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Optical Character Recognition (OCR) enhancement using an approximate string matching technique

Kraisak Kesorn* and Phornsiri Phawapoothayanchai

Department of Computer Science and Information Technology, Faculty of Science, Naresuan University, Phitsanulok 65000, Thailand

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Abstract

Many researchers have focused on improving optical character recognition (OCR) efficiency by developing new techniques using image processing based methodologies. However, the major limitations of image processing techniques are their complexity and computational intensity. Thus, they are not applicable to some real-time application. The main highlight of this paper is that we present a new method for enhancing OCR using a simple approximate string matching technique to complement existing OCR algorithms. The experimental results revealed that the proposed methods can enhance the performance of OCR algorithms measured by precision. The accuracy of Thai word recognition was increased by up to 85.72% compared to use of traditional OCR techniques.

Keywords: OCR, Character recognition, Thai language, Approximate string matching

1. Introduction

Optical character recognition (OCR) is an interesting research topic in the fields of artificial intelligence and image processing [1]. The major process of OCR is the analysis of an image that consists of several characters and converting them into text. OCR can help save time in some tasks e.g., data entry [2]. However, if this process is ineffective or unreliable, it will result in poor recognition performance. Several researchers have tried to improve OCR techniques for various languages. The most advanced and high performance OCR is in the English language and several software packages are available in the market at present [3]. OmniPage [4] is an example software that has a high recognition power, up to 99%. However, performance for Thai character recognition is still far below that for English. As such, this motivates us to improve the OCR techniques for the Thai language. This paper introduces a framework, which was developed to contribute to the Thai OCR performance using an approximate string matching (ASM) technique. The novelty of this research is that ASM can enhance image processing power, which makes the Thai OCR more reliable. The remainder of this paper is organized as follows. Section II surveys the existing state-of-the-art frameworks related to the proposed method. Section III presents our proposed technique to enhance Thai OCR. Section IV shows our experimental results and discussion. Finally, Section V concludes discussing the novelty and limitations of the work, and suggested directions of further study.

2. Literature review

OCR has been an active research area in computer science more than 70 years [5]. In Thailand, OCR software was first available in the market in 1996 and it is still under development.

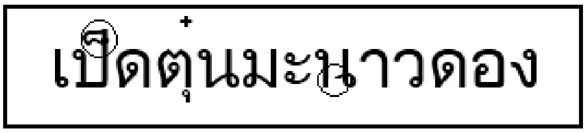

Figure 1 Typically errors of Thai language OCR

The Thai language is more difficult to recognize than English because it contains many intonation marks and vowels. Many errors in Thai OCR are caused by the absence of spaces between words and incompleteness of the letters as illustrated in Figure 1. This leads to the lower recognition power of Thai OCR. Therefore, Thai researchers have put a huge effort in developing and improving Thai OCR techniques to facilitate character recognition through application of various techniques. Borji and Hamidi [6] presented a method to exploit a support vector machine (SVM) to improve Persian language recognition. Ramanathan et al. [7] applied a SVM to English OCR incorporating a Gabor Filter. However, this method had some limitations, e.g., only an image size of 1024x768 could be processed. Neural networks (NN) have been used for Thai

*Corresponding author. Tel.: +66 5596 3263
Email address: kraisakk@nu.ac.th
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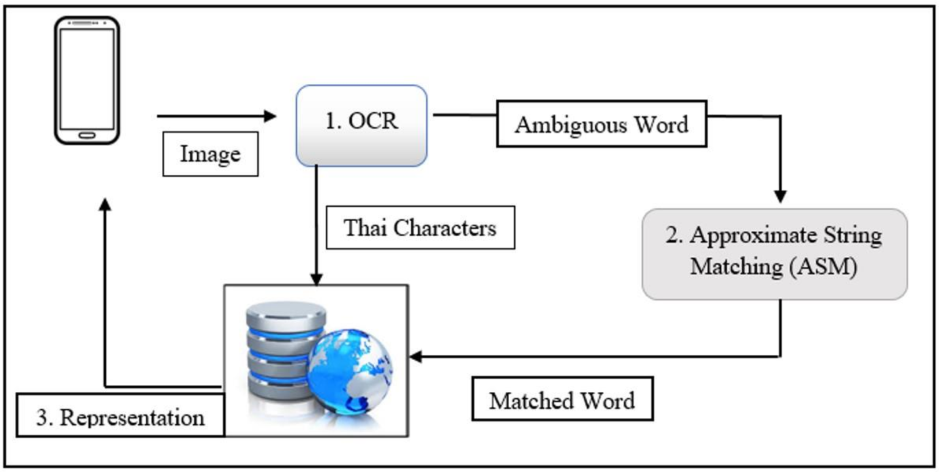

Figure 2 Overview of the proposed framework

OCR as proposed by Leelasantitham and Kiattisin [8]. All characters and numbers were resize to 40x80 pixels and used a three-layer back propagation neural network to process the letters. The results shown that an accuracy of up to 97% was archived. While a single technique was exploited for OCR, many researchers hybridized various methods to improve OCR performance. For example, Leesom and Surinta [9] proposed a method for Thai OCR based on histograms and character differences. They found that a histogram based technique obtained the best recognition performance of up to 97.11%. Sangkathum [10] proposed to a method for printed Thai character recognition using topological properties. The nearest neighbor value was used as a classifier for printed Thai character recognition and obtained a 96.96% accuracy. The main limitation of this research is it can process images of only 600 dpi with the character sizes 16, 18, 20, and 22 point.

Low image resolution is an important limitation for computer vision and especially OCR systems. Dong et al. [11] presented a technique for facilitating OCR using a Super-Resolution Convolutional Neural Network (SRCNN) for text image super-resolution. The result of this method boosted the baseline OCR performance by 16.55%. Similarly, Ugale and Joshi [12] proposed a technique to improve OCR performance using an image resolution expansion technique. Their results shown that images with 300 dpi resolution or higher realized greater recognition than lower resolutions e.g., 150 dpi. The major limitation of this work is it was tested on printed text images. No handwritten images were evaluated. Therefore, it is questionable that 300 dpi will be adequate for handwritten image recognition.

Handwritten character recognition is a very difficult task since writing styles and pen movements of users vary [13]. Kumar et al. [14] and Gupta et al. [15] proposed novel methods for recognition of handwriting. Their methods worked based on a neural network technique in an Indian language. The proposed method involved segmentation of a handwritten word using heuristics and artificial intelligence. The experimental results were found to be satisfactory.

Recently, several researchers developed an application on mobile devices for OCR. Fragoso and Kleban [16] presented an application called “Singleclick Augmented Reality Translator” to translate vocabulary into local languages using a Google Translation API. Martinez [17] applied numeric recognition on android devices using Template and achieved a 97.30% accuracy. Indonesian-English translation application based on OCR was developed by Abdurrahman [18]. However, the translation performance obtained was only 70% precision. Several factors affect the translation performance, such as the recognition algorithm used and the quality of the mobile camera. While many researchers have focused on improving the quality of OCR algorithms, the current research pays attention to enhancement of an existing OCR algorithm for the Thai language by incorporating a technique to the post-processing step of OCR. We hypothesize that this post-processing step can increase the accuracy of recognition and this is the main objective of this research. A more detailed presentation of the framework is described in the next section.

3. Proposed framework

This research presents a framework to enhance Thai OCR performance for language translation tasks using approximate string matching (ASM), which is applied in the post processing step after image processing. A mobile device (Android-based) was used as a camera to capture words of interest which were later converted into text and translated into English. This application aimed at assisting foreign tourists to communicate with local people. The framework was comprised of three levels: 1) character recognition, 2) approximate string matching and 3) data representation. Figure 2 shows an overview of this framework.

The framework begins by taking a photo using a mobile device to capture a text string that a user wants to translate. An OCR algorithm was applied to the captured image and converted the image into Thai characters. This is called the character recognition step. Then, the system combined those characters into a word and matched it to a word in a lexicon. In some cases, there were errors in the character recognition step resulting from several problems, e.g., character recognition errors caused by incompleteness of the letter or low quality of the mobile camera. If errors occur, the system will deploy ASM to handle the errors. ASM will select the closest word from the lexicon based on a similarity computation. Further details of ASM techniques will be given below. Finally, the result of the recognition process is presented to a user via a mobile device.

3.1 Approximate string matching

ASM is used to resolve uncertainty problems when an OCR technique cannot match the captured string with a word in the lexicon due to a close similarity score. In other words, ASM is exploited when there are more than one word from lexicon matching the word from OCR. ASM works based on edit operations and cosine similarity [19], where the outcome is neatly bounded in the range [0, 1]. Cosine similarity is commonly used in several research fields, e.g., information retrieval and text mining, to measure the similarity between two vectors (or two string in a vector space) based on the cosine of the angle between them. Letting $\{P\}_{i=1}^{N}$ be the set of all words in the lexicon, the similarity between the extracted word (ϖ) and the word (ρ) in the lexicon is measured using the inner product as shown in Eq. (1):

$$sim(\varpi,\rho) = \frac{\vec{\varpi}\cdot\vec{\rho}}{\|\vec{\varpi}\|\|\vec{\rho}\|} = \frac{\sum_{i=1}^{n}\varpi_i \times \rho_i}{\sqrt{\sum_{i=1}^{n}\varpi_i^2 \times \sum_{i=1}^{n}\rho_i^2}} \tag{1}$$

ASM is a technique of finding strings that approximately match a pattern (rather than exactly). It is considered a fuzzy technique for matching problems, in which n-character differences are allowed in the match, i.e., a character can be in ϖ but not in ρ, or a symbol in ρ but not in ϖ. Furthermore, characters in ϖ and ρ can differ in certain positions, but the number of differences should less than n. The edit distance measure compared strings using simple edit operations, e.g., insert (ins), delete (del), and substring (subs).

The edit operations are usually written as $a \to b$, which is a pair $(a,b) \neq (\varepsilon,\varepsilon)$ of strings where $|a| \leq 1$ and $|b| \leq 1$. In this approach, ε represents the zero-length empty symbol. The edit operation $a \to b$ is applied to an input string I to get an output string J. We can state that the input string I is transformed into the output string J through the edit operation $a \to b$. Typically, there are three types of edit operations:

1) ins – insert a symbol (a), $(\varepsilon \longrightarrow a)$
2) del – delete a symbol (a), $(a \longrightarrow \varepsilon)$
3) subs – substitute one symbol (a) for another symbol (b), $(a \to b)$

For any edit operation $(x \to y)$, we can allocate a cost $c(x \to y)$. We can easily determine the cost using a weighting function. The total cost for edit operations can be computed as Eq. (2).

$$\text{Total cost} = \sum_{i=1}^{n} c(e_i) \quad e_i \in \{ins, del, subs\} \tag{2}$$

For any given string in the terms ϖ and ρ, more than one transformation of strings may occur. The edit distance (ED) for the strings P$(p_1, p_2, p_3, \ldots, p_n)$ and Q$(q_1, q_2, q_3, \ldots, q_n)$ is defined by the minimum cost of the edit operations of that string (Eq. 3).

$$ED_{i,j} = \min \begin{cases} ED_{i-1,j} + \beta_{del}(p_i), \\ ED_{i-1,j-1} + \beta_{subs}(p_i, q_j), \\ ED_{i,j-1} + \beta_{ins}(q_j), \end{cases} \tag{3}$$

Algorithm 1: Thai OCR incorporating an ASM technique

Input : ϖ
Output: Thai word retrieved from a dataset
10: Capture term (ϖ), Initialized parameters ($\mu, \alpha, \delta, \theta$) = 0;
20: μ = Ocrapiservice (ϖ)
30: Retrieve terms, t_i, from lexicon where $i=1,2,3,\ldots,n$ and $t \in T$
40: IF $\mu \neq$ NULL **THEN**
50: FOR EACH t_i
60: α = sim (μ, t_i) //Compute similarity between μ and t_i using Eq. (1)
70: IF $\alpha > \emptyset$ **THEN**
80: $\theta = \alpha$ //Find maximum value of similarity
90: END IF
100: END FOR
110: ELSE
120: FOR EACH t_i
130: // Apply ASM technique to μ by computing Eq. (2), and (3)
140: δ= ASM (μ, t_i)
150: IF $\delta < \emptyset$ **THEN**
160: $\theta = \delta$ //Find minimum cost of edit operations
170: END IF
180: END FOR
190: END IF
200: Return θ

Algorithm 1 shows the major steps of our method. Let $T = \{t_1, t_2, t_3, \ldots, t_n\}$ be a set of terms in the dataset and ϖ is a word captured by a camera and processed using OCR. If the Ocrapiservice can process a captured term (ϖ) without error, the system will retrieve terms from lexicon and compute similarity between a query term and terms from lexicon. The highest similarity term will be presented to a user. However, if an error occurs during processing the captured term, an ASM technique will be exploited to find the most suitable term measured by the minimum cost of edit operations using Eqs. (2) and (3).

3.2 Experimental design and setting

The system was implemented to work on an Android operating system. At this stage of implementation, we focused only Thai food terms collected from various sources, e.g., www.importfood.com, www.kcal.memo8.com, and www.knorr.co.th. We deployed seven OCR techniques including those of Ramanathan et al. [7], Leelasantitham and Kiattisin [8], Leesom and Surinta [9], Sangkathum [10], i2ocr [20], Newocr [21], and Ocrapiservice [22]. These techniques were integrated with an ASM to study performance improvement. AngsanaUPC is a popular Thai font and it was used in all experiments of our research. The back camera of a mobile device with 8M pixels was used to capture images of Thai words. Figure 3 (a-b) illustrates examples and results of our system. As shown in Figure 3 (a), the original term is spelled incorrectly, but our system recommended the correct word to the user due to its high similarity score resulting in a correct recommendation. Figure 3 (b) demonstrates the result of translation from Thai, “กล้วยบวชชี”, to English “Banana in coconut milk”.

(a) (b)

Figure 3 Demonstration of Thai OCR incorporating an ASM technique

Table 1 Comparison of various OCR tools incorporating ASM

Tools	Original recognition performance (%)	Recognition performance of OCR+ ASM (%)	Improvement (%)
Ramanathan et al. [7]	55.47	71.12	15.65
Leelasantitham and Kiattisin [8]	65.42	82.57	17.15
Leesom and Surinta [9]	54.27	72.57	18.3
Sangkathum [10]	64.58	83.24	18.66
i2ocr [20]	52.29	68.13	15.84
Newocr [21]	50.26	64.79	14.53
Ocrapiservice [22]	***66.55***	***85.72***	***19.17***

4. Results and discussion

To verify the effectiveness of the developed system, we conducted experiments using about 500 different images of Thai words taken by cameras of mobile devices. The experiments considered several aspects that could affect the performance of the OCR algorithm. First, we examined the quality of digital cameras of mobile phones and the performance of OCR. The following evaluation metric was used to evaluate the effectiveness of OCR and justify theoretical and practical development of the developed system. Precision (Eq. 4) is the fraction of the correct words presented to the system considering the total number of words in the lexicon.

$$\text{Precision} = \frac{\text{correct words}}{\text{total number of words in lexicon}} \tag{4}$$

4.1 Conventional methods and comparison to the presented method

This research compares the proposed method (ASM) to conventional methods to determine how much ASM can improve the performance of those methods. Table 1 gives the results using various tools to recognize the terms in a dataset. Ocrapiservice [22] obtained the highest recognition precision, 66.55% followed by i2ocr [20] and newocr [21] at 52.29% and 50.26% respectively. Furthermore, Ocrapiservice showed the best improvement, up to 85.72% (a 19.17% increase) when it was integrated with ASM. Similar performance was seen using other methods and the improvements were more than 10%. For other techniques [7–10], their performance was lower when they were not integrated with ASM because they can only work properly on some limited image sizes and they just ignored words that they were unable to recognize. This resulted in poor performance. Experimental results indicate that ASM can improve the quality of recognition because it can effectively recognize ambiguous symbols when OCR algorithms alone cannot. Therefore, the hypothesis of this research is validated. However, the camera angle used when taking photos of words can affect the power of OCR. Therefore, the next experiment explored the effect of camera resolution and camera angle on the power of OCR. Since Ocrapiservice achieved the best recognition performance, we employed it in this framework for the remaining experiments in this study.

4.2 Camera resolution and recognition performance

We suspected that the quality of the camera used may affect the power of OCR. Therefore, the next experiment investigated an effect of camera resolution on recognition performance. The mobile phone camera resolutions examined were 3M, 5M, 8M, and 13M pixels with images of 500 words. Figure 4 indicates that a camera with 13M pixels had the highest recognition, 87%, whereas the 3M pixel camera had only 68% precision. Camera resolution and OCR performance were significantly correlated. A higher camera resolution yielded better precision. This is because higher

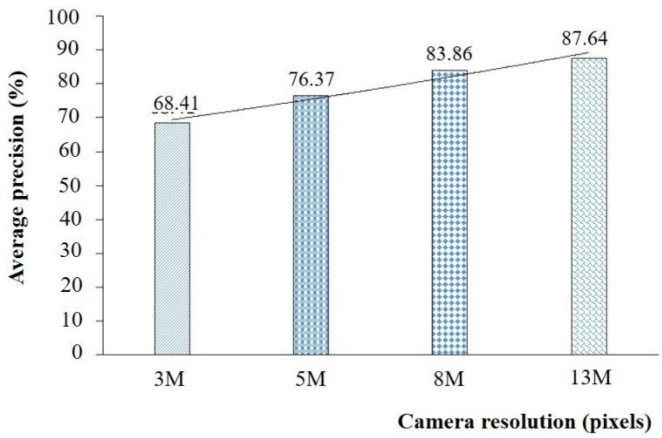

Figure 4 Precision comparison between various digital camera resolutions.

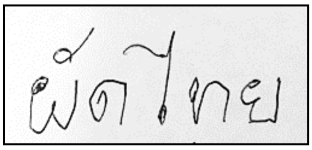

Figure 5 An example of handwritten symbols used in the experiment.

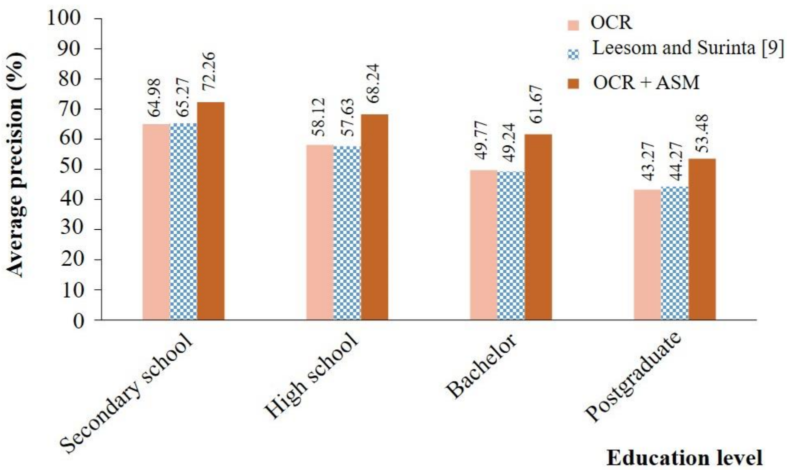

Figure 6 Average precision of OCR (Ocrapiservice), Leesom [9], and OCR+ASM techniques regarding different levels of education background

resolution cameras provide clearer and sharper images leading to higher OCR performance.

4.3 Handwriting recognition evaluation

Previous experiments were conducted using printed text. We further investigated the performance of our method to recognize handwritten images, which are more challenging to OCR systems. We randomly invited people of different ages and educational backgrounds to write some words. This is because we hypothesize that people of various ages and educational background have different handwritten qualities. Finally, 100 people were recruited (54% female and 46% male) to produced 100 handwritten words. Figure 5 shows an example of handwritten of "ผัดไทย" written by a primary school student. Our method was compared to traditional OCR systems such as Ocrapiservice, and, Leesom and Surinta [9]. One particular OCR framework was especially designed for handwriting recognition [9]. Figure 6 shows that OCR (Ocrapiservice) and [9] had similar performance when applied to handwriting recognition. This is because both methods focus on improved image processing methods to recognize Thai characters. Unfortunately, some uncertainties occur such as errors from an image processing technique, incompleteness of some characters, or ambiguity of various words. However, our method (OCR+ASM) obtained higher recognition performance than OCR or [9] because we did not ignore unrecognized or ambiguous words when using an image processing technique. Unrecognized words were further processed using ASM and matched to the word with the highest similarity score. This significantly increased recognition performance. Figure 6 depicts the average recognition precision of an OCR+ASM technique against conventional OCR and Leesom and Surinta [9] examining educational level. These results revealed

Figure 7 Digital angle ruler

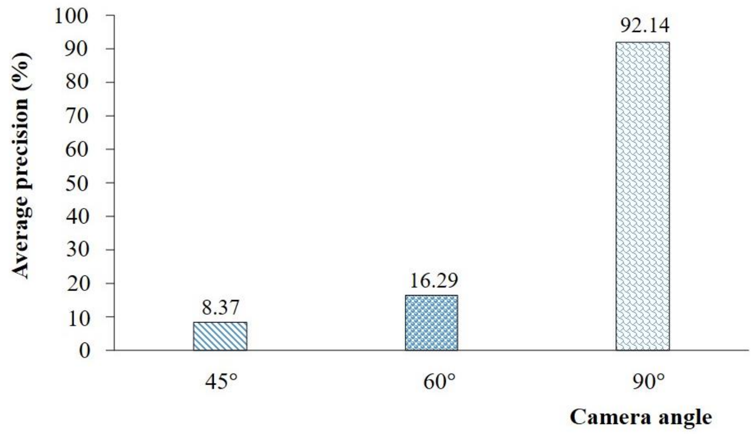

Figure 8 OCR+ASM performance regarding the different camera angels

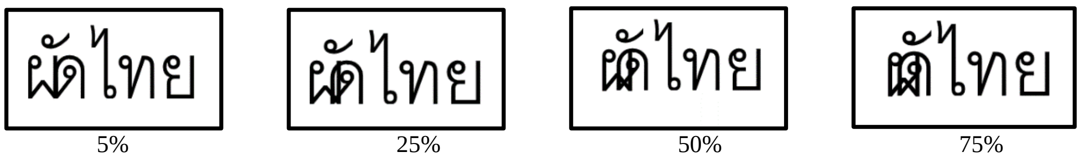

Figure 9 Example of overlapping between characters in a word

that OCR+ASM can recognize handwritten characters of secondary school students more effectively with 72.26% precision, whereas the handwriting of postgraduate students is the most difficult to recognize showing a precision of only 53.48%. Generally, people with higher education have poorer handwriting. If we compare this result with those in Table 1, it can be seen that handwriting is more difficult to recognize since the OCR recognition performance for this is lower than for printed characters.

4.4 Camera angles and OCR performance

This experiment aimed to evaluate OCR+ASM performance as a function of camera angle. We used a mobile phone to take photos of words at three different camera angles, 45°, 60°, and 90°. To obtain accurate camera angles, a digital angle ruler (Figure 7) was used. Figure 8 demonstrates how camera angle affects the performance of OCR+ASM. The highest precision, 92.14%, was achieved by using a 90° of camera angle which was significantly different from 60° and 45°, where 16.29% and 8.37% precision were respectively achieved. This is because an image of word taken from a 90° camera angle results in a clearer image than other angles yielding greater recognition. In contrast, OCR+ASM cannot separate the characters of a word when some of them are missing or overlap, which can occur at 45° or 60° camera angles. Therefore, we can conclude that lower camera angles result in higher levels of error.

4.5 Character overlap and OCR performance

This experiment compared the performance of OCR+ASM in word recognition with various percentages of overlap among characters in a word. Overlapping characters is an important problem because it can lower the precision of OCR. Figure 9 shows an example of overlap among characters in a word with four different overlap values, 5%, 25%, 50%, and 75%. We modified 50 words with various degrees of overlap and used them with traditional OCR (Ocrapiservice) and OCR+ASM. Figure 10 illustrates the recognition results comparing these two methods with respect to the degree of overlap between letters. From this figure, it can be seen that with more overlap of characters, lower OCR precision was obtained. This is because

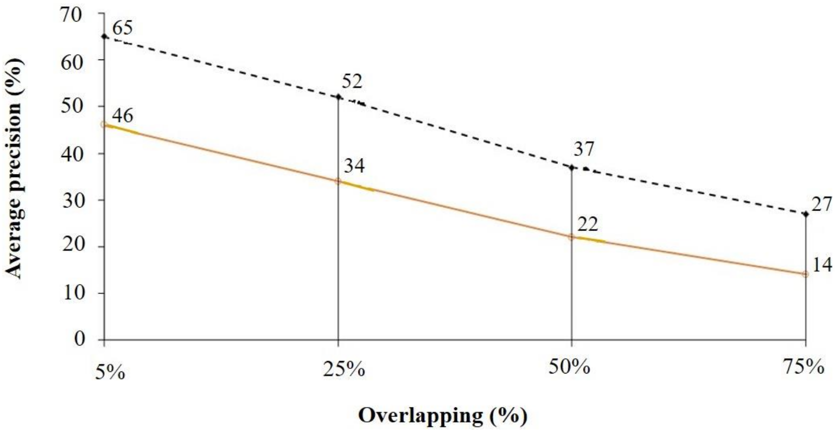

Figure 10 Recognition performance of OCR+ASM with various degrees of overlap between characters

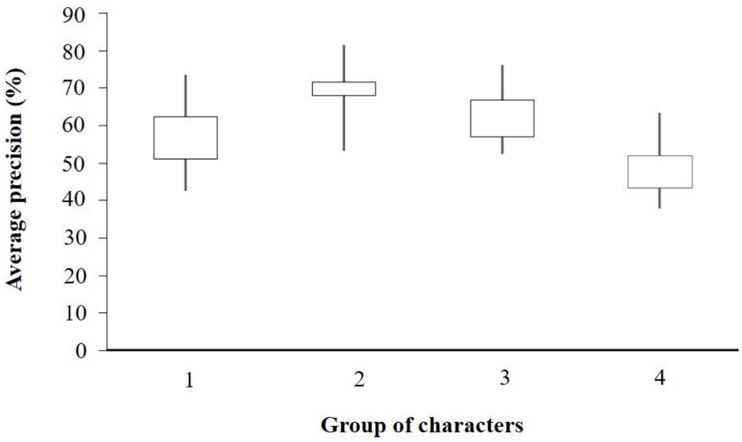

Figure 11 Average precision of OCR+ASM in recognition of similar Thai language letters

traditional OCR does not have a mechanism to assist the system when a recognition error occurs. It does not try to find any similar words that best match that the image being examined. Consequently, its precision is lower when higher degrees of character overlap are encountered. However, incorporating ASM into the traditional OCR can significantly increase the recognition power of OCR.

4.6 Recognition performance with sets of similar characters

Several Thai characters are quite similar, as is shown in Table 2. Those characters are difficult to differentiate using software and thus, lower OCR recognition is achieved. Therefore, we evaluated the quality of our technique by applying it to such characters. We separated the characters into four groups based on their physical similarity. Figure 11 shows average precision recognizing words with these characters in the same group such as “ข้าวผัดไข่” and “ข้าวผัดไซ่”. The experimental results showed that the most difficult group to recognize is group 4, with the lowest average precision, 53.48%, followed by groups 1, 3, and 2 at 62.28%, 66.79%, and 71.63% respectively. It is clearly seen that characters in the same group had slight physical differences and this can confound OCR techniques even when they are not overlapping each other. Group 2 of characters showed the highest precision. This could have resulted from their fewer physical differences than characters in other groups.

Table 2 Sets of similar characters in the Thai language.

Group	Characters			
1	ก	ถ	ภ	
2	ข	ฃ	ช	ซ
3	ด	ต	ค	ฅ
4	ล	ส		

5. Conclusions

This research proposes an enhanced technique for conventional OCR. Our contribution is novel in that we proposed to exploit an approximate string matching (ASM) technique to resolve the ambiguous problem of words when OCR cannot recognize some Thai characters. We conducted various experiments to investigate the effect of several factors on the performance of OCR. These include the effects of camera resolution, camera angle, text overlap, similarity of characters, and the ability to read handwriting. The experimental results demonstrate that our method can significantly improve the accuracy of recognition by 19.17%. This confirms that ASM can increase the power of OCR, which is consistent with the results in Table 1. The Thai language is one of the most difficult languages for OCR to read with precision because of the high similarity of some characters.

One possible direction of our future work is using more advanced image processing techniques to improve the recognition power of OCR. For example, local features of an image such as SIFT descriptors [23] can potentially be used to mitigate the effects of camera angle changes because it is invariant to scaling, translation, illumination, and rotation [19, 24].

6. Author contributions

P. Phawapoothayanchai and K. Kesorn collected data for the experiment. They also conceived, designed the experiments, and wrote the paper. P. Phawapoothayanchai implemented the OCR system. K. Kesorn was involved in discussions and analysis plans for the paper from its inception, including the idea of the data analysis. The authors declare that no competing interests exist. The funder had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

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