than the predefined threshold, then this curve may restrain a head. The head membership function can be defined as

$$\mu(h)=\begin{cases}1, & d\le\beta\\ 1-\left(\dfrac{d-\beta}{\beta}\right), & \beta\le d\le(\beta\times 2)\\ 0, & d>(\beta\times 2)\end{cases} \qquad (1)$$

where d is the distance between each point and b is a distance threshold.

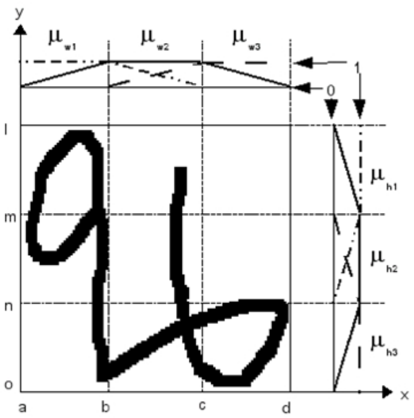


Fig. 5. Segmentation region (3x3)

Fig. 6. Thai character with 1 and 2 strokes

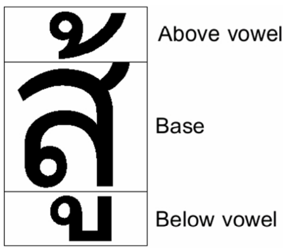


Fig. 7. Levels of Thai character

- *Loop detection*: Loop is a circle line occurring in the same line as shown in Fig. 8. To detect this feature, the crossing point is first detected by using the technique proposed in [14]. This crossing point contains rich information to indicate the loop feature. If a crossing point is found, a loop is detected by using the one used in head detection. Otherwise, it is without loop.
- *Main angle detection:* Almost Thai characters comprise of main angles as shown in Fig. 8. A number of angles relate with characteristics of each character signal. To detect this feature, each angle value is calculated; if that angle value is greater than the predefined threshold, it is identified as a main angle.
- *Head and loop directions:* Although some Thai characters are similar, they can be distinguished by head and loop directions, such as ‘ถ’ and ‘ภ’. In Fig. 12, there are four cases of head and loop directions. In this work, the directions are defined into four types: left, right, up, and down directions. To identify these directions, the position of reference point (beginning point) is compared to the center of the head or the loop. The left and right directions are determined by X-axis whereas the up and down directions are determined by Y-axis.

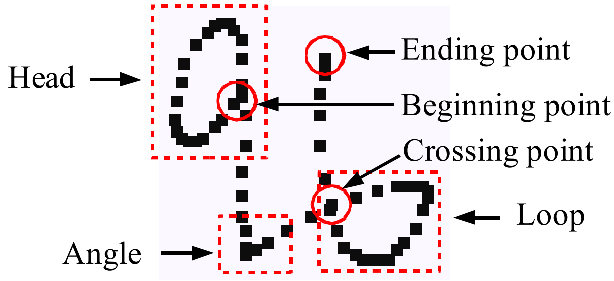


Fig. 8. Specific features of a character

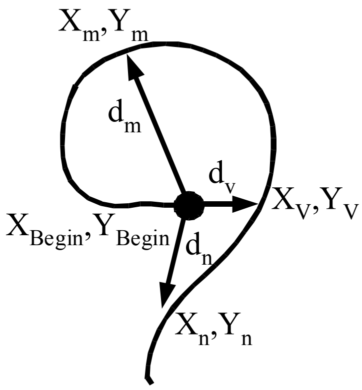


Fig. 9. Distance of beginning coordinate compared with next coordinate

2.3 Recognition

This process is a heart of handwriting recognition system. Such system is designed for collaborating with neural network and fuzzy logic. Recognition process is a three-stage procedure. Firstly, the rough classification procedure identifies the input-character signals into one of six groups defined in Tables 1 and 2. Then, the generic features are fed to the input of a neural network. If the outcomes of the neural network are greater than the predefined threshold, then the corresponding result is a final result. Otherwise, the specific features are applied to the fuzzy logic process. The details of each stage are described as follows.

2.3.1 Rough Classification

In this research, the higher accuracy of recognition system is essential. Thus, character grouping is the way to improve system’s accuracy. In this case, the Thai characters are classified their characteristics into six groups as shown in Tables 1 and 2. The simple characteristics, which are the number of strokes and writing levels, are used to identify an observed signal into one of six groups. Then, the neural network is applied to classify the characters in each group. Consequently, there are six neural network models. The next subsection describes the detail of each neural network.

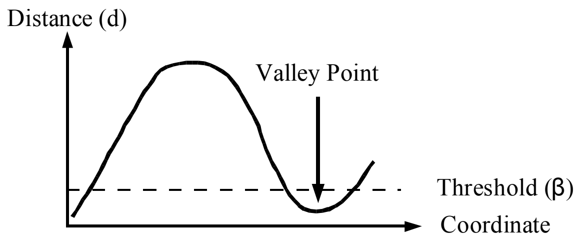


Fig. 10. Graph of distance

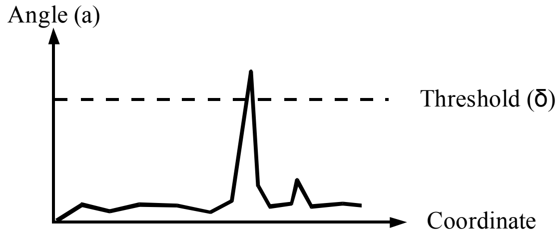


Fig. 11. Graph of angle

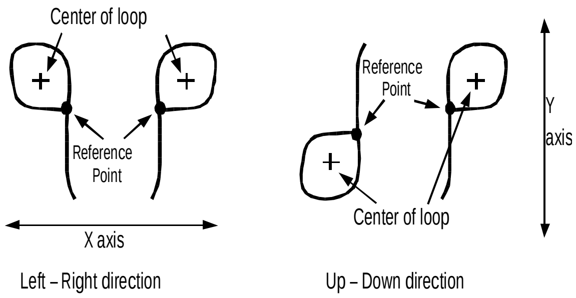


Fig. 12. Directions of head or loop

2.3.2 Neural Network Process

In this work, the feed-forward multi-layered percept is used. The three-layer standard is selected. The generic features are fed to the input layer. A number of nodes in the output layer are represented with a number of characters in each group as defined in Tables 1 and 2. A number of nodes in hidden layer can be determined by means of

$$h \approx \frac{i+o}{2} \qquad (2)$$

where i and o are a number of input and output layers, respectively. Here, the standard back propagation algorithm, the chemical SNNS toolkit [12], is applied to generate and train the neural networks.

2.3.3 Fuzzy Logic Process

For previous work [10], Thai online character recognition by fuzzy logic system relies on more than 150 rules. This leads to high computation. Therefore, In this subsection, we design the fuzzy logic system with simple fuzzy rules. These simple fuzzy rules are based on the specific features and their

Table 1. Thai characters with 1 stroke

Level	Thai Characters
Base	ก ข ฃ ค ฅ ฆ ง จ ฉ ช ซ ฌ ฎ ฏ ฑ ฒ ณ ด ต ถ ท ธ น บ ป ผ ฝ พ ฟ ภ ม ย ร ล ว ห ฬ อ ฮ ฤ ฦ า ฯ เ โ ไ ใ
Upper vowel	อั อำ อิ อี อึ อ็ อ่ อ้ อ๊ อ์
Lower vowel	อุ อู
Number	๐ ๑ ๒ ๓ ๔ ๕ ๖ ๗ ๘ ๙

Table 2. Thai characters with 2 stroke

Level	Thai Characters
Base	ญ ฐ ศ ษ ส ะ แ
Upper vowel	อื อ๋

membership functions are defined and summarized in Table 3. The summation of all membership functions in Table 3 can be defined as

$$\begin{aligned} M^c &= M^c_{head} + \ldots + M^c_{ldir} \\ N^c &= N^c_{head} + \ldots + N^c_{ldir} \end{aligned} \qquad (3)$$

where M and N are the similarity and dissimilarity, respectively. For classification, there is only one character C, which yields the maximum value M^c. Hence, the recognized character is defined as

$$i_M = \arg \underset{j \in C}{Max}\left(M^j\right) \qquad (4)$$

where C denotes a Thai character in considering group. How ever, if there are many characters having the same value of M^c, then the recognized character is defined as

$$i_N = \arg \underset{j \in C}{Min}\left(N^j\right) \qquad (5)$$

3. EXPERIMENTAL RESULTS

In order to evaluate our system, we have set up Thai character signal database from NECTEC online handwriting corpus. In this experiment, we have prepared entirely 14,220 Thai character signals (from 60 writers, each writer wrote three times for each character, 44 Thai characters, 25 Thai vowels and 10 Thai numbers) and applied to the proposed system. The significant factor of performance evaluation is system accuracy. In the first step, we determine the number of each stroke. This number is used for assigning the number of points (η) of down-sampling procedure. The suitable number can make performance of the neural network system better. To work properly and obtain a low error rate, 30 point number is the best value for using in our work as shown in Fig.13.

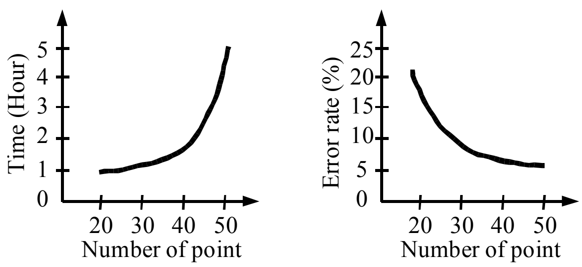
In the neural network process, Thai online character signal corpus is divided into two sets: training and testing sets. For training set, the first two written characters for each writer are used to train the system. The remaining characters are used as the testing set. Hence, there are 9,480 samples in the training set and 4,740 samples in the testing set. In the fuzzy logic process, the training and testing sets are set up the same as the neural network process. In the first experiment, we have applied only two generic features to the single hidden layer model of neural networks. The experimental results show that the accuracy is approximately 76.62% as illustrated in Table 4. In the second experiment, we have also evaluated the improved recognition system by combination of neural networks and fuzzy logic. The predefined thresholds, ρ and σ, of the membership function are set to 0.5 and 0.8, respectively. The experimental results illustrate that the system accuracy is greatly improved, approximately 86.28%, as shown in Table 4.

Table 3. Membership functions

Specific Features	Membership Functions
Head	$M^C_{head} = \begin{cases} 1, if\left(a^C_{head} > \rho\right) \wedge \left(u_{head} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{head} = \begin{cases} 1, if\left(a^C_{head} > \rho\right) \vee \left(u_{head} > \sigma\right) \\ 0, Otherwise \end{cases}$
Loop	$M^C_{loop} = \begin{cases} 1, if\left(a^C_{loop} > \rho\right) \wedge \left(u_{loop} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{loop} = \begin{cases} 1, if\left(a^C_{loop} > \rho\right) \vee \left(u_{loop} > \sigma\right) \\ 0, Otherwise \end{cases}$
Angle	$M^C_{angle} = \begin{cases} 1, if\left(a^C_{angle} > \rho\right) \wedge \left(u_{angle} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{angle} = \begin{cases} 1, if\left(a^C_{angle} > \rho\right) \vee \left(u_{angle} > \sigma\right) \\ 0, Otherwise \end{cases}$
Size ratio	$M^C_{size} = \begin{cases} 1, if\left(a^C_{size} > \rho\right) \wedge \left(u_{size} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{size} = \begin{cases} 1, if\left(a^C_{size} > \rho\right) \vee \left(u_{size} > \sigma\right) \\ 0, Otherwise \end{cases}$
Beginning position	$M^C_{bpos} = \begin{cases} 1, if\left(a^C_{bpos} > \rho\right) \wedge \left(u_{bpos} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{bpos} = \begin{cases} 1, if\left(a^C_{bpos} > \rho\right) \vee \left(u_{bpos} > \sigma\right) \\ 0, Otherwise \end{cases}$

Table 3. Membership functions (cont.)

Specific Features	Membership Functions
Ending position	$M^C_{epos} = \begin{cases} 1, if\left(a^C_{epos} > \rho\right) \wedge \left(u_{epos} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{epos} = \begin{cases} 1, if\left(a^C_{epos} > \rho\right) \vee \left(u_{epos} > \sigma\right) \\ 0, Otherwise \end{cases}$
Head position	$M^C_{hpos} = \begin{cases} 1, if\left(a^C_{hpos} > \rho\right) \wedge \left(u_{hpos} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{hpos} = \begin{cases} 1, if\left(a^C_{hpos} > \rho\right) \vee \left(u_{hpos} > \sigma\right) \\ 0, Otherwise \end{cases}$
Loop position	$M^C_{lpos} = \begin{cases} 1, if\left(a^C_{lpos} > \rho\right) \wedge \left(u_{lpos} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{lpos} = \begin{cases} 1, if\left(a^C_{lpos} > \rho\right) \vee \left(u_{lpos} > \sigma\right) \\ 0, Otherwise \end{cases}$
Angle position	$M^C_{apos} = \begin{cases} 1, if\left(a^C_{apos} > \rho\right) \wedge \left(u_{apos} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{apos} = \begin{cases} 1, if\left(a^C_{apos} > \rho\right) \vee \left(u_{apos} > \sigma\right) \\ 0, Otherwise \end{cases}$
Head direction	$M^C_{hdir} = \begin{cases} 1, if\left(a^C_{hdir} > \rho\right) \wedge \left(u_{hdir} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{hdir} = \begin{cases} 1, if\left(a^C_{hdir} > \rho\right) \vee \left(u_{hdir} > \sigma\right) \\ 0, Otherwise \end{cases}$
Loop direction	$M^C_{ldir} = \begin{cases} 1, if\left(a^C_{ldir} > \rho\right) \wedge \left(u_{ldir} > \sigma\right) \\ 0, Otherwise \end{cases}$ $N^C_{ldir} = \begin{cases} 1, if\left(a^C_{ldir} > \rho\right) \vee \left(u_{ldir} > \sigma\right) \\ 0, Otherwise \end{cases}$



(a) Training time (b) Error rate

Fig. 13. Comparison of training time and error rate with the number of points in training process

Table 4. Accuracy of each character group

Groups	Total signals	Accuracy (%)	
		NN	Improved NN
1	8,640	73.29	82.55
2	1,260	82.18	91.98
3	1,800	82.56	92.67
4	360	91.22	97.22
5	360	90.87	96.94
6	1,800	76.98	89.50
Total	14,220	76.62	86.28

4. CONCLUSION

In this paper, we have proposed the Thai online recognition system using the combination of a neural network and fuzzy logic. In this method, we consider two types of features: generic and specific features. The former, i.e., the generic features, is classified by means of the neural network. The latter, i.e., the specific features, is used by fuzzy logic when the output of the neural network is unreliable, less than a predefined threshold. In this way, the experimental results show that the proposed method can perform accurately up to 86.28%. However, although the objective has been reached, some limitations have still remained. For example, the actual system only works for one or two stroke signals.

For the future works, the system should be improved the accuracy by using new features, reducing the model's size, and others.

5. ACKNOWLEDGEMENT

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