Firearm Classification using Neural Networks on Ring of Firing Pin Impression Images

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KEYWORD

Firearm Classification
Ring Image
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ABSTRACT

This paper implements two layer neural networks with different feedforward backpropagation algorithms for better performance of firearm classification using numerical features from the ring image. A total of 747 *ring images which are extracted from centre of the firing pin impression have been captured from five different pistols of the Parabellum Vector SPI 9mm model. Then, based on finding from the previous studies, the six best geometric moments numerical features were extracted from those ring images. The elements of the dataset were further randomly divided into the training set* (523 *elements*)*, testing set* (112 *elements*) *and validation set* (112 *elements*) *in accordance with the requirement of the supervised learning nature of the backpropagation neural network* (*BPNN*)*. Empirical results show that a two layer BPNN with a* 6-7-5 *configuration and tansig/tansig transfer functions with 'trainscg' training algorithm has produced the best classification result of* 98%*. The classification result is an improvement compared to the previous studies as well as confirming that the ring image region contains useful information for firearm classification.*

1 Introduction

Since long time ago, criminal acts have been a trouble to the humanity. Crime rates which involve handguns and other firearms are increasing since the 19th century due to the advancement in weapon technology and the mass production of handguns worldwide. Therefore, the effort to substantiate and analyze a firearm used in crimes as an evidence to the court, or so called as forensic ballistics, is really essential in helping to reduce the number of the rising number of crimes. In forensic unit of Royal Malaysian Police (RMP), forensic ballistics involves the analysis on brunt of bullets and the projectile characteristics to ascertain significant evidence that could assist the judgment in the legal system. Moreover, tool mark and firearm inspections involve weaponry, ammunition, as well as mark printings analysis purposely to draw verification of particular firearm or tool used in a certain crime. These marks and projectiles physical attributes on the head of cartridge casings play an important role as robust means from where a bullet is discharged [WIDROW et al., 1994; SMITH *et al.*, 1995]. Unique markings on the cartridge casings and the bullet projections are produced once a bullet is launched. There are in total more than thirty different features of these marks that can produce traceable ballistics fingerprinting similar to normal human fingerprints [BURRARD, 1951]. Here, the type, the model, and the attributes of each individual weapon works successfully as firearm fingerprints. Hence, this forensic technique is used as the elementary to the legal evidence, so that crimes involving firearm can be solved.

There have been several automatic ballistics identification systems invented such as IBIS, CONDOR, ALIAS, FIREBALL and EVOFINDER which help investigators to correlate crime cases by comparing individual characteristics on the bullets and the cartridge case images collected in the current crime to the previous evidences in the database [SMITH and LI, 2008; GERADTS *et al.*, 2001; SMITH and CROSS, 1995]. Usually such task consumes extensive time constraint since it involves comparison with the vast amount of existing evidences in the previous records and the huge amount of firearms to be matched. Problems usually occur whenever the investigators make wrong judgment by naked eye inspection, also known as human errors. It is also such a burden to the investigators because manual inspection needs careful planning and expertise.

Therefore, the firearms cataloguing using numerical features of the ring firing pin impression image via feedforward backpropagation neural network (BPNN) is proposed in this study due to the efficiency and effectiveness of artificial neural networks (ANNs) in the subject of clustering and classification [WIDROW *et al.*, 1994]. This has been proven by the adaptability of ANNs to many fields such as robotic, finance, medicine, and even social studies. The aim of this study is firearm recognition based on the supervised features of ring firing pin impression images using the two layer feedforward BPNN.

In Section 2 previous research related to firearm identification were reviewed, and section 3 explains in detail the background of the data used. Section 4 gives a brief description on the neural network approach implemented, and Section 5 presents the results together with concise discussions on the neural network models adapted and the different backpropagation training algorithms. Lastly, section 6 presents the overall conclusion of the findings and recommendation for further work.

2 Prior research

BONFANTI and KINDER [1999] pointed out that a clear-cut firearm fingerprints starts from the moment of the bullet is released until it hits the target, where every particular mark presents either on the bullet, the cartridge case or the firing barrel. Then, XIN *et al.* [2000] proposed an identification method for firearm official recognition based on magazine cases, mostly at the centre firing tool of cartridge cases from used fired bullets. They initiated an interactive system as well as suitable procedures from which the identification rate can be attained at a greater significant level. Later, GERADTS *et al.* [1999, 2001] emphasized that the firing pin is robust consist of individual details for characterization of the cases. In addition, GHANI *et al.* [2010, 2009a, 2009b] then recommended that the numerical features extracted from the firing pin impression images compilation are feasible features in firearms identification. They successfully formed significant basic statistical besides moment based numerical features for comparison indicators in forensic ballistics specimens. In a recent study, LENG and HUANG [2012] proposed a novel criterion called circle moment invariants for superior firearm classification using the circle-centralized images.

The implementation of neural network in firearm identification had been started since the year of 1994 where KOU *et al.* [1994] used the Self Organizing Feature Map (SOFM) technique for firearm credentials. Their work was only in terms of documented proof that previous research have been done on the subject, and no report on successful events. GERADTS *et al.* [1999, 2001] successfully developed an image matching polar algorithms for firearm identification using the firing pin impression and breach face marks. Their work proved that the extrude effect can be compared easily and efficiently by correlation analysis. As for the suitable lighting conditions needed for subject clarification, errors minimization and output optimization, a pre-processing step was applied via the histogram equalization method, where this has been shown to produce an improved output with greater reproducibility. XIN *et al.* [2000] used fusion strategy interactively to achieve better results using cartridge cases with primer at the center of the cases. However, there was no report of successful features developed at the end of

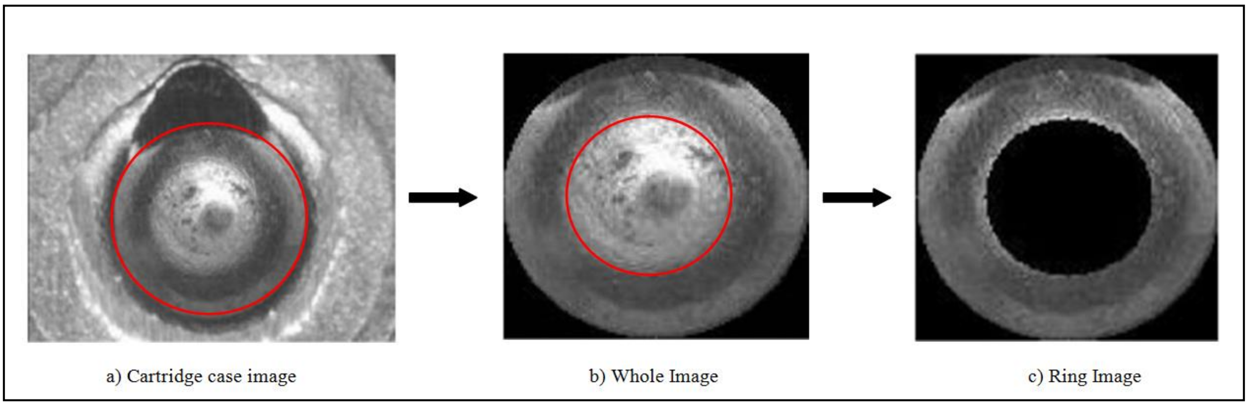

Fig. 1. Extracted regions from cartridge case image

the study. Later, KONG *et al.* [2003] and LI [2006] used neural network based focusing on the SOFM neural network model and integrated it with the decision making strategy itself for firearm identification. Their results show that the hybridized SOFM model produced a fine performance and strength. Based on our previous study [KAMARUDDIN *et al.*, 2011], numerical features of whole firing pin impression images were used to classify firearms. Similar to this study, ANNs was used for classification performance comparison based on cross-validation results.

3 Data background

The numerical features used are secondary data initiated by GHANI *et al.* [2010]. Figure 1(a) shows the image of a head of a cartridge case, Figure 1(b) the whole of the firing pin impression image, and Figure 1(c) shows the ring image of the firing pin impression, our region of interest extracted from the whole image (b). There were originally 16 features of ring firing pin impression image [GHANI *et al.*, 2010, 2009a, 2009b] but in this work we only considered the selected best six features identified in the previous studies.

The sample size of this study is 747 numerical feature vectors, which means we have sufficient sample elements as inputs in the neural network method as proposed by MASTERS [1993] whereby the minimum number of inputs in a neural network should be more than hundreds.

The dependent variables or categorical variables are the different types of pistol used, labeled as A, B, C, D and E. The independent variables are the best six geometric moment features of the ring image which are interval variables. The neural network method was implemented using MATLAB R2010a.

In Table 1, the descriptions and notations of the selected six features of the ring image of firing pin impression as the independent variables is clearly shown. The feature with notation M_{03} implies the geometric moment with order-3. The features adapted were based on the recommendations from our previous studies. For further details and descriptions on the features used, please refer to the GHANI *et al.* [2010, 2009a, 2009b].

Table. 1. The 6 best features of the ring firing pin impression images

No	Description	Notation
1.	M_{00} RING IMAGE	MR_{00}
2.	M_{03} RING IMAGE	MR_{03}
3.	M_{10} RING IMAGE	MR_{10}
4.	M_{11} RING IMAGE	MR_{11}
5.	M_{12} RING IMAGE	MR_{12}
6.	M_{21} RING IMAGE	MR_{21}

4 Neural network approach

Neural network replicates the mechanism of an ordinary human brain functions and complexity in learning ambiance and making judgments which involves a massively parallel distributed processor (neurocomputer) that has a natural tendency for storing experiential knowledge and automatic surroundings adaptation ability. The procedure of learning process is known as learning algorithm. Exertion on artificial neural networks has been provoked by the understanding of human brain complex mechanism with the support of the conventional digital computer.

Using adequate data descriptions and estimated outcomes, the arrangement of the artificial neural network can be formed easily. Multilayer perceptrons (MLPs) are basically the feedforward networks with several hidden neurons and at least a hidden layer. In this study, a two layer learning neural network was employed.

A two layer feedforward BPNN is used to recognize the five different types of pistols. The two layers in the network consist of a computed hidden layer and a target output layer. The neurons in the input layer are related to the normalized inputs of numerical features of the firing pin impression images, and the number of output elements is linked to the number of distinct classes which are the different types of pistols under study. In the hidden layer, the weight matrices are linked to the inputs as input weights (IW). Then, the weight matrices are linked from the hidden layer to the output layer by layer weights (LW). Moreover, S1 and S2 denote first and second layer respectively. In neural network, the outputs of every intermediary layer are the incoming inputs to the subsequent layer. In our case, layer 2 was analyzed as a layer network with $LW^{2,1}$ weight matrix of S2 x S1 dimension, where S1 was outputs of the first layer and S2 are the output layer neurons. The inputs to layer 2 can be denoted as A1 whereas A2 is the network desired outputs, Y. B1 and B2 signify bias of the first and the second layer respectively. Meanwhile, F1 and F2 refer to the activation functions of layers one and layer two in the two layer network respectively. Overall, the equations the two layer neural network adapted in this study can be simplified as:

first layer,

$$A1 = F1(IW^{1,1}[P] + B1) \qquad (1)$$

second layer,

$$\begin{aligned} A2 &= F2(LW^{2,1}[A1] + B2) \\ &= F2(LW^{2,1}[F1(IW^{1,1}[P] + B1)] + B2) \end{aligned}$$

$$A2 = Y \qquad (2)$$

The common learning rule for a training set of the MLP is the backpropagation algorithm (BPA). Basically, BPA involves two stages; feedforward and backward phases. At the feedforward stage, the inputs are propagated forward through the input nodes to compute the output units, and then at the backward phase, the connection weights are updated by subtracting the computed and the actual units at the output layer [MASTERS, 1993; EBERHART and DOBBINS, 1990].

In the study, supervised training was the main concern whereby the inputs and outputs are known at the very beginning [PANCA *et al.*, 2010]. Under pattern recognition theory, the data were separated into three sets; training (70%), testing (15%) and validation (15%) sets. The training set consists of important inputs to be recognized parallel to the outputs of desire. The subset or samples in the training set were selected and learned automatically one by one in the network. In our case, we have altogether six samples due to the six geometric moment features of ring firing pin impression images as inputs. For each sample, the outputs obtained at the end of the network were matched up to the desired outputs until all subsets of training samples were completely processed, where the weights that connections of the neurons in the network were updated. Here, the errors of every layer of the network's result were reduced, and optimal results were acquired with respect to the desired outputs.

Figure 2 shows the procedure of finding the optimal feedforward BPNN. From the figure, the first five steps are taken from GHANI *et al.* [2009b] which are cartridge case inputs, image processing and segmentation, and numerical features selection using Geometric Moments. In this paper, our further attempts are towards constructing the two layer feedforward BPNN starting from normalizing the data to adjusting weights and biases using different backpropagation training algorithms exist in MATLAB for the optimum classification results.

The MATLAB Neural Network Toolbox [DEMUTH and BEALE, 2001] is proficient to execute the faster training methods and not just gradient descent algorithms, which converge from ten to one hundred times faster. The faster algorithms can be devided into two categories, heuristic approaches (e.g. traingda, traingdx and trainrp) and numerical optimization approaches (e.g. traincgf, traincgp, trainscg, trainbfg, trainoss, and trainlm). Heuristic approaches are advancement from the standard gradient descent algorithm, while numerical optimization approaches are the application of standard optimization techniques. The significant part of this study is the use of random backpropagation training algorithms because not every single algorithm is best suited to all problems according to DEMUTH and BEALE [2001].

A two layer network of sigmoid activation function in the first layer and linear activation function in the second layer is efficient to compute any functional relationship of inputs and outputs [DEMUTH and BEALE, 2001]. In the study, two different approaches of network architectures were applied; a two layer tansig/tansig network (Figure 3), and a two layer tansig/purelin network.

We focused on the use of tansig activation function in both first and second layers because it was the most flexible transfer functions for learning the boolean values (0 to 1). The inputs and outputs of the network were automatically transformed into binary values during data normalization and after that the classification values were created by the network. The two layer tansig/purelin network is able to embody any functional inputs and outputs relationship with adequate neurons.

5 Results and discussion

At this point, the classification performances are explained briefly based on two distinct neural network approaches with different types of BPA using overall correct classification rate with respect to the six features of ring firing pin impression image.

Backpropagation Training Algorithms	Overall Correct Classification Rate	Number of neurons	
		L1	L2
traingd	91%	7	5
traingdm	76%	7	5
traindx	65%	7	5
trainrp	45%	7	5
traincgf	68%	7	5
traincgp	71%	7	5
traincgb	73%	7	5
trainscg	98%	7	5
trainbfg	74%	7	5
trainoss	83%	7	5
trainlm	66%	7	5
trainbr	49%	7	5

Table. 2. Classification rates using different backpropagation training algorithms based on the two layer network of tansig/tansig transfer functions

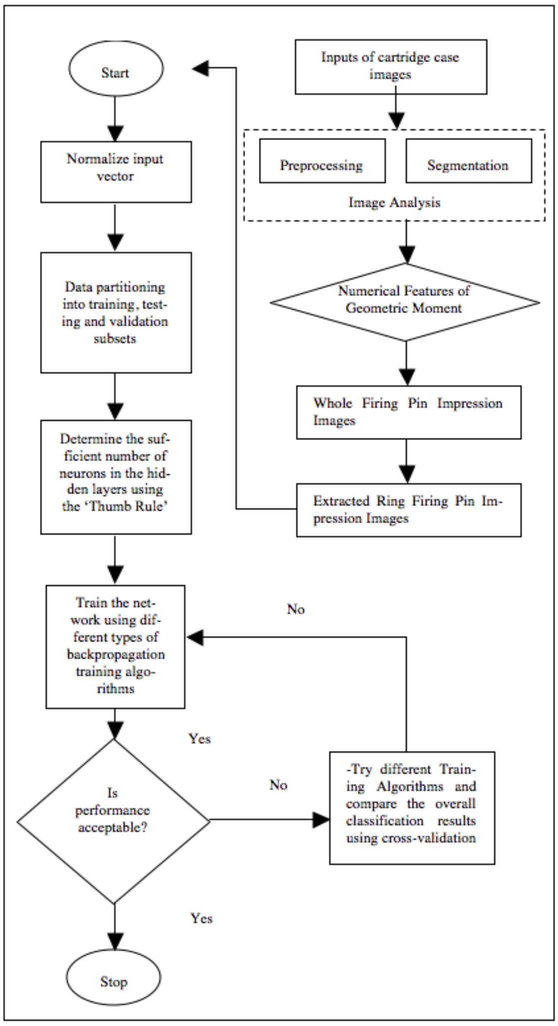

Fig. 2. The procedure of the study

Table 2 presents the classification results from the 6 x 523 inputs. The two layer tansig/tansig network learned the inputs and classified them correct to the types of pistol used in an efficient manner. It is clear that almost all the pistols were classified correctly with greater than 70% correct classification rates, such as traingd (91%), traingdm (76%), traincgp (71%), traincgb (73%), trainbfg (74%) and trainoss (83%). However trainrp and trainbr were not suitable in such case where the overall correct classification rates were less than 60%; 45% and 49% respectively. It is clearly proven here that using the numerical features of ring firing pin impression image are adequate to classify the firearms used. Apparently, trainscg training algorithm in a linear two layer feedforward BPNN with tansig/tansig transfer functions shows the best result of overall correct classification rate based on ring firing pin impression image (98%).

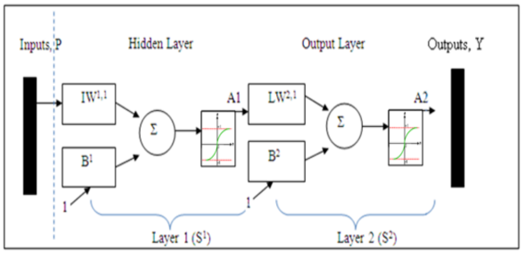

Fig. 3. Two layer tansig/tansig network

Backpropagation Training Algorithms	Overall Correct Classification Rate	Number of neurons	
		L1	L2
traingd	91%	7	5
traingdm	76%	7	5
traindx	65%	7	5
trainrp	45%	7	5
traincgf	68%	7	5
traincgp	71%	7	5
traincgb	73%	7	5
trainscg	98%	7	5
trainbfg	74%	7	5
trainoss	83%	7	5
trainlm	66%	7	5
trainbr	49%	7	5

Table. 3. Classification rates using different backpropagation training algorithms based on the two layer network of tansig/purelin transfer functions

On the other hand, Table 3 shows the classification results based on different backpropagation training algorithms approach using overall correct classification rate with respect to the features of ring firing pin impression image. Here, the configuration of the two layer tansig/purelin with 6-7-5 linear structure network was implemented. In the same way as the previous tansig/tansig network, the different backpropagation training algorithms were also implemented in order to investigate their suitability in the network and classification performance by the overall correct classification rate greater than 70%. Based on Table 3, the suitable backpropagation training algorithms include traingdm (74%), traincgf (71%), traincgp (79%), traincgb (82%), trainscg (85%), trainbfg (78%) and trainoss (78%). However, it appeared that trainlm produced the highest score of 93% which indicates that the algorithm classify the most target set to the validated set correctly according to the types of pistol used.

6 Conclusions

Overall, the best model in this research was the linear two layer feedforward BPNN with tansig/purelin transfer functions using 'trainscg' training algorithm with 6-7-5 network configuration. The overall correct classification rate of 98% further assure the effectiveness of using the numeric geometric moment features in firearm cataloguing. We can conclude that the numerical features of the ring firing pin impression images are better indicators in firearm classification compared to our previous work using numerical features of whole firing pin impression images in [KAMARUDDIN *et al.*, 2011], where the overall classification rate was 96%. The result is also confirming that the ring image region contains useful information for firearm classification. The classification result is as good as the work done by LENG and HUANG [2012].

Further works will be carried out using the basic statistical features produced in the earlier studies [GHANI *et al.*, 2010, 2009a, 2009b], as well as to investigate on the use of other neural network techniques, such as the convolution neural network where the nuances of the images can be learned in more detailed and more efficiently.

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