2007

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Li, D. (2007). Li, D. (Ed.). Firearm identification with hierarchical neural networks by analyzing the firing pin images retrieved from cartridge cases. *In Li, D. Proceedings of the Sixth International Workshop for Applied PKC (IWAP2007), Mt. Lawley Campus, Edith Cowan University, 3rd-4th December, 2007.* Western Australia: Edith Cowan University. pp.70-78

Firearm Identification with Hierarchical Neural Networks by analyzing the firing pin Images retrieved from cartridge cases

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Abstract

When a gun is fired, characteristic markings on the cartridge and projectile of a bullet are produced. Over thirty different features can be distinguished from observing these marks, which in combination produce a "fingerprint" for identification of a firearm. In this paper, through the use of hierarchial neural networks a firearm identification system based on cartridge case images is proposed. We focus on the cartridge case identification of rim-fire mechanism. Experiments show that the model proposed has high performance and robustness by integrating two levels Self-Organizing Feature Map (SOFM) neural networks and the decision-making strategy. This model will also make a significant contribution towards the further processing, such as the more efficient and precise identification of cartridge cases by combination with more characteristics on cartridge cases images.

Keywords: Firearm identification; Neural networks; Image processing.

Introduction

A precise tool for identifying the firearm from which a bullet is discharged [1] [2] is the analysis of marks on bullet casings and projectiles. When a gun is fired, characteristic markings on the cartridge and projectile of a bullet are produced. Over thirty different features within these marks can be distinguished, which in combination produce a "fingerprint" for identification of a firearm [3]. In cases where the use of firearms is involve, this forensic technique is the vital element for legal evidence. It will be possible to identify not only the type and model of a firearm, but also each individual weapon as effectively as human fingerprint identification can be achieved; given this means of automatically analyzing features within such a firearm fingerprint.

Due to the skill required and intensive nature of ballistics identification, law enforcement agencies around the world have expressed great interest in the application of ballistics imaging identification systems to both introduce reliability (or repeatability) to the process, and also to greatly reduce the time for a positive identification. Several ballistics identification systems are available either in a commercial form or in a beta-test state. A Canadian company, Walsh Automation, has already developed a commercial system called "Bulletproof", which can acquire and store images of projectiles and cartridge cases, and automatically search the image database for particular striations on projectiles but not impressed markings or striations on cartridge cases. This inherent limitation of the system with respect to cartridge cases of the system has prohibited its use. The Edith Cowan University of Australia, in conjunction with the Western Australia Police, has developed a prototype database called FIREBALL [4]. It has the capability of interactively obtaining position metrics for the impression of firing-pin mark, ejector mark, and extractor mark and also of storing and retrieving images of cartridge cases heads. The limitation of the system is that the position and shape of the impression images must be located and traced manually by users.

The papers on the automatic identification of cartridge cases are hardly to be found. Le-Ping Xin [5] proposed a cartridge cases based identification system for firearm authentication. His work was focused on the cartridge cases of center-fire mechanism. And he also provided a decision strategy from which the high recognition rate would be achieved interactively. Chenyuan Kou et al. [6] described a neural network based model for the identification of the chambering marks on cartridge cases. But no experiment results were given in their paper.

In this paper, the method proposed, is a system for identifying the firing pin marks of cartridge cases images automatically using a hierarchical neural network model. The main focus is on the consideration of rim-firing pin mark identification. The system will also make a significant contribution towards the efficient and precise identification of cartridge cases in the further processing, such as the locating and coding of ejector marks, extractor marks and chambering marks of cartridge cases. In Section 2, the SOFM neural network and the methods of image processing in our study is described briefly. The capturing and preprocessing of cartridge cases images are presented in Section 3. The model based on a hierarchical neural networks for identification of cartridge cases images is proposed in Section 4. Section 5 gives a numeric experiment. Finally, the conclusion is presented in Section 6.

SOFM and Image Processing

2.1 SOFM Neural Network

We pick the Self-Organizing Feature Map (SOFM) neural networks as the basic classifying units in our identification system. This system has been applied to the study of complex problems such as speech recognition, combinatorial optimization, control, pattern recognition and modeling of the structure of the visual cortex [7], [8], [9] and [10]. The SOFM we used is a kind of un-supervised neural network models, it in effect represents the result of a vector quantization algorithm that places a number of reference or codebook vectors into a high-dimension input data space to approximate defined between the reference vectors, the relative values of the latter are made to depend on ate to its data set in an ordered fashion. When local-order relations are each other as if there neighboring values would lies along an "elastic surface". By means of the self-organizing algorithm, this "surface" becomes defined as a kind of nonlinear regression of the reference vectors through the data points [11].

We employ the standard Kohonen's SOFM algorithm summarized in Table 1, the topology of SOFM is shown in Fig.1.

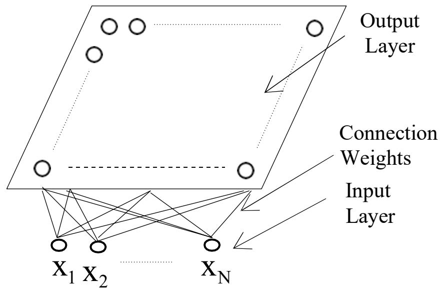


Fig.1. The topology of SOFM

2.2 Image Processing, Feature Extraction

Contrast Enhancement. One of the general functions in image preprocessing is the contrast enhancement transformation [12], and function is expressed in Equation (1). Low-contrast images can result from poor lighting conditions, lack of dynamic rang in the imaging sensor, or even wrong setting of a lens aperture during image acquisition. The idea behind contrast enhancement is to increase the dynamic range of the gray levels in the image being processed. The image shown in Fig.2b is transformed by contrast enhancement.

Polar Transaction. During the stage of image preprocessing, polar transformation is also a useful tool. In our study, the polar transformation can bring us some advantages: In the test phase (see Section 4), we only move the detecting windows over the testing images in direction of horizontal and vertical rather than rotating the testing images or the detecting windows. This will decrease the numerical error and increase the efficiency. Under the Polar Systems, we can get more informations about the testing images. Some images that have similar shapes may be different in shapes and be distinguished in Polar Systems.

Table 1. The Unsupervised SOFM Algorithm

Step1. Initialize the weights for the given size map. Initialize the learning rate parameter, neighborhood size and set the number of unsupervised learning iterations.
Step2. Present the input feature vector $x = [x_1, x_2, \cdots, x_n, \cdots, x_N]$ in the training data set, where x_n is the nth element in the feature vector.
Step3. Determine the winner node c such that $\lVert x - w_c \rVert = \min_i \{ \lVert x - w_i \rVert \}$
Step4. Update the weights, w_i's, within the neighborhood of node c, $N_c(t)$, using the standard updating rule: $w_i(t+1) = w_i(t) + \alpha(t)[x_n - w_i(t)]$, where $i \in N_c(t)$.
Step5. Update learning rate, $\alpha(t)$, and neighborhood size, $N_c(t)$. $\alpha(t+1) = \alpha(0)\{1 - t/K\}$; $N_i(t+1) = N_i(0)\{1 - t/K\}$, where K is a constant and is usually set to be equal to the total number of iterations in the self-organizing phase.
Step6. Repeat 2-5 for the specified number of unsupervised learning iterations.

$$f(x) = \begin{cases} \dfrac{y_1}{x_1} x, & x < x_1 \\ \dfrac{y_2 - y_1}{x_2 - x_1}(x - x_1) + y_1, & x_1 \le x \le x_2 \\ \dfrac{255 - y_2}{255 - x_2}(x - x_2) + y_2, & x > x_2 \end{cases} \quad (1)$$

Feature Extracting. In the recogniton system, feature extracting plays an important role. In the real application, the time consuming of feature extracting technique is also a crucial factor to be considered. So we pick up the morphological gradient [12] of the images processed by the two steps mentioned aboved as the images features. We deal with digital image functions of the form $f(x, y)$ and $b(x, y)$, where $f(x, y)$ is the input image and $b(x, y)$ is a structuring element, itself a subimage function.

Gray-scale dilation of f by b, denoted $f \oplus b$, is defined as

$$(f \oplus b)(s, t) = \max\{ f(s - x, t - y) + b(x, y) \mid (s - x), (t - y) \in D_f; (x, y) \in D_b \} \quad (2)$$

where D_f and D_b are the domains of f and b, respectively.

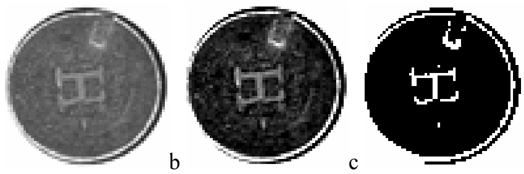
Gray-scale erosion of f by b, denoted $f \ominus b$, is defined as

$$(f \ominus b)(s,t) = \min\{ f(s + x, t + y) - b(x, y) \mid (s + x), (t + y) \in D_f; (x, y) \in D_b \} \quad (3)$$

where D_f and D_b are the domains of f and b, respectively.

The morphological gradient of an image, denoted g, is defined as

$$g = (f \oplus b) - (f \ominus b). \tag{4}$$



a b c

Fig.2. Low-contrast image, a. Result of contrast enhancement, b. Result of threshold, c.

3 Cartridge Cases Images

There are two general types for the firing mechanism: the firing pin is either rim-firing mechanism or center-firing mechanism, as shown in Fig.3. The firing pin mark of cartridge case is formed when the bullet is fired. It is one of the most important characteristics for identifying the individual firearm. A variety of firing pins marks have been used in the manufacture of firearms for the rim-firing cartridge cases. In our study, the cartridge cases belonged to six guns can be classified into six types by shape of firing pin marks (shown in Fig.4).

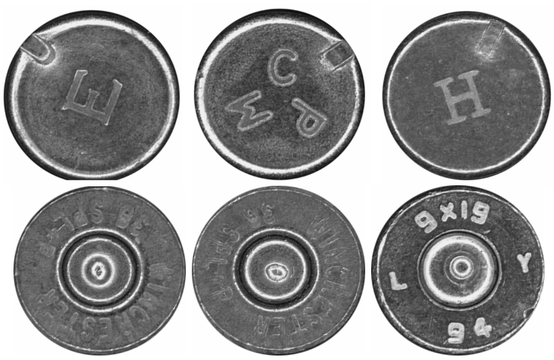


Fig.3. Rim-firing, first row; Center-firing, second row.

All the images of cartridge cases are obtained through the optical microscope in the real application. So some information such as the depth of the impression will be dismissed. Other factors such as the lighting conditions, the material of cartridge cases, and the stamp letters of manufacturer can bring strong noise into the cartridge cases images or damage the shapes of the cartridge cases images. These would all bring many difficulties to feature extracting and identifying. The lighting conditions for the image capturing of cartridge case is crucially importance. In order to produce high contrast of striation (firing-pin mark) on the cartridge cases, the illuminator must be installed at an angle of greater than 45 degree from normal to the plane of the head of the cartridge [1].

The 150 rim-fire cartridge cases, which are belonged to six guns, provided by the Western Australia Police are captured through the optical microscope, one image for each, formed 150 BMP files in gray scale size by 244×240 pixels, and classified into six types by shape of firing pin marks. They are: 1. U-shaped pin mark, 2. Axe-head pin mark, 3. Rectangular (Short) pin mark, 4. Rectangular (Long) pin mark, 5. Square pin mark, 6. Slant pin mark. Examples of the six types are shown in Fig.4 (The numbers below these figures labeled the class number associated with each cartridge cases). We choose 50 images including the images of all the six guns randomly to form the set C_0 and form the testing set T for the rest images. Then, the images of set C_0 are processed through the image processing and feature extraction stage (shown in Fig. 5) discussed in Section 2.2.

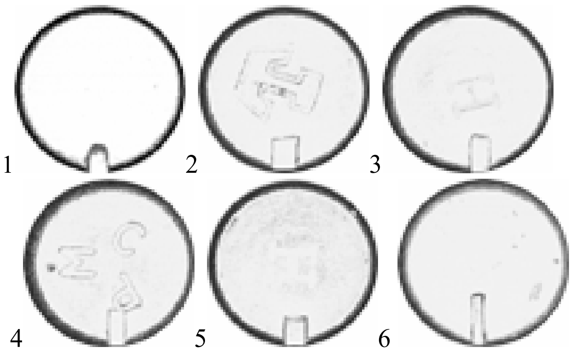


Fig.4. Six type of cartridge cases images

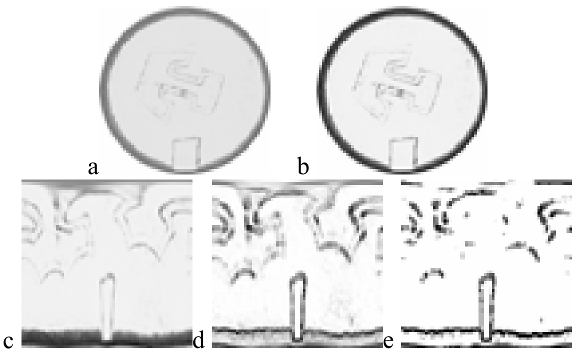
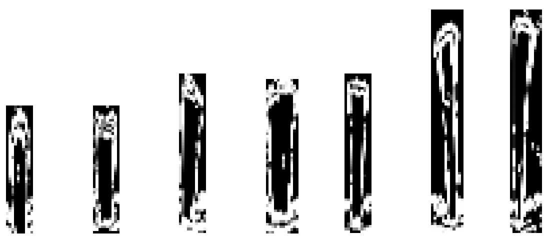


Fig.5. The original image a, the contrast stretching b, the polar transformation c, the morphological gradient d, the threshold e.

Now that the above transformations for the images of every type is finished, we need a "window" operation:
First, windows, size by $n_i \times m_i$ pixels, are used to copy the sub-images---the firing pin marks of the cartridge cases images processed before, where i stands for the label of the class to which the firing pin marks belong. The sizes of six type windows associated with six type firing pin marks are as follows in Table2. Second, the images (the firing pin marks) within these six type windows are copied into windows with size normalized by 48×196 pixels to meet the need of having unified input units of SOFM. The process is shown in Fig.6. In addition, we process part of images obtained as mentioned above in the manners: a. Shifted up to two pixels by the direction left, right, up, and down. b. Scaled by factor 0.95 and 0.90, this is in order to make our model have some robustness to subtle changes in the testing cartridge cases images. All the images we obtained through these processing above, with the number of 350, are combined into a training set C for the model based on SOFM, which will be discussed in the following section.

Table2. The Size (in pixels) of Six Type Windows

Type 1	20×96	Type 2	20×96
Type 3	20×120	Type 4	24×116
Type 5	20×120	Type 6	24×168



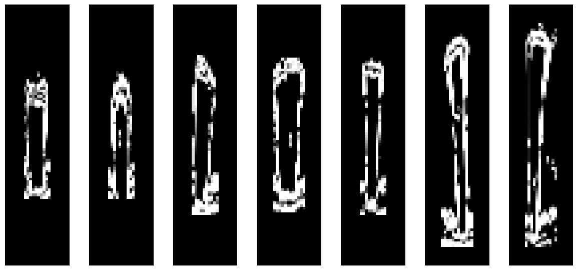


Fig.6. Six type of firing pin marks within windows with size normalization. The first row shows the six firing pin marks within six type windows. The second row shows the firing pin marks within windows with size normalization.

4 Hierarchical Identification Model

In this section, a hierarchical firearm identification model based on cartridge cases images is proposed. The structure of the model, the training, testing of SOFM, and decision-making strategy is given in details in following parts, respectively.

Identification Model. The system proposed is comprised of three stages as shown in Fig.7, the preprocessing stage mentioned in Section 2 and Section 3, the classification stage based on neural networks involving two levels SOFM neural networks and the decision-making stage. In our study, the two levels SOFM neural networks are:

The first level, which has one SOFM neural network (as shown in Fig.1) labeled by $SOFM_0$ acting as a coarse classifier among the training (or testing) patterns presented to it. The training or learning processing is the same as that mentioned in Section 2, which belongs to the type of unsupervised learning.

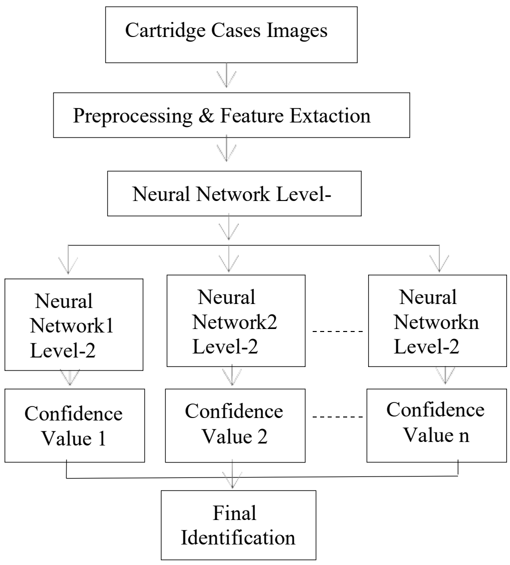


Fig.7. The proposed identification system

The second level neural networks are composed of several child SOFM networks denoted by $SOFM_i$ i = 1, 2, - , n , where n is the number of child SOFM networks, making fine identification among the patterns classified by $SOFM_0$ (or the output of $SOFM_0$).

Training. In our study method, The training or learning processing for $SOFM_0$ is as same as that mentioned in Table1, which belongs to the type of unsupervised learning (we use the images of C to train the $SOFM_0$. The number of neurons in input layer is48 x 196, corresponding to the size of windows normalized mentioned before). In the training phase, a neuron can be removed from the network, when the neuron of output layer is inactive for a period of time. A neuron may be considered inactive if it is not chosen frequently as the winner over a finite time interval. After being trained, the neurons, which are active with high output value in the output layer of $SOFM_0$, stand for the classes to which the training images (or the testing specimens) belong. In our study, the training set C has been parted into several subsets by the result of classification of $SOFM_0$. Combination of these subsets in proper manners achieve training sets for the SOFMs of second level. The second level SOFM neural networks are generated when the positions of two classes in the output layer are very close or overlapping. The training sets are formed by combining the two of class patterns those are close or overlapping. The training processing is as same as $SOFM_0$.

Testing. The testing procedure for firearm identification system is as follows:

Step1. Select a testing cartridge case image from the testing set T , and present this testing pattern to the first stage of identification system--the preprocessing stage.

Step 2. Select a type of window from all types in turn, then move this window over the testing pattern processed in Step1 at every location by every pixel horizontally and vertically, pick up the sub-images.

Step3. Present all the sub-images to the $SOFM_0$ in turn, and then to $SOFM_i$ by the result of $SOFM_0$, and calculate the confidence values with Formula (5) for each sub-image. Return Step2 until all type windows are used up.

Step4. Present these confidence values to the third stage, the decision-making stage, and calculate the finnal result for the testing cartridge case image by Formula (6) and (7).

Decision-making Strategy. Due to the reasons of noise, lighting conditions, and the trademarks on the head of cartridge cases images, the following situation could generally be encountered in the testing phase:

a. More than one sub-image under this type window is classified to include a firing pin mark; for a testing cartridge case image, when a type of detecting window is used over the image.

b. For a particular testing cartridge case image, when all types of windows are used over the pattern, more than one sub-image under the different windows is classified to include a type of firing pin mark.

We use a final decision-making mechanism in decision-making stage to solve these problems mentioned above and improve the performance and accuracy, defining a Confidence Function D(i, }) for the testing pattern i to the }th class which measures the ratio between the testing pattern distance to the weight vectors and the average distance of training patterns to the weight vectors, as follows:

$$D(i, \}) = D(\})/D(i, \}), \qquad (5)$$

where dist(}) is the average distant when all the training patterns, which belong to the }th class, are tested with the }th type window, dist (i, }) is the distant resulted when the ith testing pattern is tested using the }th type window. Defining a decision-making rule as follows: i ∈ Class K , if

$$D(i,k) = \min_{\}} \{D(i, \}) > �_{\}}\}, \ \} = 1,\ 2, \cdots n, \qquad (6)$$

where $�_{\}}$ $\} = 1,\ 2, \cdots n$, is an appropriate threshold selected for the class } by experiments. In generally, for the unbalanced distribution of training patterns we get in the pattern space, results the unbalance in the neural network for each class. Hence, $�_{\}}$ for every class is not unique.

Defining a rejection rule as follows, testing pattern i is rejected by all classes, if

$$D(i, \}) < �_{\}}, \ \} = 1,\ 2, \cdots n, \qquad (7)$$

where $�_{\}}$ $\} = 1,\ 2, \cdots n$, is same as in Formula (6).

5 Experimental Results

In our study, we use the following experimental parameters (shown in Table 3) for $SOFM_0$, Level 2 SOFMs and get experimental results over Training set C .

The neurons of the output layer of $SOFM_0$ are divided into six areas separately, through which the specimens of each class are represented, when the training phase is finished. The training set C is divided into three subsets for the training three sub-networks of the second level by the fact: the distribution area of each class is not balanced, some classes are near, and others are apart, in following manner:

Subset c_1 including images labeled with class 1 and 2 is selected as the training set of $SOFM_1$,

Subset c_2 including images labeled with class 3 and 5 is selected as the training set of $SOFM_2$,

Subset c_3 including images labeled with class 4 and 6 is selected as the training set of $SOFM_3$.

Table3. Experimental Parameters for $SOFM_0$, Level 2 SOFMs and Results over Training set C

	Input Layer	Output Layer	(0)	$A_i(0)$
$SOFM_0$	48 x196	9x9	0.60	7
$SOFM_1$	48 x196	3x3	0.05	2
$SOFM_2$	48 x196	5 x 5	0.05	3
$SOFM_3$	48 x196	5 x 5	0.05	2
	training pattern	right rate	error rate	rejection rate
	350	100%	0%	0%

We have the experiment results over testing set T as follows:

Table 4. Experiments Results

Testing pattern	Right rate
100	97.0%
Rejection rate	Error rate
3.0%	0%

Analysis of experiment results

From the results of Table 4, we can see: Identification model in our study can make the combination of location and identification of firing pin mark of cartridge case images into one stage. It shows that the model proposed has high performance and robustness for the testing patterns in aspects as follows: Having high accuracy in location and identification of firing pin marks. Some testing results under Cartesian co-ordinates are shown in Fig.8. Having robustnesses to the noise patterns, to the damaged and deformed patterns shown in Fig.8(8-13). Having some robustnesses to the scaled patterns.

We also see that there still are rejections for some patterns, and we found that the rejection is caused mainly by the following reasons: the high noise on the cartridge images; the letters of trademark on the cartridge images; the similitude of one pattern with others in some location.

Further Work. In order to improve our model to achieve higher performance, we will do some further researching in following aspects:

To improve the quality of image capturing and preprocessing. To extract some fine features with more complex techniques to represent the patterns (training or testing). To integate multiple classifier combination using different features sets.

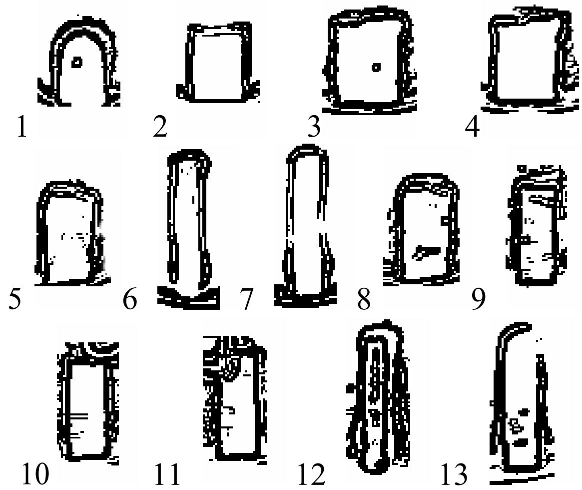


Fig.8. Some right identification results of testing set T

6 Conclusion

In this paper, we have mainly focused on the consideration of rim-firing pin mark identification. Using a hierarchical neural network model, this study is investigating a system for identifying the firing pin marks of cartridge cases images automatically. The identification model in our study can make the combination of location and identification of firing pin mark of cartridge case images into one stage. It shows that the model proposed has high performance and robustness for real testing patterns. The efficiency of this system will also make a significant contribution towards the efficient and precise identification of ballistics specimens in the further processing, such as the more efficient and precise identification of cartridge cases by combination with more characteristics on cartridge cases images.

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