Indonesian Journal of Electrical Engineering and Computer Science
Vol. 12, No. 1, October 2018, pp. 356~362
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v12.i1.pp356-362 ❒ 356

Structuring Elements of Hit or Miss to Identify Pattern of Benchmark Latin Alphabets Strokes

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Article Info

Article history:

Received Jun 1, 2018
Revised Jul 10, 2018
Accepted Jul 25, 2018

Keywords:

Handwriting stroke
Morphology
Hit or miss
Structuring element

ABSTRACT

Identification of features in correct alphabet stroke formation is a primary factor in acknowledging handwriting legibility. Hit–or-Miss transform is a morphology operator that is often applied to identify geometric features. Identifying the correct structuring elements (SEs) provides a good geometric feature extraction. Therefore this research proposes to identify generic SEs representing alphabet strokes. The handwriting font used is Syazalina83v3 which is popularly use in teaching writing for lower primary school children in Malaysia. The methodology consists of four phases which are alphabet selection; image pre-processing; manual measurement and hit or miss algorithm with single and various combination of 2x2, 3x3 and 5x5 SE window size; and SEs performance using Pearson correlation. The combination of horizontal and vertical, right diagonal and left diagonal SEs performs well with very strong correlation in detecting Simple Straight Line(SSL), Complex Straight Line(CSL) , Curve Line (CL) and Combination of Curve Line and Simple Straight Line(CLSSL) based on Evan's correlation guide.

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1. INTRODUCTION

Assessing handwriting in Latin alphabets involves analyzing the composition of correct geometric character strokes. Each alphabet stroke patterns formation has a specific direction and sequence, length and curvature; relative to the subsequent strokes in an alphabet. In order to facilitate teaching and learning, word processors fonts are used to create the relevant materials for this matter. Fonts like Comic Sans Ms, Syazalina83v3, Century Gothic, Tw Cen MT, Tw Cen MT Condensed, Tw Cen MT Condensed Extra Bold and Primetime are recommended by a group of Malaysian teacher in facilitating teaching and learning [1]. Syazalina83v3 font was created by a primary school teacher and designed based on printed Malaysian text book [2]. These font stroke formations are frequently used to teach level one primary school children aged six years old. Many attempts have been made to automatically identify correct letter formation to speed up the assessment process.

Various methods and approaches have been used to recognize the correctness of the handwritten formation through stroke pattern decomposition such as pattern recognition, Artificial neural network, evolutionary algorithms and morphology algorithms. Pattern recognition based methods are popular in solving problems related to identification of text, numbers or image. In text studies areas, it is widely used in identification of shapes and strokes in Latin alphabets [3-4], Chinese strokes [5], Gurumukhi [6-8] and

Arabic characters [9-10]. Chain code were applied by [11-13]on handwritten Arabic alphabet to detect order, total, likeness and direction of strokes. Chain codes were also used to compares stroke formation of handwritten Latin alphabets to conventional rules of alphabet formation taught in school [3]. However, chain code are found to be susceptible to noise and demand high memory and processing power [14].

Artificial Neural Network (ANN) based method is another handwriting assessment method used by researchers. ANN is a computational model that replicate the capability of human brains neural networks to learn and relearn as its neural network changes based on input fed and output produced. It was applied in analyzing personality of a person based on offline handwritten small letter 't' [15-16] and to assess children handwriting based on the typology of stroke type, sequences, and direction of Latin alphabet formation [17-18]. The strokes are classified into three types of stroke patterns which are straight line, complex straight line and curve. Each stroke would have its own range of BPNN neuron value. The tested handwriting values will then be compared to BPNN neuron value of reference alphabet [17]. In another research, BPNN values and correlation analysis methods were used to analyze the accuracy of six complex straight line Latin alphabet formations. BPNN are known for its accuracy and versatility, the accuracy of BPNN depends on numbers of train data fed. The higher the volume of training data is supplies to BPNN, the more accurate the result will be. However, due to these facts, it was discovered that BPNN is time-consuming due to the needs to train lots of data and complexity of processing [18]. Evolutionary algorithm (EA) based techniques which were inspired from the biological evolutions are also used in detecting alphabet strokes. Genetic Algorithm (GA) is one of the widely applied EA techniques are based on the evolutionary ideas of natural selection and genetics. It was used to detect and extract handwriting strokes and features [19] using the concept of fitness function. GA's pattern recognition result is highly dependent on fitness function design. Poor design of fitness function will result in inefficient or incomprehensible recognition product.

In general morphology means the study of a particular form, shape, or structure. Convex and concave hulls are useful morphology concepts used for a wide variety of application areas, such as pattern recognition, image processing, statistics, and classification tasks. However, it was discovered that convex hull could not comprehensively identify the geometrical features of a shape [5]. In certain application it does not fully reflect the geometrical characteristics of a dataset since it doesn't follow the path of the outermost points. To overcome the drawback of convex hull algorithm, concave hull algorithm was introduced. The concave hull approach is a more advanced approach used to capture the exact shape of the surface of a dataset; nevertheless, formulating the set of concave hull is difficult [20]. Boundaries extraction, Hit-or-Miss Transform (HMT) and region filling are other examples of widely used application of morphology algorithms [21-22].

The HMT is a fundamental operation on binary images which has been widely used for 40 years [23]. HMT is a well-known morphological transform that provides an extremely powerful set of tools for image processing. The input of HMT are binary images and a specifically designed template called structuring element (SE). Structuring elements (SE) is a pre-defined template used to identify groups of connected pixels that comply with certain geometric properties of the analyzed binary images based on its foreground and background. The accuracy of this algorithm is greatly dependent on its shape and size of the SE. [24] Thus this study is conducted with the purpose of seeking for the appropriate general SE decomposition of HMT that can accurately extract and recognized Latin alphabet images.

2. RELATED WORKS

Chea et al [3] expressed that Latin alphabets are combination of stroke patterns categorized as simple straight lines, complex straight lines and curve lines. Latin alphabets formation are made up of simplest of elements which are one or more straight lines comprising of vertical, horizontal or diagonal lines to a more complex curve lines comprising of a whole circle or semi-circle. Fifteen Latin alphabet comprises of are single directional straight lines consisting of a combination of horizontal (|), vertical (_) or diagonal(/ and \ ) . These can further be divided into two groups that is simple straight lines (A, E, F, H, I, K, M, N, T, X, Y) and complex straight lines which combines two or more complex lines within one single stroke (L, V ,W,or Z). Three letters are made up entirely of curved lines which are C, O, S. Letters such as B, D, J, P, R, U are constructed from straight lines and curves, or semi-circles (bowls) connected in various way. Finally, two letters G and Q are essentially circular, but consist of short bar or spur (straight or curled) to differentiate them from similar curved letters which is C and O respectively.

HMT is capable of identifying certain geometric properties based on relative ordering of pixel values known as structuring elements. The structuring elements are represented as a small matrix of pixels, each with a value of 1 or 0. The dimensions of the matrix determine the overall size of the structuring element, and its shape is determined by the pattern of ones and zeros. Usually HMT uses the fixed SE pair in the global image, and only extracts the object of the same size and shape on the foreground image. Some researchers matched SE as 'fits' while others as 'hits' [25]. HMT has been used to recognize handwritten Bengali numerals [26-27] and the study's results in an accuracy of more than 96% recognition for most of the numerals. The program shown an accelerated average time taken by the program to identify each numeral even for a very low-spec computer. Eugene and Edward [28] developed a class of structuring-element pairs for segmentation-free character recognition via the morphological HMT for recognizing Courier font. Both hit and miss structuring elements are selected so that the hit-or-miss transform can be applied across the test image without prior segmentation. Although they uses basic HMT method, it was proven to achieve high rates of accuracy on text and very robust with respect to the threshold level for the input gray-scale data.

No literature on finding the appropriate general SE decomposition was found however there are several literatures describe SE on various usage for image recognition. Doh et al [29] studies the choice of SEs for the recognition of a class of various objects. They start from two sets: a set of hit SEs that fit the objects to be recognized and a set of miss SEs that fit the background. The research resulting on using synthetic hit SE composed of the intersection of all hit SEs and a synthetic miss SE composed of the union of all miss SEs for better recognition of diverse objects . Zhao and Daut [30] present a technique which uses upper and lower bounds to determine the SEs for use in the HMT using a priori knowledge edge of the shapes to be detected. This technique uses the skeletons of both the object to be recognized and its complement as SEs.

3. METHODOLOGY

The methodological approach taken in this study consist of four phase as shown in Figure 1. The initial phase is the alphabet selection based on complexity of stroke formation. These involves selecting eight Latin alphabets divided into four based on their complexity. These groups are Simple Straight Line (SSL), Curve Line (CL), Complex Straight Line (CSL) and Combination of Complex Straight Line and Simple Straight Line (CCSL). Phase two is image pre-processing. These comprises of two processes which are binarization and thinning. Phase three is shape recognition consisting of two process which are manual measurement and hit or miss algorithm. Final phase is performance evaluation. The performance of various SE template size that most appropriately describe the chosen Latin alphabet stroke formation are evaluated.

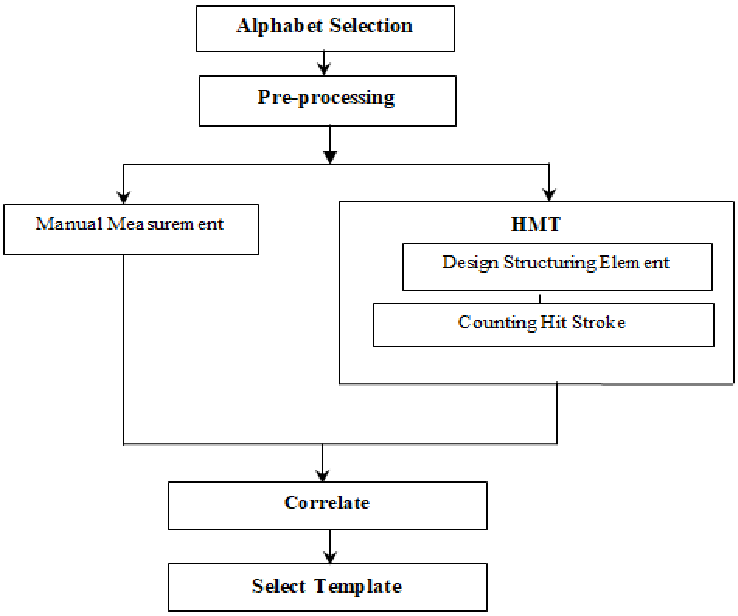


Figure 1. Methodology for Selecting Appropriate General SE Decomposition

3.1 Alphabet Selection Based on Complexity of Stroke Formation

Latin alphabet comprises of twenty six letters and composed of two main strokes formation, which are straight line and curve lines. In this study, uppercase letters are grouped into four categories of stroke patterns which are Simple Straight Line (SSL), Curve Lines (CL), Complex Straight Line (CSL) [3] and combination of the three strokes (CLSSL). Two alphabets are selected from each category in this study. The selected alphabets are depicted in Table 1 according to their complexity.

Table 1. Stroke Pattern and Selected Alphabets

Stroke Pattern	Alphabets(Syazalina3v3)
Simple Straight Line(SSL)	A
	E
Curve Lines(CL)	C
	J
Complex Straight Line(CSL)	L
	V
Combination of SSL ,CL and CSL (CLSSL)	B
	G

Alphabet A and E are selected to represent SSL, C and J represent CL, L and V represent CSL and B and G represent CLSSL.

3.2 Pre-processing

This section discussed on the image pre-processing task as in Figure 2. In this process, the eight alphabets are cropped and saved in jpeg format. The current jpeg format shows that the images are in grayscale format. In order to increase identification accuracy of the alphabet strokes, the images are converted to binary format and thinning operation respectively.

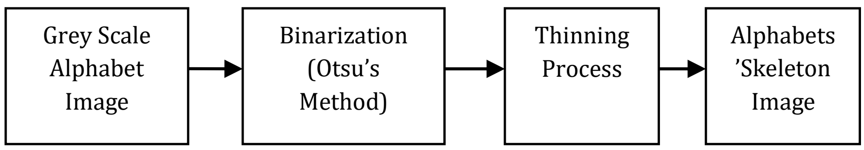


Figure 2. Pre-processing

The binarization process converts the grey level image to black and white images to minimize the intra-class variance. Otsu’s thresholding method was selected. Next is the morphological thinning process to reduce the alphabet image to a single pixel thickness. This reduces the processing time as well as remove the possibility of detecting false trivial details [31] Figure 3 shows the result of binarization and thinning.

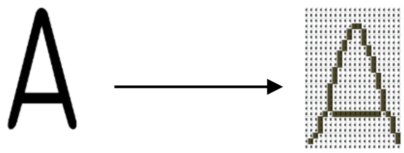


Figure 3. Binarization and Thinning of the Test Image

3.3 Shape Recognition

This phase consists of a two main process which is manual measurement and utilization of hit or miss algorithm.

3.3.1. Manual Measurement

The manual measurement was done by using a ruler. The binarize image of the eight alphabets are printed and every stroke are measured in centimeters. The strokes are measured as vertical, horizontal, left and right diagonal. These stroke measurements are recorded in a form of table. Table 2 shows the manual measurement value:

Table 2. Manual Measurement (cm)

Line Category	Manual Measurement (cm)					
	Alphabet	Stroke |	Strokes -	Strokes /	Strokes \	Total
Simple Straight Line (SSL)	A	0	4	7.8	7.8	19.6
	E	7.2	11.6	0	0	18.8
Curve Line (CL)	C	2.5	4.9	3.4	3.9	14.7
	J	6	4.4	1.5	2	13.9
Complex Straight Line	L	6.8	3.4	0	0	10.2
	V	0	0	7.6	7.6	15.2
Combination of SSL and CL	B	6.5	7.9	3.6	3.6	21.6
	G	6.5	7.3	4.5	3.7	22

3.3.2. Hit or Miss Transform Algorithm

The effectiveness of HMT detection heavily depend on design of SE. The design of SE must comply with the structure of the object that are to be detected.

1) Structuring Element Design

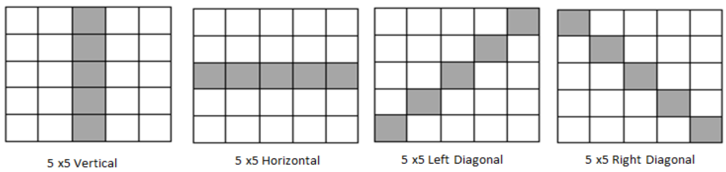
There are two main characteristics that are directly related to SE that is shape and size. Shape is crucial for recognizing object while size is imperative to set the observation scale and criteria to differentiate image object as well as features.

As stated in the literature [3], most Latin alphabets strokes consists of a combination of horizontal (|), vertical (_) or diagonal lines(/ and \ ). Thus the SE are design accordingly in a 2 x 2, 3 x 3 and 5 x 5 matrix size that represents horizontal, vertical, left diagonal and right diagonal strokes. These SE are apply with the HMT algorithm where the hit count is correlated with the count from the manual measurement. Based on [3], the SE pattern are design to be horizontal, vertical, left diagonal and right diagonal. The designs are shown in Table 3.

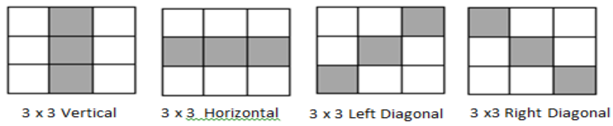
Table 3. Structuring Element Shape and Size

Structuring Elements Size | Structuring Element Shape

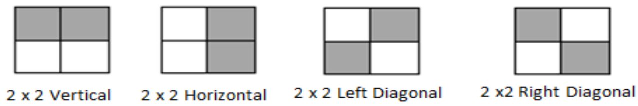
5 x 5



3 x 3



2 x 2



2) Counting stroke using Hits Algorithm

The hit process will match it to the intended pixels (1s), which represented the stroke image, and remove unwanted pixels (0s) of the structure that it want to miss. Hit or miss algorithm are executed using the SEs in table 2. Only the hits where the SE fully matched the object structure are counted.

Hit or miss algorithms are formulated using the followings formula:

$$A * B = (A^{a} X) \cap [Ac^{a} (W - X)]$$

B denotes the set composed of X and its background, the match/hit (or set of matches/hits) of B in A,

X is set formed from elements of B associated with an object while (W – X) are set formed from elements of B associated with the corresponding background.

Initially only the Se of the same window size are executed on all the selected alphabets. Later, a combination of different size windows are tested. To avoid the differentiation for the different sizes the results are calculated based on percentage of the total counts.

3.4 Correlation between HMT and Manual Measurement

The collections of results are correlated against the manual measurements. Pearson correlation is used to assess the linearity of the results. The assessment is done by analyzing the strength of the correlation coefficient. The stronger the correlation the better the object description. This correlation is based on Evans correlation guide [32] as shown in Table 4.

Table 4. Evans Correlation Guide

Correlation Value	Description
0.00-0.19	Very Weak
0.20-0.39	Weak
0.40-0.59	Moderate
0.60-0.79	Strong
0.80-1.00	Very Strong

4. RESULTS AND ANALYSIS

Two SEs are found to be the most fitting template: 5x5 with3x3 and 5x5 with 2x2. They produced the same score for coefficient correlation of all letters except for the correlation of letter G, which is slightly different as 5x5 with 3x3 value is r = 0.59 and 5x5 with 2x2 value of r =0.60.

5. CONCLUSION

This study discusses on applying morphology hit and miss algorithm in extracting an alphabet image. The proposed methods depicts that it is successful in determining the most appropriate SE for feature extraction purposes. Based on the experiment, the combination of small size SE

And large size SE are most appropriate for detecting the strokes composition of alphabets image. Based on the conducted empirical experiments, 2x2 SE are best for extraction for diagonal strokes line and 5x5SE for best for extracting both vertical strokes and horizontal strokes. The combined SE will be used in future studies for detecting correct handwriting strokes and legibility of handwritings in Latin alphabet among children in lower primary school.

ACKNOWLEDGEMENT

This work was supported by the Universiti Teknologi MARA, Institute of Research Management & Innovation (600-IRMI/MYRA 5/3/LESTARI (070/2017)).

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