Feature Extraction method for Classification of Approved Halal Logo in Malaysia using Fractionalized Principle Magnitude

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Abstract

This paper presents new feature extractors called the Fractionalized Principle Magnitude (FPM) that is evaluated in the classification of approved Halal logo with respect to classification accuracy and time consumptions. Feature can be classified into two groups that are global and local feature. In this study, several feature extractors have been compared with the proposed method such as histogram of gradient (HOG), Hu moment, Zernike moment and wavelet co-occurrence histogram (WCH). The experiments are conducted on 50 different approved Halal logos. The result shows that proposed FPM method achieves the highest accuracy with 90.4% whereas HOG, Zernike moment, WCH and Hu moment achieve 75.2%, 64.4%, 47.2% 44.4% of accuracies, respectively. Furthermore, two other databases also have been used that is traffic sign and Outex database. The accuracy performance and classification time are compared with FPM and other method.

Keywords

Feature Extractor; Fourier Principle Magnitude; Logo Classification

Introduction

Object detection is an important task in computer vision community with the purpose of allowing computers automatically detect semantic objects, like human faces, ntiate between an approved Halal product and a non-Halal product. Since the Halal condition of product especially the food, is very important for the Muslims, the classification of the Halal logo becomes significant.

Islamic department of Malaysia (JAKIM) has listed out the approved Halal logos. There are around 50 Halal

logos from 31 countries over the world approved by JAKIM. Unfortunately, most of the Muslims in Malaysia do not recognize these logos since there are so many logos to be remembered.

To overcome this problem, a tool is needed to help the Muslims in Malaysia to classify the approved Halal logos. Since the logo can be distinguished using its visual information, the classification can be done using computer vision and image processing. To accurately classify the logo, a good feature extractor is necessary. Some of the feature extractors used in logo classification are histogram of oriented gradients (HOG), Hu moment, Zernike moment and wavelet co-occurrence histogram (WCH). However, even though these feature extractors hold high accuracy, their algorithms are too complex and time-consuming. Therefore, in this paper, a new, simple and high accuracy feature extractor has been proposed based on Fourier transform that is called Fractionalized Principle Magnitude (FPM) the combination of principle magnitudes of the Fourier transform extracted from the fractionalized images.

With the development of fast Fourier transform (FFT), Fourier transform becomes one of the fast methods to extract features and is widely used in feature extractor application. For example, K. Muzzammil and Deok-Hwan Kim proposed localized angular phase which utilizes the phase from the Fourier transform in localized polar space. Besides that, Feng Zhou., Ju Fu Feng and Qing Yun Shi proposed texture descriptor by using the magnitude of the 1D Fourier transform. Ville Ojansivu and Janne Heikkilä proposed blur insensitive texture descriptor using the phase of the local Fourier transform coefficients. K. Muzzammil, Shao-huPeng, Hyun-Soo Kim and Deok-Hwan Kim proposed a 2D local Fourier transform based texture descriptor where spatial distribution of gray levels of neighborhood pixels can be extracted. Furthermore K. Muzzammil and Deok-Hwan Kim has used Fourier transform in spectral feature extraction techniques in target detection of hyperspectral images.

This paper is organized as follows: in section 2, related works are discussed. In section 3, the detail explanations about FPM are presented. In section 4, the results and their analysis are presented. Finally, the conclusion is given in section 5.

Related Works

Histogram of Oriented Gradient

Histogram of Oriented Gradients (HOG), a technique for object detection, generally is applied to pedestrian detection based on the evaluation of comparison between the histograms regarding of gradient orientation among the localization of an images. The concept of the HOG is similar with that of edge orientation, scale-invariant feature transform (SIFT) descriptor and shape contexts, but it is regarding on a dense grid of uniformly spaced cells and used overlapping local contrast normalization for improved accuracy. Computation of each histogram is divided into small region called cells. The group of cell is combined to become a block. Then each cell is compiled using HOG and the combination of histogram represents descriptor. The illumination changes depend on strength of the normalization of the gradient. The performance of the HOG is related to the effective of local contrast normalization of each block.

Zernike Moments

Zernike moment, a set of orthogonal with simple rotation properties, as one of the tools of object recognition with a lower resistance to scaling, translation and rotation of the image will change with regard to the resolution or noise [10]. The Zernike polynomials are a set of complex, orthogonal polynomials defined over the interior of a unit circle x2+y2=1,

$$V_{nm}(x,y) = V_{nm}(\rho,\theta) = R_{nm}(\rho)e^{jm\theta} \tag{1}$$

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}} (-1)^s \frac{(n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!}\rho^{n-2s} \tag{2}$$

where n is a non-negative integer, m is an integer such that n-|m| is even and $|m| \le n, \rho = \sqrt{x^2+y^2}$, and

$$\theta = \tan^{-1}\frac{x}{y} \tag{3}$$

Projecting the image function onto the basic set, the Zernike moment of order n repetition m is:

$$A_{nm} = \frac{n+1}{\pi}\sum_x\sum_y f(x,y)V_{nm}(x,y),\ x^2+y^2 \le 1 \tag{4}$$

Equation (4) shows the Zernike moment in a rotated image different from the original image. The difference lie in that the equation is regarding on the phase shift but not in magnitudes. Therefore, A_{nm} can be used as a rotation invariant feature of the image function. Since $A_{n,-m} = A_{nm}$ and therefore $|A_{n,-m}| = |A_{nm}|$, so $|A_{nm}|$ is defined as feature size. Since A_{00} and A_{11} are the same for all of the normalized symbols, they will not be used in the feature set. Therefore the extracted features of the order n start from the second order moments up to the nth order moments.

Moments Invariant

Moment invariants are related to the characteristic of pattern regarding position, size, and rotation of the image. The idea of the moment invariants was come from Ming-Kuei Hu in year 1962, who introduced six orthogonal invariants and one skew orthogonal invariants based on algebraic invariants [8]. Moment invariants have been applied to many applications especially pattern recognition, image registration and image reconstruction.

There are two dimensional of order (p + q) of a digital image f(x, y) that can be defined as follows:

$$m_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} x^p y^q f(x,y),\ p,q = 0,1,2,\ldots \tag{5}$$

The central moment of f(x, y) can be defined as:

$$\mu_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left(x-\bar{x}\right)^p\left(y-\bar{y}\right)^q f(x,y),$$

$$p,q = 0,1,2,\ldots$$

$$\text{Where } \bar{x} = \frac{m_{10}}{m_{00}} \text{ and } \bar{y} = \frac{m_{01}}{m_{00}} \tag{6}$$

scaling normalization of central image moment can be defined as:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}},\ where\ \gamma = \frac{p+q}{2}+1,\ p+q = 0,1,2,\ldots \tag{7}$$

From the central moment, Hu has defined seven methods as follows:

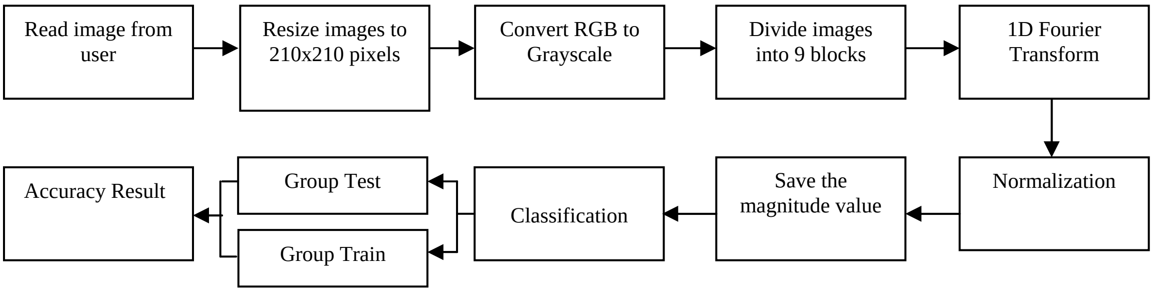

FIG. 1 THE FLOW OF THE SYSTEM

$$
\begin{aligned}
&\phi_1 = \eta_{20} + \eta_{02} \\
&\phi_2 = \left(\eta_{20} - \eta_{02}\right)^2 + 4\eta_{11}^2 \\
&\phi_3 = \left(\eta_{30} - 3\eta_{12}\right)^2 + \left(3\eta_{21} - \eta_{03}\right)^2 \\
&\phi_4 = \left(\eta_{30} + \eta_{12}\right)^2 + \left(\eta_{21} + \eta_{03}\right)^2 \\
&\phi_5 = \left(\eta_{30} - 3\eta_{12}\right)^2\left(\eta_{30} + \eta_{12}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right] \\
&+\left(3\eta_{21} - \eta_{03}\right)\left(\eta_{21} + \eta_{03}\right)\left[3\left(\eta_{30} + \eta_{12}\right)^2 - \left(\eta_{21} + \eta_{03}\right)^2\right] \\
&\phi_6 = \left(\eta_{20} - \eta_{02}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2\left(\eta_{21} + \eta_{03}\right)^2\right] + \\
&4\eta_{11}\left(\eta_{30} + \eta_{12}\right)\left(\eta_{21} + \eta_{03}\right) \\
&\phi_7 = \left(3\eta_{21} - \eta_{03}\right)\left(\eta_{30} + \eta_{12}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right] + \\
&\left(3\eta_{12} - \eta_{30}\right)\left(\eta_{21} + \eta_{03}\right)\left[3\left(\eta_{30} + \eta_{12}\right)^2 - \left(\eta_{21} + \eta_{03}\right)^2\right]
\end{aligned} \tag{8}
$$

Wavelet Co-occurrence Histogram

Wavelet co-occurrence histogram (WCH) is a method of object detection especially in logo detection. Ali Hesson and Dimitrious Androutsos used WCH for logo detection in their experiment, and the results showed that WCH is better in representation of the image feature compared to Edge Directional Histogram (EDH). Wavelet transform is used to produce a signal with a good resolution especially in spatial and frequency domain. One of the examples of wavelet transform is Haar transform, which is grouped into two types of filter that is low pass filter and high pass filter. There are four sub-bands used to apply the Haar transform namely Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH) filters. The sub-band is represented with low pass filter and high pass filter in different order. Each wavelet transform can be divided into three dimensional vectors that are horizontal, diagonal and vertical, each of which represents pixel of the image. The first and second dimensions represent the pixel vectors and the third dimension represents the distance between the two vectors.

Proposed Method

Fractionalized 1D Principle Magnitude

This section presents the proposed fractionalized principle magnitude (FPM) algorithm using the magnitude of the 1D Fourier transform. Figure 1 shows the general flow of the system used to analyze the performance of the feature extractor methods.

The experiment begins with the reading of the Halal logo images from the database. All the images are resized into 210x210 pixels then converted from RGB to Grayscale image. Further, each image is divided into blocks with the size 5x5 fractions where each block is stored block location of the image as showed in the Figure 2.

a) Image size 210x210 b) Block of size 3x3 fractions c) Image size 42x42

FIG. 2 THE GRAPHICAL ILLUSTRATION OF DIVIDING IMAGE INTO 5x5 FRACTION

1D Fourier transform will be applied to the each fraction of the 2D Halal logo image. To achieve that, the 2D image needs to be converted to the 1D array. The entire first row is stored followed by the second array. The formula to arrange 2D image f(x, y) to 1D array is as follows:

$$f_{1D}(v) = f\left(\left\lfloor \frac{v}{W} \right\rfloor, v \bmod W\right), v = 0,1,\ldots W \times H - 1 \tag{9}$$

where W is the width of the 2D image and H is the height of the 2D image. For better understanding,

Figure 3 showing the graphical interpretation of the formula (9), gives an example of conversion from a 5x5 fraction 2D image to a 1D array. The reason for converting 2D data to 1D array is to reduce the dimensionality of the data.

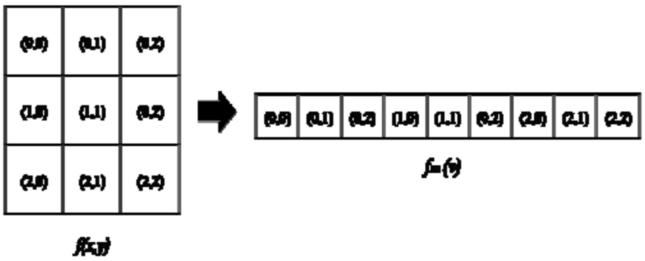

FIG. 3 THE GRAPHICAL ILLUSTRATION OF CONVERTING 2D IMAGE TO A SINGLE ARRAY

After the acquisition of the 1D array of the image, its Fourier transform can be calculated using 1D discrete Fourier transform formula as follows:

$$F_{1D}(n) = \sum_{v=0}^{H*W-1} f_{1D}(v) e^{-\frac{2\pi jnv}{H*W}}, n = 0,1,....,H*W-1 \quad (10)$$

The output of the Fourier transform is in complex number, by means of which, the magnitude and the phase of the 1D Fourier transform can be calculated using the following formula:

$$Mag\_F_{1D}(n) = \sqrt{\mathrm{Re}\left\{F_{1D}(n)\right\}^2 + \mathrm{Im}\left\{F_{1D}(n)\right\}^2}, \quad (11)$$

Because of the robustness and consistency value of the magnitude, the magnitude of the Fourier transform is only utilized as the feature. Among all of the magnitude, only 4 values; coefficients $Mag\_F_{1D}(1)$, $Mag\_F_{1D}(2)$, $Mag\_F_{1D}(3)$ and $Mag\_F_{1D}(4)$ are selected.

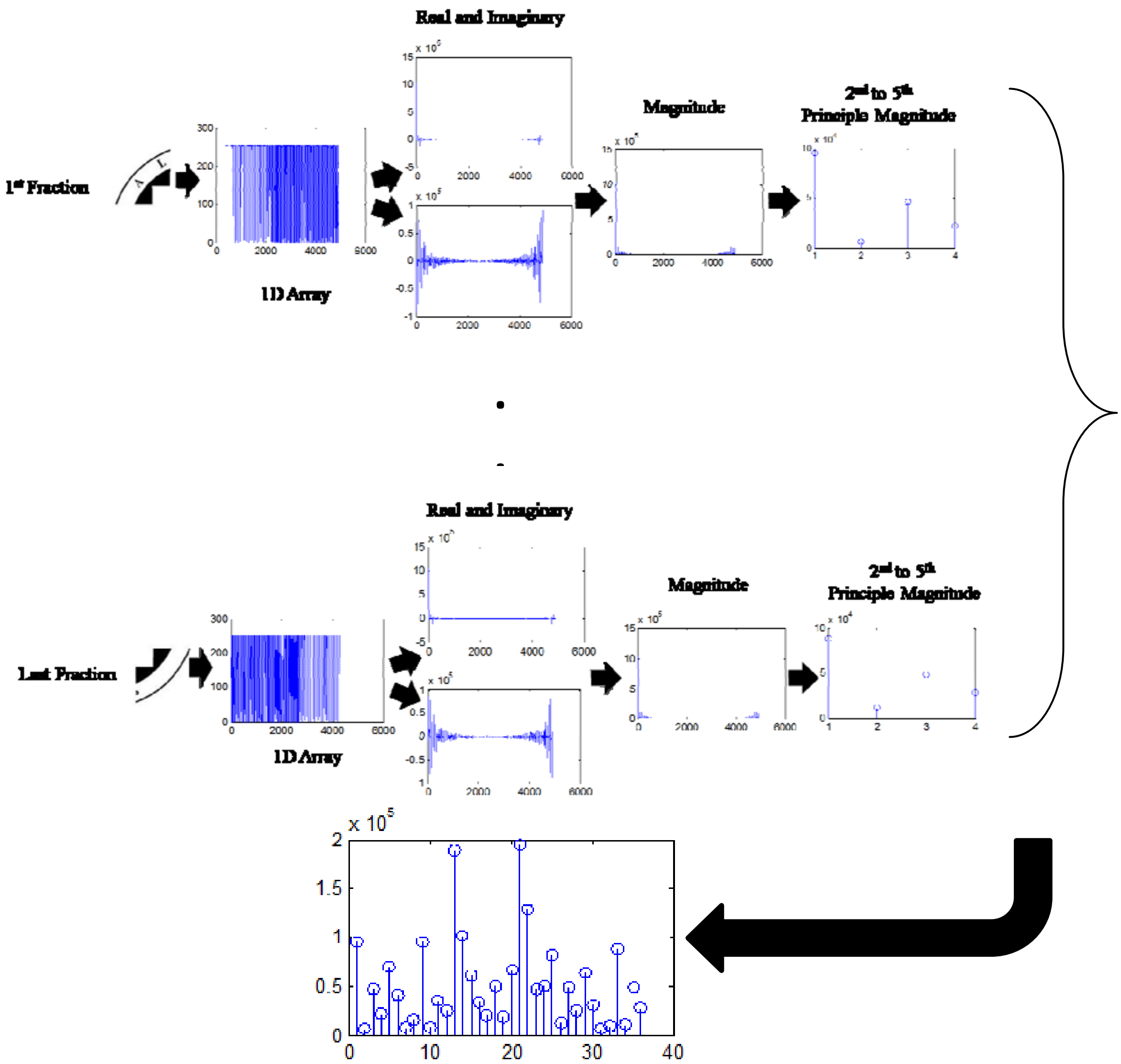

FIG. 4 THE FLOW OF TRANSFORMATION FROM 2D IMAGE INTO 1D FOURIER TRANSFORM FOR ONE DIRECTION

Fourier transform is similar to the summarization of the signals from the lowest frequency to the highest frequency. The low frequency contains the most significant information. So we select top four of the lowest frequency except for the lowest frequency coefficient which is removed due to its inclusion of an extremely large value compared to other low frequency coefficients that will disturb other values of the feature vectors.

As it is well known that the four values only gathered from the first fraction of the logo can be labelled as follows:

$$M\_F_{1D}^{1}=\begin{Bmatrix} Mag\_F_{1D}(1), Mag\_F_{1D}(2), \\ Mag\_F_{1D}(3), Mag\_F_{1D}(4) \end{Bmatrix} \quad (12)$$

The final feature vector is the combination of the 4 principle magnitude of all of the 25 fractions of the logo resulting in 100 elements, can be labelled as follows:

$$Final\_vec=\left\{M\_F_{1D}^{1}, M\_F_{1D}^{2}(z), \ldots, M\_F_{1D}^{25}\right\} \quad (13)$$

For the classification, KNN classification is applied to this system. It is known that KNN classifier is the simplest classification among other machine learning algorithms. The image is compared based on its similarity with the neighbor. In this experiment we used the value of k=1, where the object is simply assigned to the class of its nearest neighbor.

Figure 4 shows the step process of feature vector beginning with 2D image until the final feature vector. The process is repeated from the first fraction to the last fraction.

Experimental Studies and Evaluation

Experiment Environment and Database

For the classification experiment, 50 class of approval Halal logo by JAKIM are used, each of which contains 5 different images and the total of Halal logo images are 250 images. As shown in Figure 5, the database images are gathered from various online resources such as JAKIM's website and Google's images.

The performance of FPM is compared with that of four other methods which are commonly used that is HOG, Hu moment, Zernike and WCH. This experiment is conducted on computer with an AMD E-350 processor 1.60GHz and 6GB of main memory. All the codes are written in MATLAB environment with Window 7 operating system.

FIG. 5 FROM (1) UNTIL (50) ARE THE EXAMPLES OF HALAL LOGO IN THE DATABASE

For the classifier, k-nearest neighbor algorithm (k-NN) is implemented. k-NN is a method to classify data into two classes or more based on the closest training. Form research done by Yang and Liu, it was stated that k-NN outperformed other approaches especially in text categorization task. It is also one of the simple machine learning methods. k-NN is just developed to perform an analysis for estimate value or probability of the data when the unknown or difficult data should be classified. In this experiment, it is assumed that value k=1 is a simple k-NN in classification between class and its nearest neighbour. Cosine similarity is implemented in this experiment to measure the different angle between two vectors.

Besides that, for the classification, cross-validation is utilized as the statistical method for evaluation and comparing learning algorithm by dividing data into two segments: one is used for test and the others used for train. In this experiment, k-fold cross-validation is in use where k is equal to 5. To measure the classification accuracy, each feature extractor is evaluated. There are 5 folds from each class used in this experiment and classification of each result of each fold is recorded. The classification accuracy for each fold is calculated using the following formula:

$$accuracy(\%)=\frac{no.of\ correctly classification}{no.of\ total\ images} \quad (14)$$

After calculating the accuracy of all of the 5 folds, the final average accuracy from each fold is calculated using the following formula:

$$average\,accuracy\left(\%\right)=\frac{total\,accuracy\,of\,each\,group}{no.of\,group} \quad (15)$$

Effect of Fraction Size of FPM

There are five different size of fraction 2x2, 3x3, 4x4, 5x5, and 6x6 applied to this experiment respectively. The performance of each fraction and the performance of each size are calculated respectively. Then the optimum size of fraction is set regarding to optimum result of accuracy and time performance. Before the fraction process is applied, the image is resized into 210x210 pixels to standardise the size of image. The feature size refers to the size number of fraction. The performance of maximum accuracy over time (AOT) is calculated using the following formula:

$$Accuracy\,AOT\left(\%\right)=\frac{Accuracy}{Time} \quad (16)$$

Figure 6 showed the result of performance AOT for five different sizes of fraction. As can be seen from the graph which the red circle is the optimum size of fraction based on the performance of the proposed method when different size is applied. The highest value of performance accuracy over time will produce the optimum value of threshold.

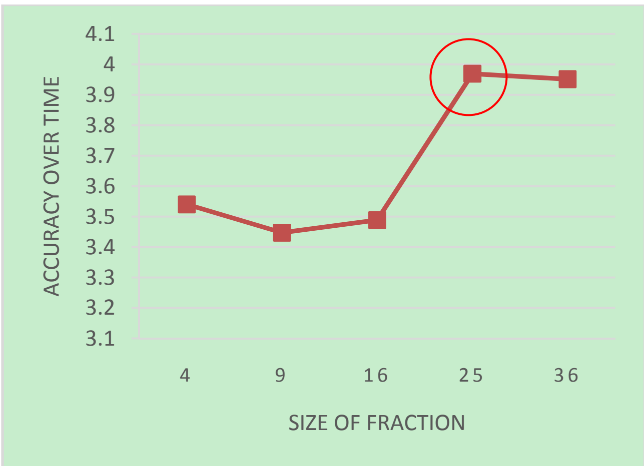

FIG. 6 THE OPTIMUM SIZE OF FRACTION

Comparative Study of FPM with Others Method Based on Classification of Feature Extraction

The experiment is conducted to analyze the classification performance of feature extractor among FPM, HOG, Hu moment, Zernike and WCH on the Halal logo database. The average classification result is showed in the Figure 7, from which it can be observe that FPM obtains the highest classification accuracy of 94% and Hu moment performs the lowest with 36%, resulting from the fact that FPM method with more significant information extracted with the information of the image is less sensitive to pose and scale changes since it resize back the image to a fixed size before it is processed. Furthermore, FPM is based on 1D Fourier transform where 2D image is transformed into a single dimensional with the localization of images. This means that FPM extracts the similar feature between the original image and different image.

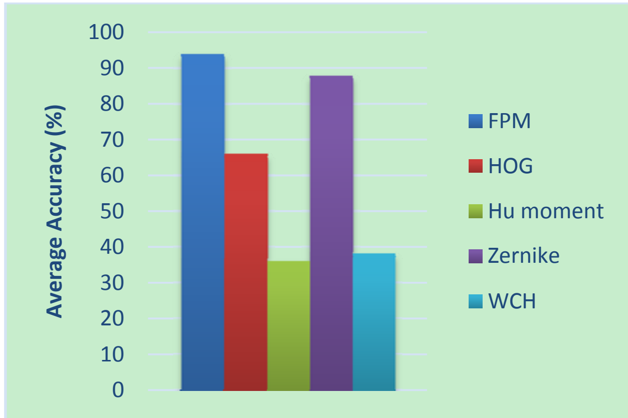

FIG. 7 AVERAGE CLASSIFICATION ACCURACY ON HALAL LOGO DATABASE

Table 1 shows the classification time of each method to classify the approved Halal logo. Based on the result, FPM holds the fastest processing speed among the others. It is due to simplicity of FPM compared to other methods. Zernike method takes the longest time to compute because the algorithm is complex and needs many calculations.

TABLE 1 CLASSIFICATION TIME ON HALAL LOGO

Method	Classification time
FPM	23.74183
HOG	102.0857
Hu moment	39.0395
Zernike	3765.757
WCH	7249.9

The performance classification can also be measured by scrutinizing the number of false positive with different threshold values used that are 40%, 60%, 80% and 100% of accuracies. The number of false positive classified logo for each feature extractor with different threshold is recorded and shown in Figure 8. It is clearly seen that FPM achieves the lowest false positive in every threshold, which means that FPM produces the lowest error rate compared to other feature extractor. For specific result of the false positive, Table 2 shows the specific value of false positive with the threshold 100%. The number of Halal logo is below than 100%. The false positive with threshold 100% is the number of wrongly classified logo using the threshold 100%. To be brief, it is the number of logo that fails to achieve 100% classification accuracy.

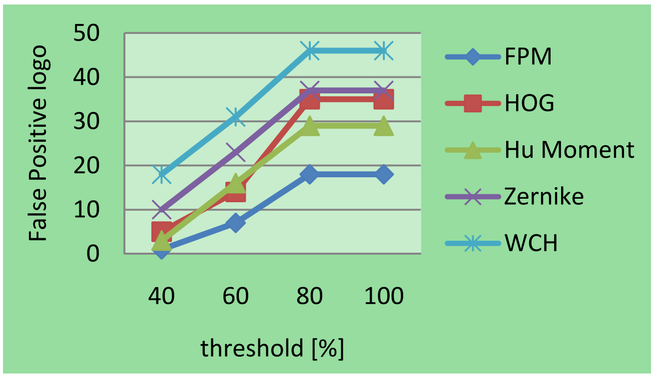

FIG. 8 THE FALSE POSITIVE THRESHOLD

TABLE 2 THE FALSE POSITIVE WITH THRESHOLD 100%

Methods	FPM	HOG	Hu moment	Zernike	WCH
False Positive	18	37	49	46	38

Evaluation Classification of FSM versus Others Method based on Traffic Sign database

In this section the application of the FPM is applied with a new database. The evaluation of the performance of FPM and other four methods are presented. Figure 9 shows the example of traffic sign database gathered from German Traffic Sign Recognition Benchmark database (http://benchmark.ini.rub.de/). For the experiment 32 classes of traffic sign are used and each class contains 10 images and the total images is 320.

FIG. 9 TRAFFIC SIGN DATABASE

The same process is repeated and the accuracy performance and classification time are calculated and then the result is compared. Table 3 shows the accuracy and classification time result for the traffic sign database by which HOG achieves the highest speed compared to other methods and computation time of HOG method is shorter compared to other. Furthermore, the average classification accuracy shows HOG achieves highest accuracy performance. HOG algorithm is similar to edge orientation histogram which is detected from the edge of the image. For the information, FPM method is compatible to the image with same dimension. So the result for FPM method will also have effect.

TABLE 3 ACCURACY AND CLASSIFICATION TIME ON TRAFFIC SIGN DATABASE

Method	Accuracy	Classification time
FPM	90	10.34
HOG	93.75	9.1608
Hu moment	25	17.8337
Zernike	62.5	1081.2
WCH	78.12	8716.1

Evaluation Classification of FPM versus Others Method Based on Texture Database

The experiment is continued using the texture database gathered from KTH-TIPS database (Available at www.nada.kth.se/cvap/databases/kth-tips). There are 40 classes of Outex used in this experiment, each of which contains 12 images. Figure 11 shows the example of Outex image database. The performance of each method is recorded using a new database.

Table 4 shows the classification time of FPM and other feature extractors. Referring to the results, the highest accuracy for Outex database is HOG algorithm with 83.3% higher than other algorithm. Meanwhile FPM algorithm with the achievement of 50% accuracy and less computation time is appropriate for images logo with specific feature. Compared to other algorithms, it is applied to flexible image or object. Although the FPM algorithm result is less but it is able to compete with other algorithm.

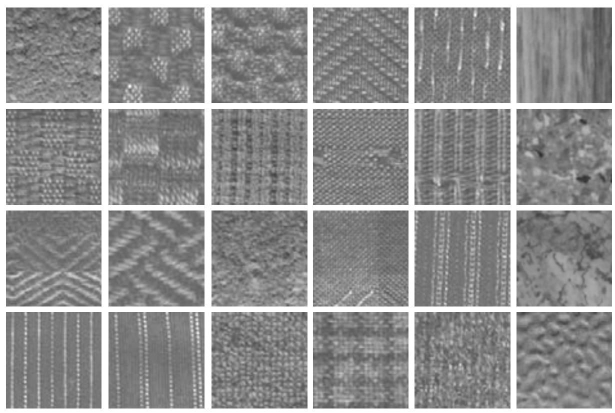

FIG. 11 THE EXAMPLE OF OUTEX DATABASE

TABLE 4 ACCURACY AND CLASSIFICATION TIME ON TEXTURE DATABASE

Method	Accuracy	Classification time
FPM	50	28.2225
HOG	83.3	40.0752
Hu moment	16.7	40.8569
Zernike	12.5	771.897
WCH	66.7	35929

Conclusion and Future Works

In this paper, a Fractionalize principle magnitude based on 1D Fourier transform is present. We evaluated the feature extractors with respect to average accuracy and time consumption of the classification of approved Halal logo. The classification is conducted using 5-fold cross validation scheme to obtain a reliable result. Regarding the result, FPM achieves the highest accuracy and the fastest computation speed compared to other feature extractors. Classification of FPM has been evaluated as well using the other database, and in this paper traffic sign and Outex database are in utilization. The performance of FPM and other methods are compared. For the future work, FPM will be embedded into Smartphone and the performance in classification of the Halal logo is tested using the image captured from the Smartphone camera directly. The performance using the Smartphone camera may different from the one conducted in this experiment and our job is to enhance FPM so that it can perform effectively on Smartphone.

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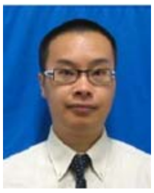

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