Object Attention Patches for Text Detection and Recognition in Scene Images using SIFT

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Abstract: Natural urban scene images contain many problems for character recognition such as luminance noise, varying font styles or cluttered backgrounds. Detecting and recognizing text in a natural scene is a difficult problem. Several techniques have been proposed to overcome these problems. These are, however, usually based on a bottom-up scheme, which provides a lot of false positives, false negatives and intensive computation. Therefore, an alternative, efficient, character-based expectancy-driven method is needed. This paper presents a modeling approach that is usable for expectancy-driven techniques based on the well-known SIFT algorithm. The produced models (Object Attention Patches) are evaluated in terms of their individual provisory character recognition performance. Subsequently, the trained patch models are used in preliminary experiments on text detection in scene images. The results show that our proposed model-based approach can be applied for a coherent SIFT-based text detection and recognition process.

1 INTRODUCTION

Optical Character Recognition (OCR) is an important application of computer vision and is widely applied for a variety of alternative purposes such as the recognition of street signs or buildings in natural scenes. To recognize a text from photographs, the characters first need to be identified, but the scene images contain many obstacles that affect the character identification performance. Visual recognition problems, such as luminance noise, varying 2D and 3D font styles or a cluttered background, cause difficulties in the OCR process as shown in Figure 1. In contrast, scanned documents usually include flat, machine-printed characters, which are in ordinary font styles, have stable lighting, and are clear against a plain background. For these reasons, the OCR of photographic scene images is still a challenge.

Many techniques to eliminate the mentioned OCR

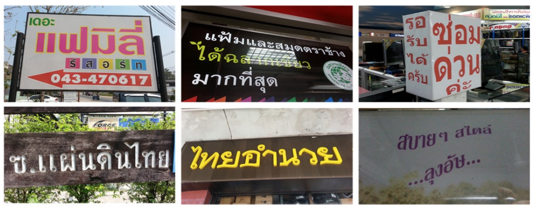

Figure 1: Sample pictures of visual recognition problems in scene images for text recognition.

obstacles in scene images have been studied. For example, detecting of and extracting objects from a variety of background colors might be partly solved by color-based component analysis (Park et al., 2007; Li et al., 2001). The difficulty of text detection in a complex background can be overcome by using the Stroke-Width Transform (Epshtein et al., 2010) and Stroke Gabor Words (Yi and Tian, 2011) techniques. In addition, contrast and luminance noise are uncontrollable factors in natural images. Several studies (Fan et al., 2001; Zhang and et al., 2009; Smolka and et al., 2002) have been conducted to conquer these problems regarding light.

However, the aforementioned methods act bottom-up and are normally based on salience (edges) or the stroke-width of the objects. In a series of pilot experiments we found that the results present a lot of false positives or non-specific detection of text (Figure 2), and the recall rates are also not very good. Hence, a more powerful method is needed.

Looking at human vision, expectancy plays a central role in detecting objects in a visual scene (Chen et al., 2004; Koo and Kim, 2013). For example, a person looking for coins on the street will make use of a different expectancy model than when looking for text in street signs. An intelligent vision system requires internal models for the object to be detected (where the object is) and for the class of objects to be

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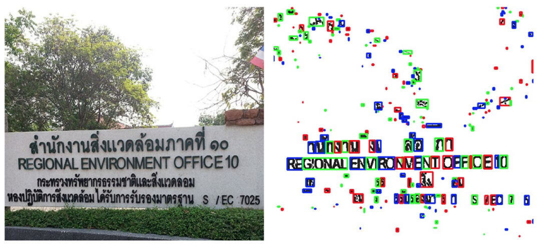
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Figure 2: Example of the Stroke-Width Transform result on Thai and English scripts.

recognized (what the object is).

A simple modeling approach would consist of a full convolution of character model shapes along an image. Such an approach is prohibitive: it would require to scan for all the characters in an alphabet, using a number of template sizes and of orientation variants. All of these processes would make the computation too expensive. Therefore, a fast invariant text detector would be attractive. It should be expectancy-driven, using a model of text, i.e., the degree of 'textuality' of a region of interest. A well-known technique for detecting an object in a scene is the Scale Invariant Feature Transform (SIFT) (Lowe, 2004). It is computationally acceptable, invariant and more advanced than a simple text-salience heuristic. Therefore, we address the question of whether SIFT is usable for both text detection and character recognition.

This paper presents the character models' construction from scene images and performance indicators for detection purposes, which can be used further to recognize a text both in English and non-English scripts. In section 2, we provide the backgrounds of the Object Attention Patch and the SIFT technique. Section 3 describe proposed algorithm in detail. Next, the performance of our model are represented, and then the applying models to character patching in a scene is demonstrated. Finally, we draw conclusions and discussions in the last section.

2 BACKGROUND

2.1 Model for Object Attention Patches for Text Detection

Text detection based on salience heuristics often focuses on the intensity, color and contrast of objects appearing in an image. The salient pixels are detected and extracted from the image background as a set of candidate regions. Saliency detection is a coarse textuality estimator at micro scale, yielding the probability for each pixel that it belongs to the salient object (Borji et al., 2012), while the information such as luminance and color space (e.g., RGB) is of limited dimensionality. In the text-detection process, the set of candidate regions is merged with its neighbors and then processed in a voting algorithm in order to eliminate non-text regions before presenting the final outputs of the text regions. Even then, there may still exist a lot of false positives and false negatives (cf. Figure 2).

We propose to increase the information used for the 'textuality' decision by using a larger region, at the meso scale, i.e., the size of characters. In this way, the expectancy of a character is modeled by attentional patches. The type of character modeling proposed here serves two purposes: detection and recognition. The requirements are that the process should be reasonably fast and able to handle variable sizes and fonts. This can be realized by exploiting the detection of small structural features, such as is done in SIFT-like methods, in combination with modeling the expected 2D layout of these key points in characters.

For each character in an alphabet, training samples are collected and computed SIFT key points. The key points are usually highly variable. In order to reduce the amount of modeling information, clustering is performed on the 128-dimensional key points (KP) SIFT descriptors, per character, yielding a code book of prototypical key points (PKP). The center of gravity (c.o.g., x, y) over all the key points for a character is computed, as well as the densities for PKPs in the character patch. This yields the expected relative (x_r, y_r) position of a PKP for this character, dubbed the point of interest (POI). The spatial relation of the PKP positions allows the expected PKPs j at relative positions and angles to be modeled, given a detected PKP i and an expected character c. Figure 3 gives a graphical description of the model. The evidence-collection process starts with the keypoint extraction, entering a scoring process for both 'textuality' and the likelihood of a character presence at the same time.

In order to evaluate this approach, we will start by considering the model as a provisory-classifier of characters. The recognition performance can be considered as a good indicator of its applicability for text detection. As a final note, the use of SIFT itself is not essential to the modeling approach. Other algorithms for detecting small structural features may also apply such as Affine SIFT (ASIFT) (Morel and Yu, 2009), SURF (Bay et al., 2008), and local binary pattern (LBP) (Ojala et al., 2002).

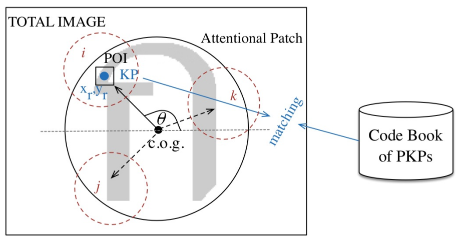


Figure 3: Schematic description of the attentional-patch modeling approach. Center of gravity (c.o.g) $\triangleq$ (0,0).

2.2 Scale Invariant Feature Transform (SIFT)

The SIFT technique is developed to solve the problem of detecting images that are different in scale, rotation, viewpoint and illumination. The principle of SIFT is that the image will be transformed to scale-invariant coordinates relative to local features (Lowe, 2004). In order to obtain the SIFT features, it starts with finding scale spaces of the original image, the Difference-of-Gaussian (Burt and Adelson, 1983) function is computed to find interesting keypoints, scales and orientation invariances. Next specifying the location where the exact keypoint is, an interesting point will be compared to its neighbors that then roughly presents maxima and minima pixels in the image. These pixels can be used to generate subpixel values in order to improve the quality of the keypoint localization using the Taylor expansion algorithm. The improved keypoints are better in matching and stability due to this technique. However, some low-contrast keypoints located along the edge, which are considered to be poor features will be eliminated.

After receiving the keypoints, the local orientation of each key point will be assigned by collecting gradient directions and then computing magnitude and orientation of the pixels around that keypoint. The result will be put into an orientation histogram, which has 360 degrees of orientation, and then divided into 36 bins. Any bin percentage that is higher than 80% (Lowe, 2004) will be assigned to the keypoint. At the end, image descriptors are created. The descriptors are computed using the gradient magnitude and orientation around the keypoint. This calculation is executed from 16x16 pixels and grouped into 4x4 cells. Each cell will be used to form the 8-bin histogram. Finally, histogram values for all the cells will be combined into 128 descriptors and assigned as the keypoint descriptor.

An important parameter in SIFT is the distance ratio threshold. In the original paper (Lowe, 2004), an optimal value of 0.8 is proposed. However, the optimality of this threshold depends on the application. In training mode, false positive keypoints are the problem whereas in 'classification testing' mode, false negatives may be undesirable. Therefore, we will use different values for this parameter in the different processing stages.

3 PROPOSED METHODS

3.1 Datasets

Figure 4 shows the overall architecture of the approach. The process starts with preparing the dataset. Some English datasets are published and widely used in computer vision research. However, it is not certain that methods for Western script are also applicable to Asian scripts, so a dataset of Asian scripts is required. We collected a new dataset of Thai script for our study because Thailand is famous for tourism and a huge number of foreigners wish to visit. It is therefore appropriate to establish a dataset of Thai text to use in OCR research and 'app' development.

The Thai image dataset is named the Thai Scene Image dataset by the author (or TSIB in short). The TSIB images are taken by smartphone under different conditions including angle, distance and lighting conditions. Most images are captured at 1,280x720 pixels of resolution. This dataset contains more than 1,500 images in total. This number of the source images provides more than 16,000 Thai characters, which cover all the 10 Arabic numbers, 44 consonants, 15 vowels, 4 tones and 4 symbols of the Thai

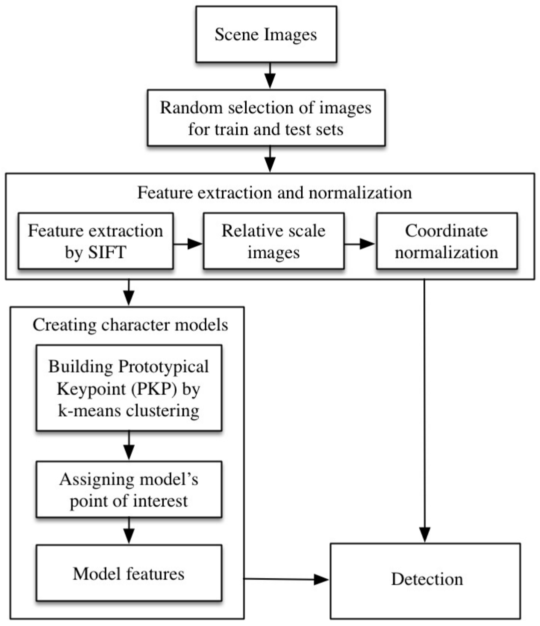

Scene Images
Random selection of images for train and test sets
Feature extraction and normalization
Feature extraction by SIFT
Relative scale images
Coordinate normalization
Creating character models
Building Prototypical Keypoint (PKP) by k-means clustering
Assigning model's point of interest
Model features
Detection

Figure 4: Character modeling architecture.

language. We took 743 images randomly to be the first version of our dataset. This preliminary dataset is composed of 25 consonants and 13 vowels (8,074 and 3,683 character image samples respectively), which often occur in Thai sentences. Some example characters of the TSIB dataset are shown in Figure 5.

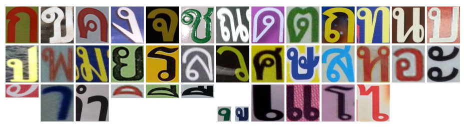


Figure 5: Example character images of the TSIB dataset.

There are other datasets employed in this paper. The Robust Reading Dataset from ICDAR2003 (Lucas and et al., 2005) and the Chars74K (de Campos et al., 2009) datasets are selected to be tested as scene images of the English scripts. They contain a total of 17,794 samples of English characters. Based on these numbers of the scene datasets, we can perform the evaluation of our proposed model by applying it to both English and an Asian language. Moreover, the Thai OCR Corpus from The National Electronics and Computer Technology Center (NECTEC)[1] that consists of 46 character classes of Thai typed letters is used. Although, these are not scene images, but they are usable in this paper for evaluating our model in an ideal situation.

3.2 Feature Extraction and Normalization

The character images are converted to grayscale in order to increase the speed and simplify the recognition process. Some character images are inverted if necessary to always have dark ink (foreground) and a light background. All the character images in each class are randomized into two sets: training and testing sets. Both of them will be processed in the feature extraction and the coordinate normalization methods. The extracted features will be used as the constituents of character models in the next step. The flow of this process is demonstrated in Figure 6.

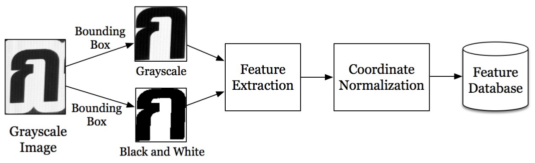


Figure 6: Process flow of feature extraction and coordinate normalization.

[1]http://www.nectec.or.th

3.2.1 Feature Extraction

Every grayscale image in the dataset is calculated for its bounding box of the character and is then cropped based on its detected box. The image is extracted features by SIFT that called keypoints (KP), which consist of the coordinate (x, y), scale, orientation and 128 keypoint descriptors, and collected into a database. In order to enlarge the number of KPs they are also extracted from a binarized (B/W) copy of the character image. After receiving all the keypoints, the original source images are no longer needed in the process. Only the keypoint vectors will be utilized.

3.2.2 Keypoint Coordinate Normalization

Since the absolute position of the character in the scene images is unknown, the local keypoints' positions needs to be in a relative scale. By the equations: $x' = \frac{x}{w}$ and $y' = \frac{y}{h}$ where w and h are character width and height, respectively. After that, the relative positions of the keypoint will be normalized to present in the same scale space as others by the equations: $x_{norm} = x' - 0.5$ and $y_{norm} = y' - 0.5$. Finally, the final keypoint vector consists of x_{norm}, y_{norm}, scale, orientation and 128 keypoint descriptors.

3.3 Creating Character Models

The number of keypoints extracted from character images in the previous section can be up to more than 10,000 keypoints for each class. With this vast number of keypoints, brute matching is undesirable. To reduce the processing time, keypoint clustering is necessary to obtain a manageable code book of the Prototypical Keypoints (PKP). This section describes the modeling procedures for characters that are performed in two parts: clustering the keypoints and assigning the character's point of interests.

3.3.1 Building Prototypical Keypoints (PKPs) using K-means Clustering

K-means clustering (Forgy, 1965) is a well-known and useful technique to partition a huge dataset into a number of k groups, i.e., clusters. The members within the cluster have similar characteristics, and the average vector known as the centroid of the cluster is a good representative of the cluster. The centroid is expected to be the Prototypical Keypoint (PKP) of each keypoint cluster.

All the keypoints of each class are clustered into several groups using the k-means algorithm in the descriptor (N_{dim} = 128). We perform using values k =

300, 500, 800, 1,000, 1,500, 2,000 and 3,000 to produce various sensitivity levels of the model and then select the centroid of each cluster to be the descriptor of the PKP. We expect that in the 2D spatial layout a distribution of the PKP's coordinates represents an important characteristic for each character class. However, defining the coordinate cannot make use of the average values of x and y since the clustering is performed in the descriptor of the keypoint. So, to determine the proper PKP's coordinate there needs to be a separate process.

Looking at a cluster of the keypoints from the previous step, the descriptor values of the keypoints are similar, but it is possible that the keypoints are located in different areas because the SIFT mechanism considers the prominent spots of an object in the picture. Some different parts of the same character may provide similar descriptor values. Therefore to find an appropriate x, y of the delegate PKP, we then perform the k-means clustering in the coordinate (x, y) within each cluster. Because of the small number of keypoints in the cluster, we use values k = 2, 3 and 4 to find the major area of the keypoints within the cluster. With k = 3, most results present an obvious major group of the cluster with lower distribution rate than other k values. Therefore, we choose k = 3 and the centroid of the major cluster is selected as the PKP's coordinate (x_{pkp}, y_{pkp}).

After that, the coordinate and the descriptor are combined to be a PKP of the model. Algorithm 1 summarizes the steps to build a PKP. By, *input*: set of raw keypoints of characters, $S_n = \{kp_{n1}, kp_{n2}, .., kp_{nm}\}$. *output*: set of PKP of characters, $F_n = \{pkp_{n1}, pkp_{n2}, .., pkp_{nk}\}$. Where m = raw keypoints in a class (1 to m); n = classes (1 to n); G = cluster of keypoints in descriptor; L = cluster of keypoints in coordinate.

Algorithm 1: Building PKP.

```
for $S_1$ to $S_n$ do
    $G_{1...k} \leftarrow classify\{S_{desc}, k-means, kgroups\}$
    for $G_1$ to $G_k$ do
        $pkp_{desc} \leftarrow getCentroid\{G_{desc}\}$
        $L_{1...3} \leftarrow classify\{G_{loc}, k-means, 3groups\}$
        $L_{max} \leftarrow selectMajorGroup\{L\}$
        $pkp_{loc} \leftarrow getCentroid\{L_{max}\}$
        $pkp = \{pkp_{loc}, pkp_{desc}\}$
    end for
    $F = \{pkp_1, pkp_2, ..., pkp_k\}$
end for
```

3.3.2 Assigning a Model's Point of Interest

Given a general code book with Prototypical Keypoints, it becomes important to associate PKPs and their relative position to character models. The assumption is that each character has points of interest (POI) that elicit keypoint detection. The POI in each character is substantial because it is an indicative feature of a character. Therefore, we need to identify the interesting points of a model.

Based on the model generated in the previous section, we scatter its keypoints on spatial layouts in order to find the distribution of the model's features. The scatter diagrams (heat maps) in Figure 7 show that the normalized PKPs (bottom row) remain almost the same important points (high density) of the character as raw KPs (top row in Figure 7). We assume that the heat area will represent spots of interest which are normally less than 10 per class according to our experimental results.

The PKP's locations (x_{pkp}, y_{pkp}) are then clustered by doing the scan for k = 5, 6, 7, 8 and 9. We found that k = 7 provides the best centroids (x_{poi}, y_{poi}), which are located in the proper area and can be considered as the POI. In order to complete the creation, every PKP of each cluster will be associated with the computed POI of the cluster. The POI assigning process is summarized in Algorithm 2. By, *input*: set of models features, $F_n = \{pkp_{n1}, pkp_{n2}, .., pkp_{nk}\}$. Where n = classes (1 to n) ; t = point of interest (1 to t); R = cluster of PKP ; P = set of POI. After computing this step, we will get a model structure elements comprising the Prototypical Keypoint (PKP) and their POIs as illustrated in Figure 8. The PKP coordinates are represented by the orange at its normalized location. The POI is marked by the yellow dot. The models are called *Object Attention Patches*.

Algorithm 2: Assigning POI to PKP.

```
for $F_1$ to $F_n$ do
    $R_{1...t} \leftarrow classify\{F_{loc}, k-means, tgroups\}$
    for $R_1$ to $R_t$ do
        $p \leftarrow getCentroid\{R\}$
    end for
    $P = \{p_1, p_2, ..., p_t\}$
    for $pkp_1$ to $pkp_k$ do
        $p \leftarrow getMemberOf\{pkp_{loc}, P\}$
        $pkp = \{pkp, p\}$
    end for
end for
$F = \{pkp_1, pkp_2, ..., pkp_k\}$
```

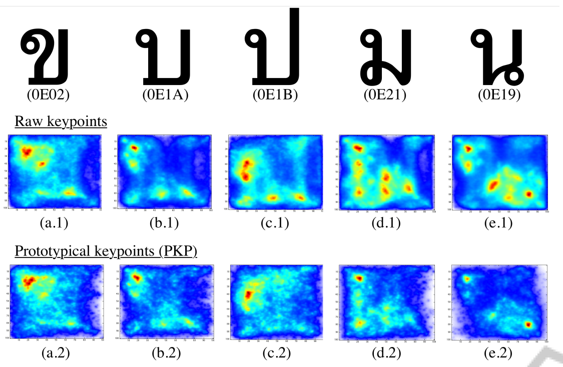


Figure 7: Samples of normalized PKP distribution of similar characters (with K << N important keypoint still retained).

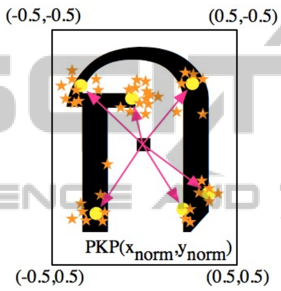


Figure 8: Object Attention Patch with SIFT keypoints in a 2D spatial layout.

4 MODEL EVALUATION

We decided to evaluate our proposed models by testing for recognition to find the accuracy rate of the model. We assume that if the model provides high accuracy in recognition, it should perform the text detection correctly. The experimaental set up as follows.

- *Number of classes*: We selected the class of character images that contains more than 100 training samples to be tested for TSIB dataset. We use 38 classes of TSIB, 52 classes of ICDAR2003 plus Chars74K divided into upper and lower case and 46 classes of Thai NECTEC datasets.
- *Number of model features*: We tested the character recognition to find the accuracy rates and confusion matrices of the model based on different amounts of the model's features: 300, 500, 800, 1,000, 1,500, 2,000 and 3,000.
- *Recognition methods*: The SIFT matching algorithm was performed as the basis to classify the testing images. However, the other modified SIFT-based methods were also performed to find the differences in the results. We then modified the SIFT matching functions by combining them with the Region of Interest (ROI), Grid regions, and the PKP's location. Algorithm 3 shows the recognition procedure that is used in this study. By, *input*: set of testing images and set of models, $Img_m = \{img_1, img_2, .., img_m\}$; $Model_n = \{model_1, model_2, .., model_n\}$. Where m = images (1 to m); n = models (1 to n); $R1$ = results of matching by descriptor; $R2$ = results of matching by location.

Algorithm 3: Recognition.

```
for $Img_1$ to $Img_m$ do
    for $Model_1$ to $Model_n$ do
        for $pkp_1$ to $pkp_r$ do
            $R1_{1...s} \leftarrow matchByDesc\{Model_{pkp}, Img_{kp}\}$
        end for
        for $R1_1$ to $R1_s$ do
            $R2_{1...t} \leftarrow matchByLoc\{Model_{pkp}, R1_{kp}\}$
        end for
    end for
    $FinalResult \leftarrow maxMatchedKp\{R2\}$
end for
```

In summary, we matched the keypoints of the testing images to the PKPs of the models based on both the descriptor and location as well as the model's POIs depending on the mentioned functions. Then, we counted the number of matched keypoints to determine the final result.

The performance evaluation starts with randomly separating source images into two groups in the proportion of 9:1 for training and testing sets. The training set goes to modeling methods and produces different numbers of the model's features: 300, 500, 800, 1,000, 1,500, 2,000 and 3,000. We do a scan matching the descriptor with the distance ratio threshold = 0.6, 0.7, 0.8, 0.92. In literature, a value of the distance ratio equal to 0.8 is suggested (Lowe, 2004) as the optimal ratio but the ratio = 0.92 provided better results in handling shape variations. The number of correctly matched characters will be calculated as a percentage, representing the classification accuracy. The accuracy rates for different datasets are plotted in Figure 9. The results show that a higher number of PKPs improves the accuracy, although at the cost of memory.

Figure 10 shows the confusion matrices for a subset of similar-shaped characters, giving an indication of the classifier performance. In Figure a, the ordinary SIFT matching classifies testing the images of classes 0E19 to 0E1A. The classification result of class 0E19, 0E21 and other classes are 2, 44, 8 and 21 respectively. The wrong classification is significantly decreased ($\chi^2 = 74.3$ and $p < 0.0000001$) when we classify them using SIFT with an attention patch (Figure b). The overall results for the attention patch approach

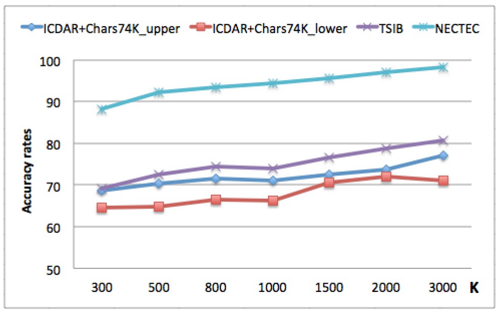
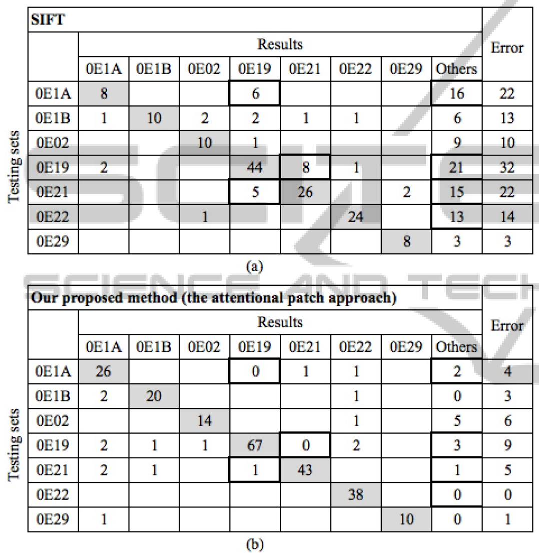


Figure 9: Character recognition results for different values of code book size k (i.e., number of PKPs).



SIFT

Testing sets	0E1A	0E1B	0E02	0E19	0E21	0E22	0E29	Others	Error
0E1A	8			6				16	22
0E1B	1	10	2	2	1	1		6	13
0E02			10	1				9	10
0E19	2			44	8	1		21	32
0E21				5	26		2	15	22
0E22			1			24		13	14
0E29							8	3	3

(a)

Our proposed method (the attentional patch approach)

Testing sets	0E1A	0E1B	0E02	0E19	0E21	0E22	0E29	Others	Error
0E1A	26			0	1	1		2	4
0E1B	2	20				1		0	3
0E02			14			1		5	6
0E19	2	1	1	67	0	2		3	9
0E21	2	1		1	43			1	5
0E22						38		0	0
0E29	1						10	0	1

(b)

Figure 10: The comparison of confusion matrices for ordinary SIFT classification (a) and our approach (b).

are given in Table 1. In summary, the performance results show our models perform acceptably in recognition with an accuracy rate of more than 70% of all the datasets. This accuracy can be increased depending on the code-book size. The similar-shaped characters is better classified substantially. For these reasons, our proposed model should be accurate enough to be used for text detection purposes.

Table 1: Classification results in percentage.

Datasets	ICDAR + Chars74K WEST upper	ICDAR + Chars74K WEST lower	TSIB Thai	NECTEC Thai (typed)
Classes	26	26	38	46
Samples	1,083	716	1,191	2,162
SIFT	41.00%	41.34%	41.68%	92.46%
SIFT+ROI	64.91%	63.55%	68.26%	97.18%
SIFTGrid	65.19%	64.07%	71.12%	97.69%
Our method	77.10%	74.93%	80.67%	98.29%

5 TEXT DETECTION USING OBJECT ATTENTION PATCHES

We have described the modeling procedure as well as the evaluation of the models in the recognition purpose. In this section, we present the preliminary results of the applying of our models to the text detection based on the assumption that our model should be able to patch a character's attentions and locate texts in the scene image. The images from the TSIB dataset are selected to be tested, and the detection method is summarized as follows.

The detection starts with the keypoints extracted from the testing image and then matched with the model's PKPs of the characters we have created. After matching, all the matched keypoints are put into the list. For each matched keypoint, we assume that the keypoint is surrounded by with some neighbors that are potentially a 'child' of the same character. The neighborhood definition is based on a minimal and maximal radius and a minimum number of KPs in that neighborhood. The number of neighbors and the radius of the area vary depending on the image size. The keypoints that are not in this criteria will be eliminated. Figure 11 gives an example of the detection results for a line of Thai text.

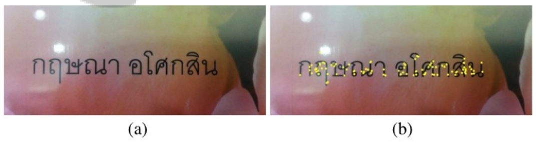


Figure 11: Extraction of characters from a background using object attention patches. (a) Original image. (b) Extraction of characters using character model attention patches.

6 DISCUSSION

We have presented a 'textuality' detector using meso-scale attentional patches in natural scene images containing text. The results are very promising for both recognition and detection. However, some issues need to be discussed.

First, creating character model must have a sufficient number of (SIFT) keypoints. If there are not enough raw keypoints from the training images, it is important to enlarge the number of keypoints. Some optional methods such as duplicating black and white or other image perturbation will be useful. Second, the number of PKPs directly affects the efficiency of detection and recognition. However, the larger the code book, the more intensive is the computation and memory consumption. The challenge is to construct reliable small codebooks based on a large representative data set of SIFT KPs. Third, there are many parameters assigned during the model creation, e.g., number of clusters, matched distance ratio threshold and number of POIs that are not absolutely determined yet. These optimal values need further experiments. Fourth, in the current modeling, the scale and orientation of KPs are ignored. It is possible that useful information is lost in this manner. Future work will address this issue.

Finally, the accuracy rates of approximately 70 - 80% are satisfactory for the character detection in scene images, but it is relatively low when compare to machine-printed paper text images at 98.29%. That may be because the PKPs are created from different images. If images quality was improved in the pre-processing, the performance would be increased. Eventually, this efficient model could improve detecting and recognizing texts more precisely in scene images.

7 CONCLUSION

This paper has presented a SIFT-based modeling of character objects for scene-text detection and recognition. The construction of models (attentional patches) from natural scenes has been described. The evaluation of character recognition and a preliminary test for text detection shows our proposed model is usable for scene-text detection and recognition purposes. For future work, an algorithm to increase text detection performance is necessary. On the basis of the current framework, there is a potential both in the improvement of the feature scheme for recognition but also for the development of, e.g., NN classifiers that use the current framework as a textuality detector.

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