Automatic Firing Pin Impression Identification based on Feature Fusion of Fractal Dimension and Geometric Moment

Norazlina Abd Razak[1,2], Choong-Yeun Liong[2], Abdul Aziz Jemain[2], Nor Azura Md Ghani[3] and Shahrudin Zakaria[4]

[1]*Centre for Telecommunication Research & Innovation (CeTRI), Fakulti Kejuruteraan Elektronik dan Kejuruteraan Komputer (FKEKK), Universiti Teknikal Malaysia Melaka (UTeM), Malaysia.*

[2]*School of Mathematical Sciences, Faculty of Sciences and Technology, Universiti Kebangsaan Malaysia, Malaysia.*

[3]*Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Malaysia.*

[4]*Fakulti Teknologi Kejuruteraan Elektrik dan Elektronik, Universiti Teknikal Malaysia Melaka (UTeM), Malaysia.*

norazlina@utem.edu.my

***Abstract*— Automatic firearms identification based on the physical evidence of firing pin impression is very vital for forensic investigation. Currently, due to complex topography of firing pin impression, the firearms identification has been performed manually and the precision of comparisons relies on the human expertise. This approach normally requires a long time to observe through a large number of image database. To overcome this problem, an automatic ballistics identification system using the feature fusion of fractal dimension and geometric moment is proposed. In this study, eight fractal dimension features and 11 geometric moment features were extracted from firing pin impression images of five pistols of the Parabellum Vector SPI 9 mm model. These features were passed to five different machine learning methods for classification. The experimental results indicated that the neural network classifier achieved the highest classification performance of 99.3%, which is a very promising result. In conclusion, the features fusion of fractal dimension techniques and geometrical moments, with neural network as classifier yields impressive results towards automatic pistol detection.**

***Index Terms*— Firing Pin Impression; Fractal Dimension; Geometric Moment; Neural Network.**

I. INTRODUCTION

At present, the existing techniques of feature extraction for the purpose of firearm identification are still not reliable. The identification of firing pin impression (FPI) is still evaluated manually due to the high complexity of its topography. In this case, the use of the automatic identification of firing pin impression as a proof in the court case is still unreliable. Due to this problem, the firearm identification in criminal case still relies heavily on the expertise and experience of the examiners. Therefore, further improvement of intelligent computerized identification of firearm is highly demanded [1]. At the same time, there is a scarcity with respect to studies on automatic identification of firing pin impression [2].

Recently, researchers found that successful firearms identification requires "ballistics signatures" with the characteristics of "individuality" and "reproducible". These "individual characteristics" can form the identity for firearm identification. Further, Zhang has proven statistically that the images of firing pin impressions (FPI) are reproducible [3].

Ballistic identification system (BIS) Evofinder includes three main integral parts, known as the Specimen Analysis System (SAS), Data Acquisition Station (DAS) and Expert Working Station (EWS). The Evofinder system can be described according to Figure 1 [4].

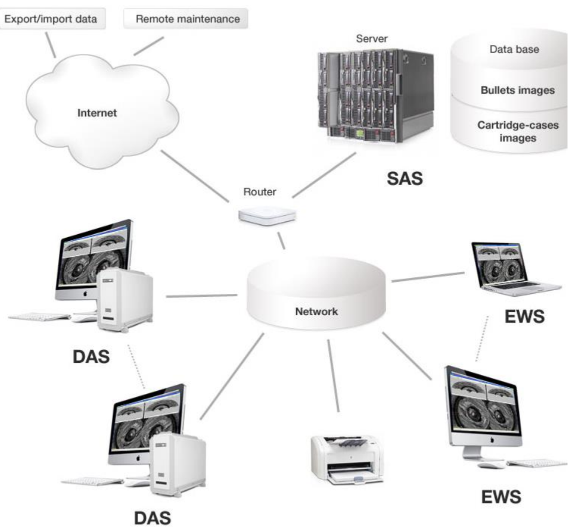

Figure 1: The components of the Evofinder system

SAS performs an automatic identification by comparing the image of FPI against the image stored in the database. DAS is a scanning device to capture digital images of FPI and to store the images into the database. EWS performs the task as a ballistic expertise, and it is able to provide hit-list of images previously saved in the database, which are similar to the image under examination [4].

The automatic ballistic identification system such as IBIS, CONDOR, ALIAS, FIREBALL and EVOFINDER have been developed to help investigators to link crimes [5][6]. It usually takes a long time to compare the crime-involved firing pin image with the stored images because of the huge number of firearm evidence in the form of images data, instead of features stored in the database. The features values to represent images are more effective to be stored in database, which is able to reduce computational time during the firearm recognition, compared to image data.

Therefore, in this experiment, the combination of extracted numerical features of geometric moment features and fractal features will be used as input to the neural network for the purpose of firing pin impression identification. Previously, the neural network has been chosen as classifier in many fields, such as robotic, medical and finance [7].

The remainder of this paper is organized as follows. In section II, the past research of firearm recognition is reviewed. The process of implementation is described clearly in section III starting from raw data collection until classification or recognition process. Section IV exhibits the results, followed by the discussion. Lastly, section V concludes the finding, and suggests for future work.

II. Past Research

There are few techniques to extract features from firing pin impression proposed by researchers. In 2010, an experiment conducted by Ghani, Liong and Jemain [8], had identified 11 best features of geometric moment, with discriminant analysis as a classifier that produce 96.7% classification rate. In 2012, the features of geometric moments were selected involving only those from firing pin impression ring images, and they produced classification result of 98% [7]. In 2017, D. Ott et al. applied the technique of congruent matching cell to identify the 3D images of breech face impressions and firing pin impressions, and found that the identification performance of firing pin impressions was better than the breech face impressions [9]. In 2018, a two-layer backpropagation neural network with 11-11-5 arrangement was used to identify firearms, and this had achieved 87% accuracy [5]. In 2019, the features of three dimension of firing pin impression were extracted by using isotropic areal spline filter, and it obtained high identification accuracy [2].

In the digital image processing, the extracted feature known as fractal dimension represents the roughness to perceive human perception about surface roughness [10]. The fractal analysis easily quantifies the complexity of an image texture surface [11]. There are several techniques to estimate fractal dimension such as box-counting, probability box-counting, differential box-counting, relative differential box-counting and box merging method [12]. The box-counting method is repeatedly used because of its simplicity and reliability [13]. For gray-scale images, the box-counting method has been enhanced to a new technique known as improved box-counting, which is commonly used to measure fractal dimension [10].

III. Implementation

A. Raw Data Collection

The raw image data of cartridge case images had been obtained from the research by Ghani et al. (2010). In this research, marks had been produced on the cartridge case, when five pistols of Parabellum Vektor SPI 9 mm model were fired. The images of the marked cartridge case were then captured by using efficient CONDOR. The five pistols were labelled as Pistol A, B, C, D and E, which produced 150, 150, 150, 149 and 148 cartridge case images respectively. The advantage of using Condor System was that the cartridge case images were not affected by lighting problem. For further improvement on classification, consistent reference is made to Ghani et al. [8][14][5].

B. Segmentation of Firing Pin Impression

The iris segmentation technique suggested by Libor Masek [15] was applied to perform the segmentation of firing pin impression. This automatic segmentation in detecting the whole image of firing pin impression using Hough transform and Canny edge detection was performed in our previous experiment, and it has achieved 93% accuracy [16]. Figure 2 shows the interest area of the FPI that has been segmented from the cartridge case image, namely the whole image. The whole image was then partitioned into two parts or regions, known as the centre image and the ring image, as shown in Figure 3.The partition process is required in order to enhance the feature residing pattern in those regions.

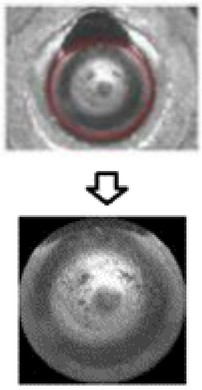

Figure 2: Segmentation of FPI (whole image) from the cartridge case image

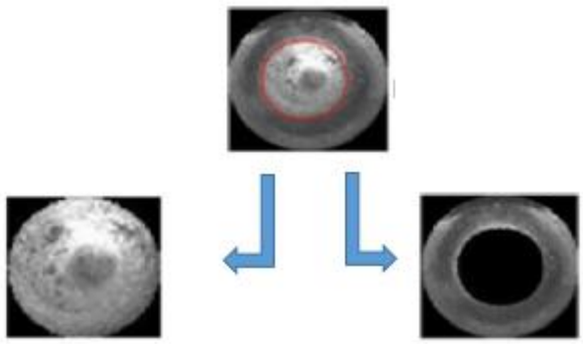

Figure 3: Partition of FPI (whole image) into centre image and ring image

C. Feature Extraction

After the segmentation process, the segmented image of firing pin impression went through the process of feature extraction. The 11 best features selected by Ghani et al. [5], were extracted by using the technique of geometric moments. While the other selected eight features has been extracted by using the technique of fractal. Therefore, there are a total of 19 features times 747 images (19 x 747) have been used as the inputs of machine learning classifier.

IV. Results and Discussion

A. Neural Network

The classification of the FPI was executed by using the neural network toolbox in MATLAB R2016a, which is a feed-forward backpropagation neural network. The architecture of the neural network used in this research is shown in Figure 4.

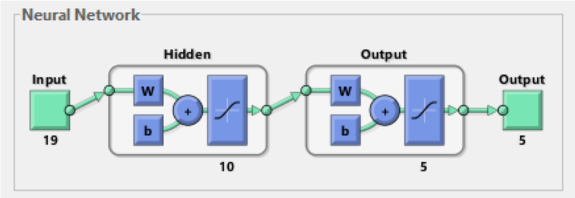

Figure 4: A two-layer feed-forward neural network architecture

The network has varying number of neurons in the hidden layer and five neurons in the output layer. In the previous study by Kamaruddin et al. [7], the backpropagation training algorithm, known as Scaled Conjugate Gradient (SCG) was used for neural network training, and it produced the highest performance, that is 98%. Therefore, this experiment has been conducted using Scaled Conjugate Gradient as the learning algorithm, with a sigmoid transfer function in the hidden layer, and a softmax transfer function in the output layer. In this experiment, 70% (523 images) of the was used for training purpose, while 15% (112 images) of the data was used for validation purpose and another 15% (112 images) for testing purpose. The two-layer feed-forward neural network structure with varying number of neurons in the hidden layer has been executed too. The results of the classification performance with different number of neurons in the hidden layer are shown in Table 1. The best performance is 99.1%, which involves 12, 14, 17, 19 and 20 neurons in the hidden layer.

Table 1
Classification Performance of Different Number of Neurons in Hidden Layer

Number of Neurons	Classification Performance
10	97.3%
11	98.2%
12	99.1%
13	98.2%
14	99.1%
15	98.2%
16	98.2%
17	99.1%
18	98.2%
19	99.1%
20	99.1%

Figure 5 shows that the best classification performance using neural network as a classifier is 99.1%. Only one image out of 112 images has been wrongly classified. The neural network has misclassified only one sample, that is sample C as sample D. Table 2 depicts the results of train accuracy, validation accuracy and test accuracy, which are considerably very high.

Figure 6 shows the overall receiver operating characteristic (ROC) curves represented by the five colored lines. All of the colored lines are close to the top-left corner of the ROC curve, which means that the neural network performs very well. Another way to measure the performance of neural network is by checking the corresponding area under the colored lines. If the area under the curve is close to one, then the performance of network is close to perfection. It is clearly seen in Figure 6 that the area under the five colored line is very close to one, which means the neural network is at the best performance.

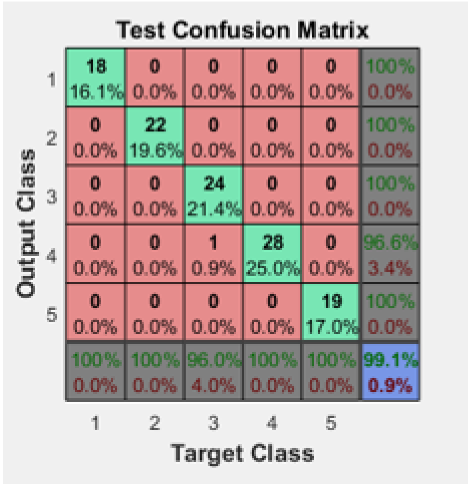

Figure 5: Test confusion matrix

Table 2
Classification Performance Using Neural Network Classifier

Item	Accuracy
Train accuracy	98.5%
Validation accuracy	99.1%
Test accuracy	99.1%

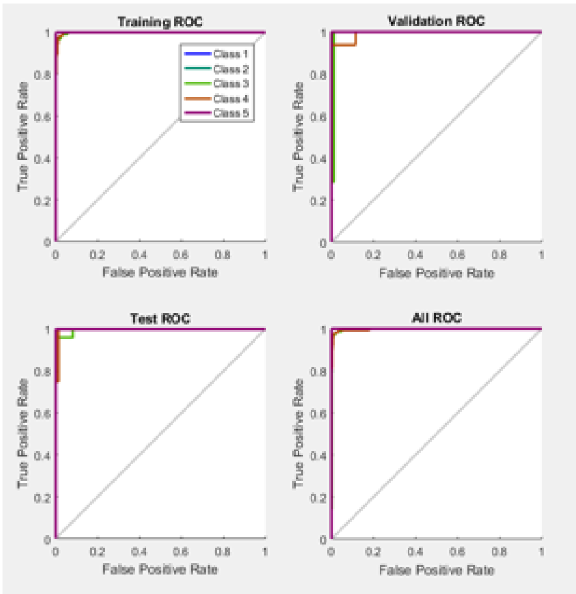

Figure 6: Receiver operating characteristic curves

B. Machine Learning

The performance of other machine learning techniques such as complex Tree, linear discriminant, quadratic Support Vector Machine (SVM) and weighted K Nearest Neighbors (KNN) has also been tested. The results are shown in Table 3.

Table 3
Classification Performance Using Five Different Classifiers

Machine Learning	Accuracy (%)
Complex Tree	91.7
Linear Discriminant	92.0
Quadratic SVM	96.7
Weighted KNN	92.2
Neural Network	99.1

After going through all of the results obtained by using various types of machine learning, we can conclude that the based on the classification result of 99.1%, which is nearly 100%, the technique of feature fusion in between the fractal dimension and the geometric moment, with the use of neural network as classifier, gives the most excellent performance in classifying these five pistols. The result shows that the recognition performance is better than the previous works conducted by other researchers.

V. CONCLUSION AND FURTHER WORK

It can be concluded that the outcome of our latest experiment on firearm identification has achieved 99.1% recognizable, which is better than the past works. For further research, we suggest that the study should focus on the latest architecture of neural network such as the Convolutional Neural Networks as the world now is leading towards the Fourth Industrial Revolution (IR 4.0), where artificial intelligence plays an important role.

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