Triangle Geometry Method Based Dominant Distribution Foreground for Digit Recognition

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***Abstract*— Digit recognition has been studied for four decades ago. Many approaches and techniques such as Hidden Markov Model, Neural Network, back-propagation and k-nearest neighbor have been applied to recognize the digit images. Recently, the triangle geometry method has been applied to extract features from triangle properties such as ratio, angle and gradient. However, a problem in determining points of a triangle was triggered due to the points' position in straight line. Thus, a method of extracting triangle features using triangle geometry based on the dominant of distribution foreground for digit recognition has been proposed. The dominant of distribution foreground is referred to the digit of '0' which is represented as a foreground image during the binarization process. The process to determine the triangle points are based on the dominant of distribution foreground. The classifiers of Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) are used to measure the classification accuracies for four types of digit datasets which are HODA, IFCHDB, MNIST, and BANGLA. The comparison results classification of accuracies demonstrated the effectiveness of our proposed method.**

***Index Terms*— Digit Recognition; Feature Extraction; Support Vector Machine; Triangle Geometry.**

I. Introduction

Digit recognition has long been an active topic to be discussed in classification and learning research. A lot of approaches have been proposed in pre-processing, feature extraction and classification. Some of the approaches have been hybrid to increase the classification accuracy [1]–[3]. Based on [4], many recognition applications have been proposed in recent years to achieve the higher recognition accuracy. The classifiers' performance can be used based on the quality of the features as much on the classifier itself. The characteristics can be represented by a virtuous set of features that are specific for one class and be consistent with changes within the class. The triangle features are used in this paper where the generated features will be extracted using triangle geometry based on the dominant of distribution foreground images.

Thus, this paper focuses on the feature extraction stage and classification of accuracy. In feature extraction stage, all generated triangle features were used and the grid search using libSVM method was used to obtain the best cost and gamma for digit datasets of HODA, IFCHDB, MNIST, and BANGLA. Then, the classifiers of Support Vector Machine and Multi-Layer Perceptron were used to measure the classification accuracies based on the best cost and gamma. The proposed method uses the dominant of distribution foreground to determine triangle points.

This paper is organized as follows. In Section 2, the related work is discussed. The proposed method is discussed in Section 3. Then, the results and discussions are presented in Section 4. Finally, Section 5 concludes this paper.

II. Literature Review

In the last of four decades ago, digit recognition has received significant attention from many researchers from various background field. The study in digit recognition has been explored in numerous languages such as Arabic [5]–[8], Chinese [9]–[14], Indian [15]–[17], Roman [18], [19], Hebrew [20]–[22] and much more.

A study of digit recognition in Indian handwritten has been demanding explored due to limited research. P. Singh et. al [15] proposes a script invariantly handwritten for identifying digits in five types of scripts such as Indo-Arabic, Bangla, Devanagari, Roman and Telugu. There are 130 elements of the feature set with a combination of six different types of moments have been implemented by [15] for estimating for each digit sample.

Behbahan and Mousavinasab [23] propose a method based on decision trees and neural network for Farsi digit handwriting. The numerical feature vector using structural features and some of the character have been extracted. A method used by [23] had generated 32 features based on pixels for each of digit. This had resulted in 98.18% for classification accuracy using backpropagation neural network (BPNN).

Next, Radwan [24] has proposed a hybrid model of the rough neural network to recognize Arabic/Farsi digital characters. However, the study was focused on recognizing digit handwriting that existing in different forms. The study of [24] has stated that the position of the path of a drawing tool on writing needs to be digitized in order to recognize the handwritten characters. The generated features based on centroid distance were produced.

In F. Al-Shareefi's studied [5], a method of haar wavelet-based zoning was proposed to recognize the handwritten recognition. The Wavelet space was divided into 8 zones where the mean, standard division and skewness were extracted. The result of the studied has shown an average recognition rate of 73% with fewer train images.

Unlike the study of M. M. Javidi and F. Sharifizadeh [25], a method based on a mixture of experts (MOE) was applied for recognizing Persian digit handwritten. In the feature extraction stage, the authors have been used characteristic loci method then followed with principal component analysis (PCA). This method has resulted in 81 components for a feature vector and each element vector represents the sum of background pixels which has a locus number equivalent to the elements.

Rajabi et al. [26] have employed a binary decision tree based on Neural Networks, Support Vector Machine and K-Nearest Neighbour for recognizing Persian digit handwritten. In the feature extraction stage, a zoning method [27] was applied where the 225 elements of feature vectors were produced. Then, the outer profiles and crossing count were applied where 45 features were extracted and 90 elements were formed. The total elements created were 315.

However, the method used by [25], [26] does not suitable to be applied in triangle geometry method. Azmi et. al [19] has proposed triangle features from several properties of triangle geometry. The triangle features that have been proposed were used to address the issue of recognizing images in the same category but in different types. The foreground and background colors which are in binary form were the first indicators to develop the potential triangle points. The potential triangle points were based on physical appearance of the digits.

In the study of [19], the centroid of the image was used to define the point C of the triangle based on the foreground color (black color). Then from the point C of the triangle, the image was divided into two parts which known as left (point B) and right (point A). The coordinate can be obtained based on a centroid point (point C) between image size. However, the centroid point was defined based on the shaded region. Thus, in this paper, a method of extracting features based on dominant distribution foreground is proposed. The details of the proposed method will be discussed in Section III.

III. PROPOSED METHOD

The proposed method emerges from the fact that some of the triangle properties can be used to extract features using the triangle geometry based on dominant distribution foreground images. The triangle properties involve are a ratio, angle, and gradient. In the beginning, these triangle properties have been used by [19] to generate nine features and extended them into 297 features by applying the zoning method [28]. Thus, this proposed method was applied the same features but with a different determination on triangle points. A zoning method was applied to increase the size number of triangle features. There are four types of zoning namely Cartesian plane zone, Horizontal zone, Vertical zone and 45's degree zone. These zoning methods have produced 33 triangles shape where each triangle has nine features.

A triangle shape is formed based on three points as shown in Figure 1. In [19], the triangle points were determined based on the centroid point of the image. In this paper, the centroid point of the image is defined using the method in [19] but the rest of the two points were determined based on the dominant of distribution foreground of the image. This proposed method uses the dominant or apparent foreground of binary that had been converted using Otsu' method [29]. The foreground used is '0'. As shown in Figure 4, the centroid point was determined by the centroid of the binary image. Then, the binary image was divided into four parts which named as Distribution 1, Distribution 2, Distribution 3 and Distribution 4. Based on [19], the point A as indicated on the right side while point B was indicated on the left side.

The determination point A and B were based on the dominant distribution pixels of '0'. In this paper, the determination of point A is based on the highest distribution pixels between Distribution 1 and Distribution 2. Meanwhile, the determination of point B was based on the highest distribution pixels between Distribution 3 and Distribution 4. However, the straight line might occur during triangle formation where the point A, B, and C was in line. Thus, each of the distribution parts will be divided again into four parts. This will make the distribution parts become smaller. Then, the same method for determining point A and B will be applied. Figure 1 shows the pseudo code of the proposed method while Figure 2 shows the process of the proposed method.

```
Start
1.  Input digit images dataset.
2.  Initialize three triangle points, A, B, C.
3.  Find centroid of image, C.
    3.1.  Initialize four divisions of binary images.
    3.2.  Find point A
          3.2.1. Count dominant pixel distribution for each division.
          3.2.2. Compare each of division.
          3.2.3. Find and calculate the coordinates, x and y.
    3.3.  Find point B. Repeat the step 3.2.1 – 3.2.3.
4.  Output the result.
End
```

Figure 1: Pseudo code of the proposed method

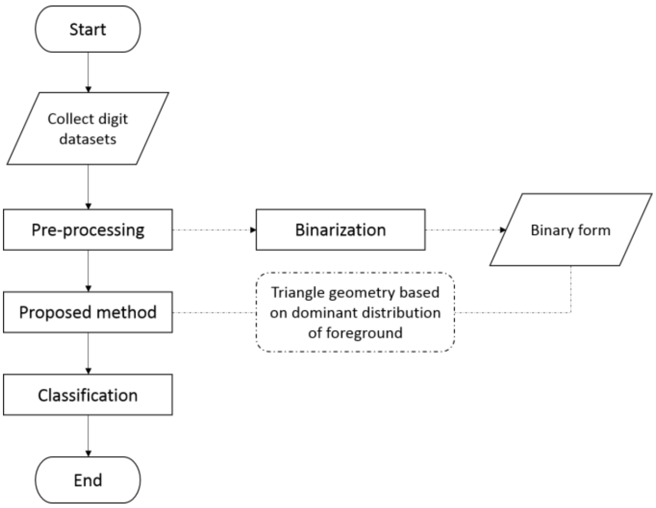

Figure 2: A process of the proposed method

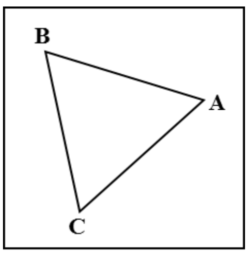

Figure 3: An example of a triangle shape

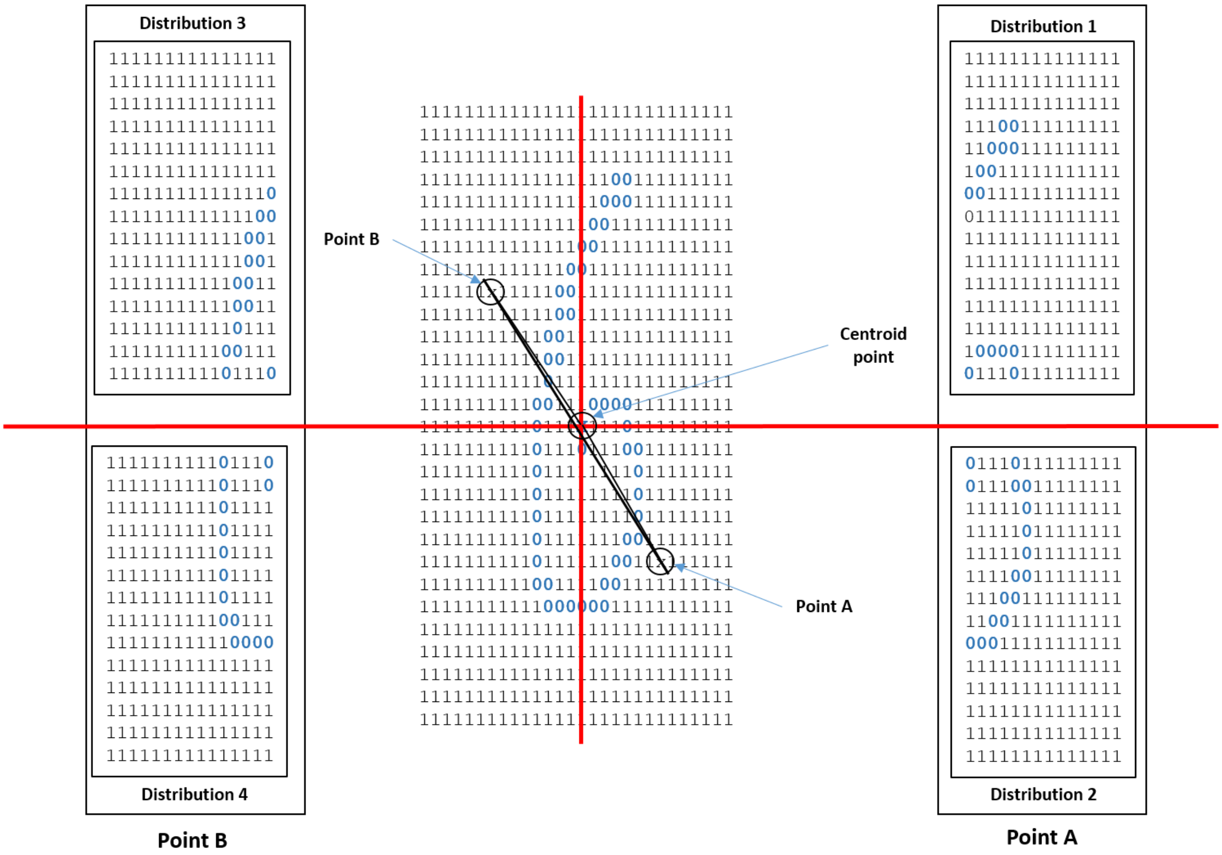

Figure 4: Proposed method based on dominant distribution foreground

IV. Result and Discussion

In the experiments, there are four types of digit datasets were used namely HODA, IFCHDB, BANGLA, and MNIST. As a brief, the datasets of Isolated Farsi/Arabic Character Database (IFCHDB) [30] and HODA [31] are known as Arabic handwritings. The BANGLA [32] dataset is one of the Indian handwritings while MNIST [33] dataset is Roman handwriting.

The IFCHDB dataset was introduced in 2006 by the Department of Electric Engineering, AmirKabir University. It contains characters and digits in Farsi/Arabic. Compare with HODA dataset, this dataset was developed in 2005 but the article about it was published two years later. HODA dataset contains Arabic handwriting.

The MNIST dataset was developed in 1992 and MNIST was named after some improvement was made [33]. For BANGLA dataset, it was developed by Pattern Recognition Unit and Vision Computer, Institute of Indian Statistic.

Each of the datasets was divided into two groups which were testing and training. Both groups of testing and training contain ten classes. For HODA dataset, the sample of the testing dataset was used is 20,000 while the training dataset is 60,000. For IFCHDB dataset, the sample of the testing dataset was used is 5,268 while the training dataset is 12,292. For BANGLA dataset, the sample of the testing dataset was used is 4,000 while the training dataset is 19,392. For the MNIST dataset, the sample of the testing dataset was used is 10,000 while the training dataset is 60,000.

The classifiers of Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) were used as a measurement for classification accuracies. However, the best value of cost and gamma for the SVM classifier are needed in achieving the highest accuracies for the datasets. Thus, the grid search method using libSVM was applied. Unlike MLP classifier, the learning rate of 0.3 was used which had been obtained using heuristic search [19]. Table 1 shows the results of the best cost and gamma for our proposed method.

Table 2 shows the comparison results of classification accuracies based on methods, classifiers, and datasets. As shown in Table 2, our proposed method had produced good results for both classifiers for datasets of IFCHDB, BANGLA, and MNIST. However, the result of classification accuracy for HODA dataset has shown not good as well as previous research for both classifiers. The accuracy result of HODA digit might possibly be influenced because of the pattern of handwritten itself. It had shown that our proposed method does not suitably apply to HODA dataset.

Table 1
Results of cost and gamma for each dataset

Dataset	Cost (c)	Gamma (γ)
IFCHDB	8.0	0.00048828125
HODA	8.0	0.0078125
BANGLA	8.0	0.001953125
MNIST	8.0	0.0078125

Table 2
Comparison results of classification accuracies (%)

Method	Classifier	IFCHDB	HODA	BANGLA	MNIST
Javidi and Sharifizadeh (2012)	MLP	-	98.160	-	-
Rajabi et al. (2012)	SVM	-	98.900	-	-
Azmi et al. (2013)	SVM	93.641	97.295	90.275	95.400
	MLP	94.856	99.695	88.775	94.060
Proposed Method	SVM	94.7229	97.365	90.950	95.440
	MLP	94.1913	96.375	89.200	93.580

V. CONCLUSION

A method of extracting features using triangle geometry based dominant distribution foreground is presented in this paper. Both techniques of SVM and MLP have been used in the experiments. The results of classification accuracies demonstrate the effectiveness of our proposed method. A successful achievement result based on classification accuracies (SVM and MLP) has indicated that the proposed method to determine the triangle points based on dominant of distribution foreground is achieved. This can be proven through the experiments done on several digit datasets. Further research is needed in increasing the performance based on training time by applying a smaller size of triangle features.

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