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Offline Handwritten Digit Recognition Using Triangle Geometry Properties

Nur Atikah Arbain[1*], Mohd Sanusi Azmi[1], Azah Kamilah Muda[1], Noor Azilah Muda[1] and Amirul Ramzani Radzid[1]

[1] Computational Intelligence and Technologies Lab,
Faculty of Information and Communication Technology,
Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya,
76100 Durian Tunggal, Melaka, Malaysia
nuratikah9.arbain@gmail.com

Abstract: **Offline digit handwritten recognition is one of the frequent studies that is being explored nowadays. Most of the digit characters have their own handwriting nature. Recognizing their patterns and types is a challenging task to do. Lately, triangle geometry nature has been adapted to identify the pattern and type of digit handwriting. However, a huge size of generated triangle features and data has caused slow performances and longer processing time. Therefore, in this paper, we proposed an improvement on triangle features by combining the ratio and gradient features respectively in order to overcome the problem. There are four types of datasets used in the experiment which are IFCHDB, HODA, MNIST and BANGLA. In this experiment, the comparison was made based on the training time for each dataset Besides, Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) techniques are used to measure the accuracies for each of datasets in this study.**

Keywords: Digit Recognition, Handwriting, Triangle Feature, Triangle Geometry.

I. Introduction

Offline handwriting recognition is handwriting that captured optically via scanner and presented handwriting as an image. In contrast, online handwriting recognition can be referred as a method which implements an automatic processing using a digitizer or any instrumented stylus that can capture any information about the pen tip, for example, the position, velocity or acceleration as a function of time [1].

Recently, research in offline digit recognition is often explored because of interest in identifying the type, pattern and origin of handwriting from various manuscripts. Most of the manuscripts have their own handwriting nature and some of them have used similar digit characters in different types of manuscript [2]. For example, the Arabic characters have been widely used in Jawi manuscripts [3]. Due to the researchers' interest in offline digit recognition, it has given the opportunity for them to explore and propose various techniques such as Hidden Markov Model (HMM), Neural Network (NN) and Triangular Block to recognize the handwriting.

However, not all techniques can be used to recognize the digit handwriting. For example, the Chinese characters contain a lot of strokes that differentiates the writers. Meanwhile, the Arabic characters consist a lot of dots and critical marks in sentences which contributed to huge challenges to the researchers. Not only that, the Roman characters are also a challenging handwriting to identify their physicality. A suitable process is needed to extract the features because slanted handwriting is hard to recognize. Thus, numerous research and experiments have been conducted to produce better accuracies in identifying the handwriting. In some cases, the techniques will be combined and modified in order to produce an appropriate approach to extract the features. This is because the combination of techniques may produce a better result of accuracy for digit handwriting. Nevertheless, not all techniques are suitable to be combined due to the certain difficulty of handwriting itself.

Over four decades ago, the studies in offline ROMAN digit recognition for characters handwriting was explored [4]. In meantime, no publicly was available for standard datasets that can be used by the researchers. However, the development in offline digit recognition was gone on a swift expansion in the last decade. The Modified NIST dataset (MNIST) was known as the largest dataset for ROMAN handwriting which was established as a result of handwritten digit classification competition that was held in summer of 1992 [5].

Besides that, HODA dataset is also known as a largest digit dataset as well as MNIST dataset. However, HODA dataset is a Farsi digit handwriting. It has contains binary images of 102,352 digits. The binary images were extracted from 12,000 registration forms where the forms were filled up by B. Sc. and senior high school students [6]. The HODA and MNIST dataset respectively are digit dataset that frequently used by many researchers in their works. The studies of digit recognition had grew speedily along with advance made on prior methods and techniques [7]–[14].

Previously, a nature of triangle geometry has been introduced to identify the digit handwriting [15]. The normalization data has been used to overcome the issue as stated in [15] where a big gap between triangle properties; such as the angle value and gradient or ratio value. The gap has affected the classification accuracies in digit recognition handwriting. The MNIST dataset has been used by [15] as a research dataset. The MNIST [5] dataset was known as a large volume of digit images and most popular among other datasets such as HODA dataset. According to [16], the number of sample for each class in this database is known as the non-uniform corresponding to real life distributions. The standard datasets of MNIST and HODA have been widely used in digit recognition handwriting and produced an impressive results of classification accuracies [17].

The study of digit recognition handwriting yields an extensive field dealing with various aspects of this difficult task. According to [16], digit handwriting recognition is a subclass of handwriting recognition problem and has become very popular in recent years. A lot of processes are required before the digit handwriting recognition can be identified such as converting handwritings to grayscale images and binary form, feature extraction and classification. At this point, the selection of feature extraction is a crucial part to obtain high digit handwriting recognition rate. The comprehensive review for recent handwriting of digit recognition is discussed in [2], [17]–[20].

This paper introduces the improvement on triangle geometry features from the previous model as in [21]. The experiments were conducted using two different machine learning techniques which are the Support Vector Machine (SVM) and the Multi-Layer Perceptron (MLP). The multi-zoning method was used in feature extraction process as similarly described in [22].

In this present paper, triangular block approach, problem and data preparation are explained in Section II. Next, the proposed method for triangle geometry features improvement is discussed in Section III. The finding from an investigation is discussed in Section IV and finally, the paper is concluded in Section V.

II. Methodology

A. Triangular Block Approach

Triangular block approach has been widely used not only in handwriting recognition but also in face recognition [23]–[25], fingerprint recognition [26]–[28], vehicle detection [29]–[31] and intrusion detection research [32], [33]. The triangle geometry has become one of a prominent method to extract features since the properties of triangle geometry can be applied. The triangle sides are clustered into three types which are equilateral, isosceles and scalene triangles, while for triangle angle there are three types of angles which are right, obtuse scalene and acute scalene triangles.

In face recognition, triangle points are acquired based on body elements such as nasal tip, eyes, nose and mouth [23]–[25]. The author of [23] has propose system for facial recognition. The facial points were defined using elastic bunch graph matching (EBGM) algorithm while Kanade-Lucas-Tomaci (KLT) was used for tracking. The geometric features were extracted from point, line and triangle composed of tracking results of facial points [23]. The architecture of the proposed facial expression recognition system used by [23] is shown in Figure 1.

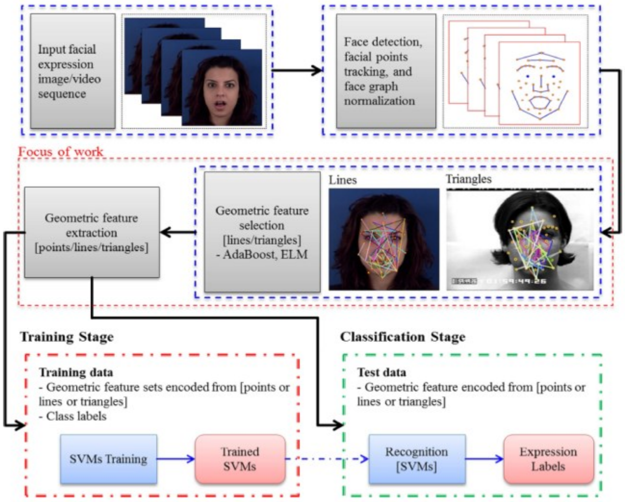


Figure 1. The architecture of proposed facial expression recognition system [23]

While fingerprint recognition, triangle points are attained based on minutiae [26]–[28]. The Delaunay triangulation is one of popular method that has been widely used in recognizing fingerprint. Based on [28], the triangulation can be referred as the maximal planar subdivision whose vertex set is P, where P denotes a finite set of points in a plane while maximal planar subdivision was defined as a subdivision where no edge connecting two vertices that can be added to the subdivision without extinguishing the planarity. The Delaunay triangulation method was used by [28] for fingerprint verification. A modification for robust minutiae based fingerprint verification was proposed by [28] where the modification was for lessen the number of comparison operations and the error rates within the matching process by performing the full analysis of Delaunay triangulation. The minutiae in [28] was represented by nodes of a coZnnected graph composed of triangles. The example fingerprint image using Delaunay triangulation is shown respectively in Figure 2 and Figure 3.

Figure 2. An example of fingerprint image 1 [28]

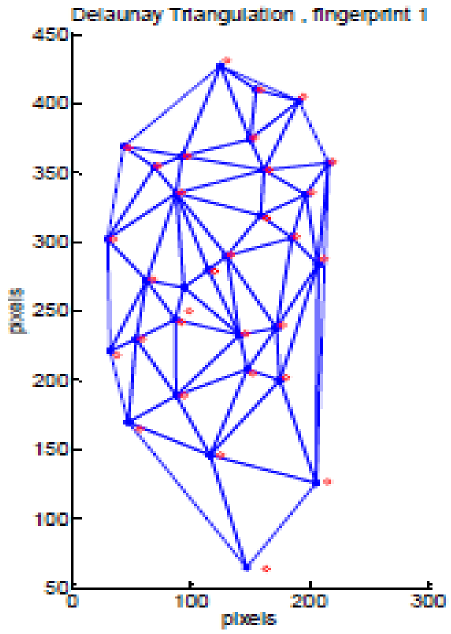


Figure 3. An example of Delaunay Triangulation image 1 [28]

The triangle geometry method also has been used in extracting features from digit images. The popular digit datasets such as HODA [6] and IFCHDB [34] have been extracted using various methods such as based on mixture of RBF experts, Field Programmable Gate Array (FPGA), decision templates method and local binary pattern [12], [35]–[37]. In [35], the RBF experts was referred as a four RBF neural network. The [35] has stated that the idea of the mixture of experts method was based on the divide and conquer principle where the complex problem was splitting into some simple problems. Thus, the final result will be the mixture of the small simple problem's solutions. Besides, the loci characterization method was applied for extracted features through 45 and 135 degree directions. Based on [35], the loci characterization feature vector for each image was determined by placing a number to each background point in the image. The example image of loci characterization feature is shown in Figure 4.

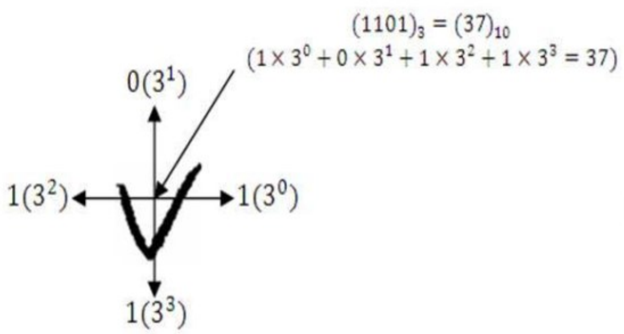


Figure 4. A loci characterization feature for digit "seven" [35]

The Field Programmable Gate Array (FPGA) is one of the feature extraction method which has been applied by [12] for offline Farsi handwritten digit recognition. The 11 features (integer) were normalized into 40×40 pixel handwritten digit images from HODA dataset. The block diagram of an FPGA is shown in Figure 5 while division horizontal and vertical section is shown in Figure 6.

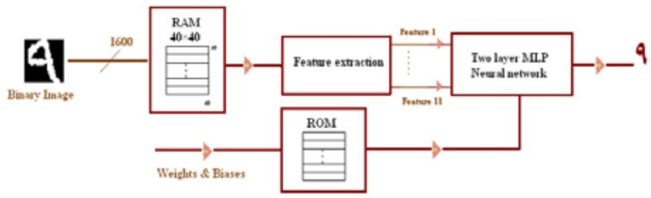


Figure 5. The block diagram of system used in [12]

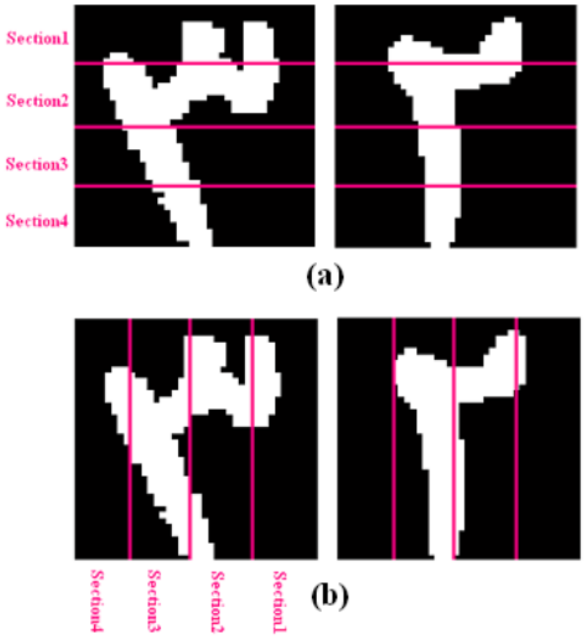


Figure 6. a) Divide into four horizontal section, b) Divide into four vertical sections [12]

Nevertheless, the ways to determine three points of triangle in face recognition and fingerprint recognition are different compare to digit recognition. The triangle geometry used in face and fingerprint cannot be applied on digit images due to the constraints in digit images. Body elements are used to determine triangle points in face recognition while minutiae are used to determine triangle points in fingerprint. The ways to determine triangle points used by face recognition and fingerprint recognition becomes constraints to the digit images because digit images do not have any body elements and minutiae. Thus, the ways to determine three points of triangle in digit recognition is using the proposed method from [21].

Based on [21], the centroid of image $\bar{x} = (\bar{x}, \bar{y})$ is used to define point C of triangle based on the foreground colour which is black. The centroid an image is given as:

$$\bar{x} = \frac{1}{|R|} . \sum_{(u,v) \in R} u \qquad \text{and} \qquad \bar{y} = \frac{1}{|R|} . \sum_{(u,v) \in R} v \quad (1)$$

The point C of triangle divides image into two parts which is left and right as shown in Figure 7.

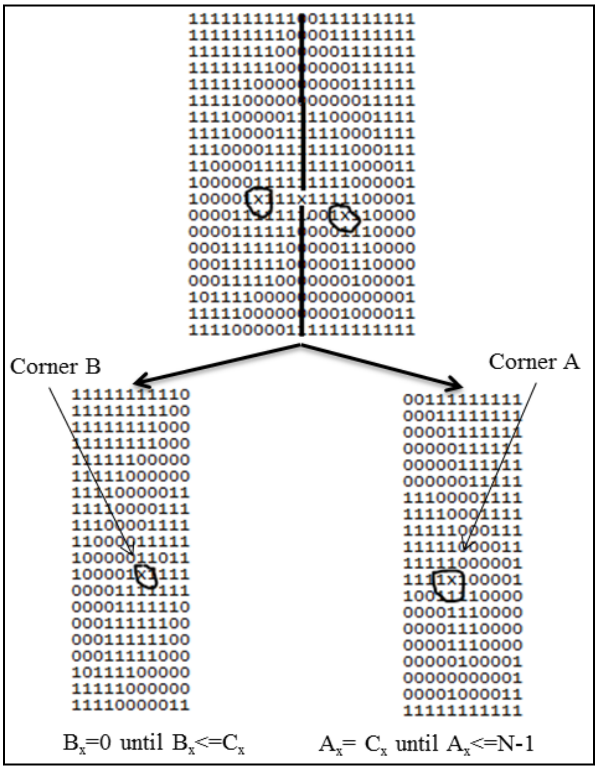


Figure 7. Segregation process of binary image (1) [21]

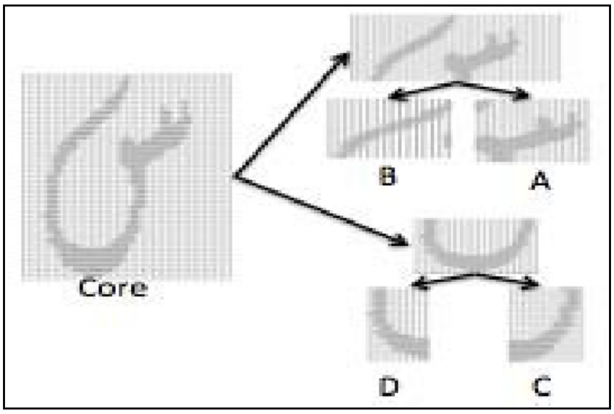


Figure 8. Segregation process of binary image (2) [21]

The study in [22] has proposed nine features for offline digit recognition. The multi-zoning method was proposed in extracting triangle features into several parts. By using the multi-zoning method, it is also used to generate number of triangle features. The triangular block was incorporated into zoning method. There are four types of zoning methods which are Cartesian plane, Vertical plane, Horizontal plane and 45 degree-based zones.

The total zones produced by zoning method are 33 zones which are also known as multi-zoning. Each of the zones will generate nine triangle features that altogether produced 297 features from total triangle features of 33 zones. The multi-zoning method has been discussed in [22]. The formula to calculate the length of a, b and c are as shown in equation (2), (3) and (4) while Figure 9 is an illustration of a triangle shape. Table 1 shows the description of triangle shape in Figure 9 while Table 2 shows the triangle features description with formula.

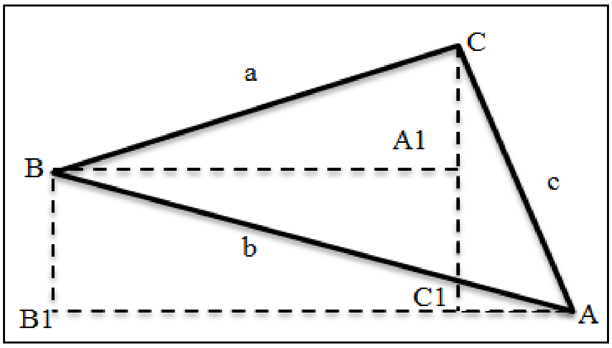


Figure 9. An illustration of triangle shape [15]

Table 1. Description of triangle shape

Corner	Position	Side Connected	Angle
A	Right	b and c	A
B	Left	a and b	B
C	Middle	a and c	C

$$a = \sqrt{((A1(y) - C(y))^2) + ((A1(x) - B1(x))^2)} \quad (2)$$

$$b = \sqrt{((B1(y) - B(y))^2) + ((A(x) - B1(x))^2)} \quad (3)$$

$$c = \sqrt{((C1(y) - C(y))^2) + ((A(x) - C1(x))^2)} \quad (4)$$

Table 2. Description formula of triangle features [15]

No	Feature	Formula
1	c:a	c:a = c/a
2	a:b	a:b = a/b
3	b:c	b:c = b/c
4	A	$A = \arccos\frac{b^2+c^2-a^2}{2bc}$
5	B	$B = \arccos\frac{a^2+c^2-b^2}{2ac}$
6	C	$C = \arccos\frac{a^2+b^2-c^2}{2ab}$
7	ΔBA	$\Delta BA = \frac{B(y)-C(y)}{B(x)-C(x)}$
8	ΔBC	$\Delta BC = \frac{B(y)-A(y)}{B(x)-A(x)}$
9	ΔCA	$\Delta CA = \frac{B(y)-C(y)}{B(x)-C(x)}$

B. Problem in Processing Data

According to [10], accuracy and speed performance are the essential parts that contributed to the whole performance of digit recognition. In pattern classification and machine learning groups, the problem of handwriting for digit recognition is a good method to test the classification performance [38]. The performance speed is influenced by the large volume of data and the number of features.

A good technique for feature extraction plays important role in data processing. Good feature extraction technique used will contribute to a smooth and faster data processing even though there is a numerous number of data.

In this paper, the discussed problem was based on research in [21]. The total features produced are 297 features while a total number of data for each dataset was more than 5000 data. In data processing, a large volume of data will take longer time for data extraction. This affected the performance during data processing.

Thus, this study proposed the ideas of combining the ratio and gradient features used in [21] in order to reduce the total features and improve the performance during data processing.

C. Dataset Preparation

Four types of digit datasets are used in this study which are Isolated Farsi/Arabic Character Database (IFCHDB) [34], HODA [6], MNIST [5] and BANGLA [39].

The IFCHDB and HODA datasets are Arabic handwritings. The MNIST dataset is one of the digit handwritings in Roman while BANGLA dataset is one of the digit handwritings in Indian language. Some datasets such as HODA and MNIST can be downloaded freely from provided website. However, IFCHDB and BANGLA datasets require the agreement form to be filled in before requesting the samples data. After completing the agreement form, samples data will be sent via email. For HODA dataset, the samples data can be downloaded from http://FarsiOCR.ir. For MNIST dataset, it can be downloaded from http://yann.lecun.com/exdb/mnist/.

In this paper, each of the datasets is divided into two sets which are the testing and the training data. Both testing and training data contain 10 classes. These datasets have broad characteristics and are employed as a benchmark for improvement purposes.

The purpose of selecting these datasets was to confirm the proposed algorithm with the characters which are not originated from Arabic handwriting. That is why the MNIST and BANGLA datasets are used in this experiment. Besides, these datasets were chosen because, in this present study, the result of accuracy and training time will be compared with the previous investigation that has employed the same datasets.

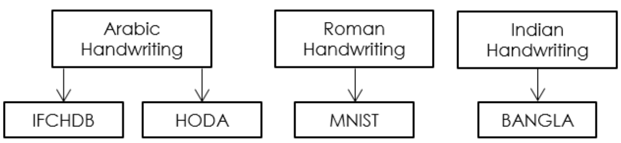


Figure 10. Digit dataset used in the experiment

Table 3. Description of MNIST and BANGLA datasets

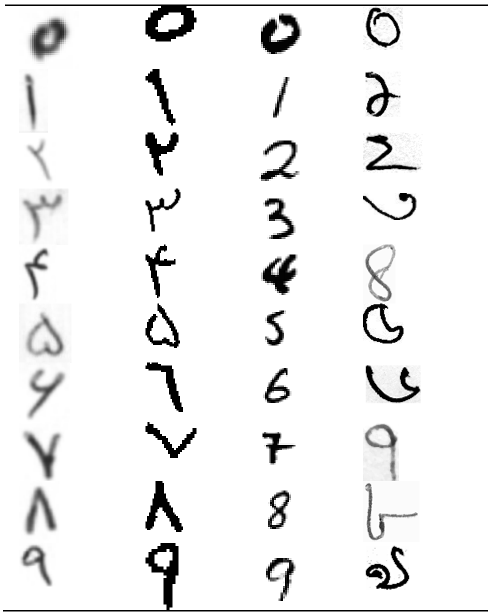
Dataset Attribute	IFCHDB [34]	HODA [6]
Scale	Gray	Binary
Training	12,292	56,790
Testing	5,268	20,000
Total	70,120	76,790

Table 4. Description of IFCHDB and HODA datasets

Dataset Attribute	IFCHDB [34]	HODA [6]
Scale	Gray	Binary
Training	12,292	56,790
Testing	5,268	20,000
Total	70,120	76,790

Table 5. An example of digit dataset images

IFCHDB	HODA	MNIST	BANGLA



III. Proposed Method

A. An Overview of Proposed Method

In this paper, the proposed method is introduced to improve the triangle features in [21] by combining the value of ratio and gradient features based on zones. There are 33 zones used in this paper. The 33 zones are using the zoning method to extract the features.

Basically, there are three elements highlighted in this paper which are the ratio, the gradient and the angle of the triangle. The three main points of the triangle which are point A, B and C are calculated based on the ratio, gradient and angle formula in Table 2. Therefore, each of zones has generated nine triangle features. After implementing the 33 zones, the total number of features produced are 297 features.

In the proposed method, the ratio and gradient features are the ratio for point A, B and C respectively while feature number 7, 8 and 9 are the gradient for point A, B and C respectively. In the proposed method, the values of feature number 1, 2 and 3 are combined and become the main ratio. For gradient, the values from feature 7, 8 and 9 are combined and produced one feature known as the main gradient.

Therefore, the new total features for each zone are five features. The angle of the triangle cannot be used because the total value of triangle angle was 180 degree. Following are the formula for calculating the main ratio and main gradient.

$$Main\ Ratio = c{:}a + a{:}b + b{:}c \tag{5}$$

$$Main\ Gradient = \Delta BA + \Delta BC + \Delta CA \tag{6}$$

Based on Figure 12, the process is started by collecting the digit dataset. The dataset contains raw images. After collecting the digit dataset, these datasets are converted into a binary form using Otsu threshold approach [40]. Once the digit image conversion is completed, the zoning method that adopts the nature of the triangle geometry is implemented in order to extract the data. The zoning method is used in the feature extraction stage. Next, the proposed method is implemented to reduce the total features from 297 to 165 features. Lastly, the final result with 165 features is produced.

In pre-processing stage, the triangle shape was performed based on the coordinates for each of the zones. However, not all triangle shape can be formed due to the collinear line occurred. The collinear line was triggered because of the coordinates for point A, B and C were too close to each other or the gradient's value produced is zero.

Thus, a detection on the coordinates of all triangle points were catered using method in [17] which is also using triangle geometry to solve the straight line problem in triangle shape formation. The proposed method of [17] was focused on detecting coordinates all points for each zones. Taking by the example using Cartesian plane zone method, the partitions were divided into five parts including main image. Using the partition in Zone A (referred Figure 11), the partition of Zone A was divided into four smaller parts. Then, the number of pixel in each partitions of Zone A was calculated and compared based on the rules stated in [17].

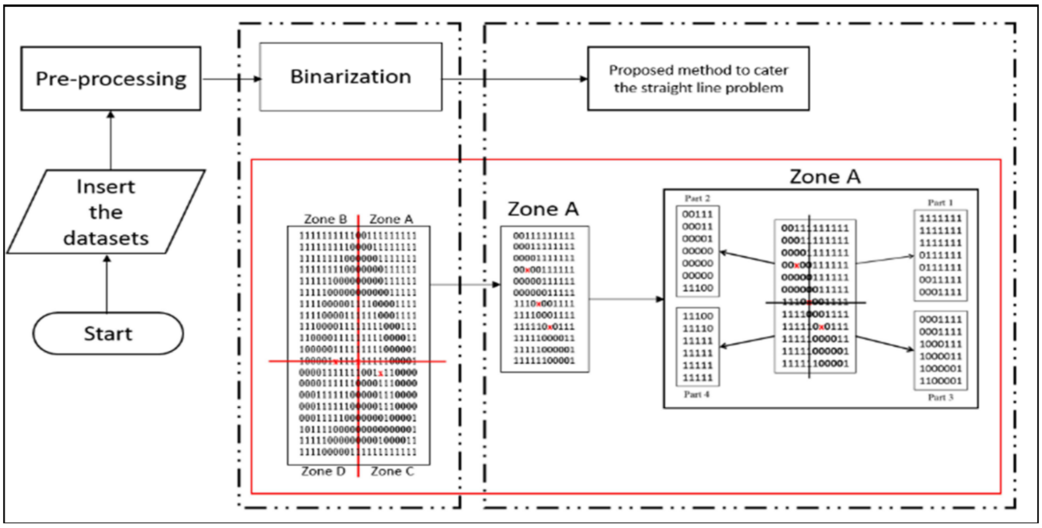


Figure 11. A process of proposed method to cater straight line problem [17]

Table 6. Description of features for proposed method

No of features	Combination of non-related	Features
1	(Ratio of point A) + (Ratio of point B) + (Ratio of point C)	Main ratio of sides
2	(Gradient of point A) + (Gradient of point B) + (Gradient of point C)	Main gradient of corner
3	Angle of point A	Remain
4	Angle of point B	Remain
5	Angle of point C	Remain

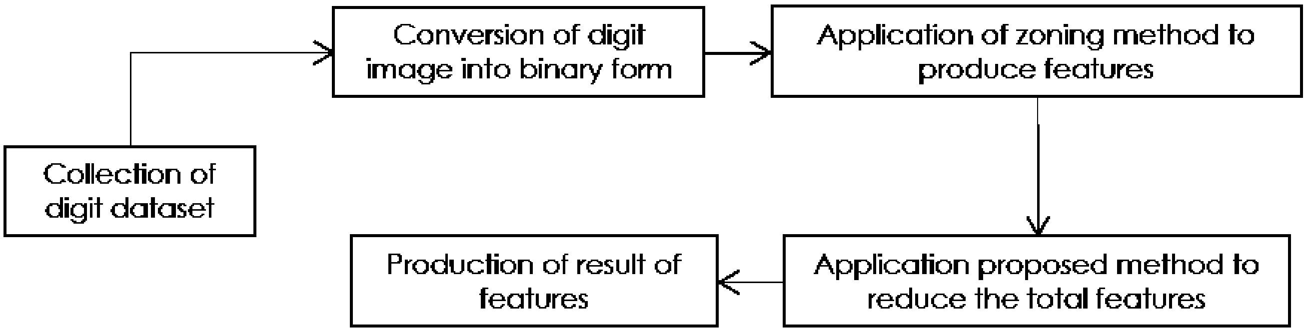


Figure 12. The process of proposed method

B. Environmental Setup

The environment setup is a crucial part of processing the data. There are two types of environment setup used. Table 7 presents the description of hardware used in this paper while Table 8 presents the description of software used.

Table 7. Hardware description

Characteristic	Item
Type of windows	Windows 8
Processor	Intel® Core™ i3-4160 CPU @ 3.60GHz
Random Access Memory	12.0 GB
System Type	64-bit

Table 8. Software description

Software	Description
Waikato Environment for Knowledge Analysis (WEKA)	Version 3.6.9
Eclipse	Mars 1.0
Java Standard Edition	Version 7 Update 76

IV. Result and Discussion

The experiment was conducted using Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) techniques. For SVM technique, the value of cost and gamma were attained from grid search using the LIBSVM tool [41]. The result of cost and gamma for each dataset is shown in Table 10. For MLP technique, the learning rate used was 0.3 which is obtained from the heuristic search. In this experiment, all digit datasets aforementioned are used. First of all, the comparison of classification accuracies is made between several prior proposed method [36], [42] including [21]. However, among several proposed methods, the proposed method of [21] is the only work that used the same triangle geometry features as in this study. Table 9 shows the comparison accuracy results from several previously proposed methods.

Table 11 and Table 12 present the comparison of classification accuracy results for each dataset between the proposed method in [21] and our proposed method using SVM and MLP techniques respectively. Table 13 and Table 14 present the results of comparing the training time taken for each of the datasets between the proposed method in [21] and our work.

Based on Table 11, the result of SVM technique accuracy for our proposed method showed better outcome compared to the proposed method in [21]. For IFCHDB dataset, the result of SVM technique accuracy increases from 93.58% to 95.63%. For HODA dataset, the result increases to 98.03% from 97.30% while BANGLA dataset result has increased from 90.28% to 93.29%. However, MNIST dataset showed value reduction from 95.35% to 93.18%. The decreased result of accuracy might be resulted from the nature of MNIST handwriting itself.

For MLP technique, the accuracy in Table 12 for the proposed method showed the unsatisfied result when compared with the proposed method in [21]. This is due to the complex calculation in MLP technique that may influence the result accuracy. Besides, the nature of handwriting itself may also influenced the result. However, the accuracy for MNIST dataset has shown impressive result where the accuracy increased from 88.66% to 96.51%. Therefore, the result of accuracy as in Table 11 and Table 12 for our proposed method showed better outcome compared to the method proposed previously in [21].

Based on Table 13, the results of training time taken for SVM technique were found to be faster than previous method [21] after applying the proposed method. For IFCHDB dataset, the result of training time taken was 88.89 seconds, 668.39 seconds for HODA dataset, 2397.38 seconds for MNIST dataset and 194.49 seconds for BANGLA dataset. According to Table 14, results of training time taken for MLP technique showed improvement after using our proposed method. For IFCHDB dataset, the result of training time taken was 1717.18 seconds, 5987.57 seconds for HODA dataset, 6198.89 seconds for MNIST dataset and 2295.55 seconds for BANGLA dataset.

Overall, the results of our proposed method have shown impressive accuracies with faster training time taken when comparing with the proposed method in [21]. Therefore, this study has proved that our proposed method has achieved the target by improving the triangle features in [21] and adopting the triangle geometry approach as in [21].

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Table 9. Comparison accuracy results from several prior proposed methods

Method		IFCHDB	HODA	MNIST	BANGLA
Characteristic Loci and Principle Component Analysis [36]	MLP	-	98.16	-	-
Zoning, Outer profiles, crossing counts [42]	SVM	-	98.90	-	-
Triangle geometry and zoning method [21]	SVM	93.58	97.30	95.35	90.28
	MLP	94.86	99.70	88.66	87.02

Table 10. Results of cost and gamma for each dataset

Dataset	Cost (c)	Gamma (γ)
IFCHDB	32.0	0.00048828125
HODA	8.0	0.001953125
BANGLA	32.0	0.001953125
MNIST	8.0	0.0078125

Table 11. Comparison of classification accuracy result for SVM technique (in %)

Method	IFCHDB	HODA	MNIST	BANGLA
Triangle geometry and zoning method [21]	93.58	97.30	95.35	90.28
Our proposed method	**95.63**	**98.03**	**93.18**	**93.29**

Table 12. Comparison of classification accuracy result for MLP technique (in %)

Method	IFCHDB	HODA	MNIST	BANGLA
Triangle geometry and zoning method [21]	94.86	99.70	88.66	87.02
Our proposed method	**93.19**	**95.32**	**96.51**	**86.53**

Table 13. Comparison of training time for SVM technique (in seconds)

Method	IFCHDB	HODA	MNIST	BANGLA
Triangle geometry and zoning method [21]	112.87	1223.82	3703.21	231.77
Our proposed method	**88.89**	**668.39**	**2397.38**	**194.49**

Table 14. Comparison of training time for MLP technique (in seconds)

Method	IFCHDB	HODA	MNIST	BANGLA
Triangle geometry and zoning method [21]	5188.68	18343.65	21751.96	6316.76
Our proposed method	**1717.18**	**5987.57**	**6198.89**	**2295.55**

V. Conclusion

This paper presents the proposed method to improve triangle features in [21] by combining the ratio and gradient (features or characteristics). The ratio and gradient formula were investigated and analyzed in order to produce a suitable approach to improve the triangle features.

Focusing on digit recognition area, there were four datasets used during the experiment. The accuracy result for each of the datasets was measured by Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) techniques. Besides, the training time for each datasets was recorded and the result were compared between the results in [21] and the present findings. The training time result showed improvement in the aspect of shorter time taken to process the data when compared to the training time in [21]. Other than that, the accuracies from the proposed method showed a better result. However, the result of accuracy might be biased by the nature of handwriting itself.

Feature extraction is an important factor in the performance of character recognition. A powerful classifier such as SVM and MLP may yield different accuracies based on different patterns features. The high recognition accuracy can be produced by selecting the suitable low-complexity classifier and proper data extraction. The best final result is obtained not only from the combination of the good classifier but also from the features itself. The improvement in features helps to attain high recognition accuracy and for sure the speed will be increased with minimum training time taken. Further research is needed to increase performance when constructing a triangle shape.

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Author Biographies

Nur Atikah Arbain was born in Melaka, Malaysia. She received her Bachelor of Computer Science in Database Management on 2015 and Master of Science in Information and Communication Technology on 2016 at Universiti Teknikal Malaysia Melaka. She is currently pursuing her PhD which is also at the same university. Her current research work is an offline subword handwriting and contributes in feature extraction domain.

Mohd Sanusi Azmi received BSc., Msc and Ph.D from Universiti Kebangsaan Malaysia (UKM) in 2000, 2003 and 2013. He joined Department of Software Enginering, Universiti Teknikal Malaysia Melaka (UTeM) in 2003. Now, he is currently a senior lecturer at UTeM. He is the Malaysian pioneer researcher in identification and verification of digital images of Al-Quran Mushaf. He is also involved in Digital Jawi Paleography. He actively contributes in the feature extraction domain. He has proposed a novel technique based on geometry feature used in Digit and Arabic based handwritten documents.

Azah Kamilah Muda is an Associate Professor at Faculty of ICT, UTeM. She has appointed as Deputy Dean of Post Graduate and Research since 2015. She received her PhD in 2010 from Universiti Teknologi Malaysia, specializing in image processing. Her research interest includes fundamental studies on data analytics using soft computing techniques, pattern analysis and recognition, image processing, machine learning, computational intelligence and hybrid systems. Her current research work is on pattern analysis of molecular computing for drug analysis, data analytic for various application and root cause analysis in manufacturing process.

Noor Azilah Muda is a Senior Lecturer and a researcher with 15 years of teaching and research experience in the Software Engineering, Database Management and Soft Computing area. Her research interest includes fundamental studies on recognizing patterns of music features and images besides involving in data related research area such as data knowledge and data analysis. Some of her works are in the area of Artificial Immune System (AIS) mechanism to recognize cells that she later investigates the mechanism to recognize different patterns of music features for music genre classification.

Amirul Ramzani Radzid received the BSc. in Computer Science (Software Development) from University Teknikal Malaysia Melaka (UTeM) in 2016. Currently he is pursuing Msc in Information and Communication Technology at Universiti Teknikal Malaysia Melaka (UTeM). His research interests include the area of image segmentation.