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TECHNICAL NOTE

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Estimation of Bullet Striation Similarity Using Neural Networks

ABSTRACT: A new method that searches for similar striation patterns using neural networks is described. Neural networks have been developed based on the human brain, which is good at pattern recognition. Therefore, neural networks would be expected to be effective in identifying striated toolmarks on bullets. The neural networks used in this study deal with binary signals derived from striation images. This signal plays a significant role in identification, because this signal is the key to the individuality of the striations. The neural network searches a database for similar striations by means of these binary signals. The neural network used here is a multilayer network consisting of 96 neurons in the input layer, 15 neurons in the middle, and one neuron in the output layer. Two signals are inputted into the network and a score is estimated based on the similarity of these signals. For this purpose, the network is assigned to a previous learning. To initially test the validity of the procedure, the network identifies artificial patterns that are randomly produced on a personal computer. The results were acceptable and showed robustness for the deformation of patterns. Moreover, with ten unidentified bullets and ten database bullets, the network consistently was able to select the correct pair.

KEYWORDS: forensic science, neural networks, striation, bullet identification, similarity

A method is proposed that searches for similarities in striation patterns of fired bullets using neural networks. Neural networks are modeled after the structure of the human brain, and the human brain has an advantage over a computer in terms of pattern recognition (1). Therefore, it is likely that neural networks might be suitable for identifying striations such as toolmarks and impressions on fired bullets.

Neural networks have great potential for use as an auto-identification system (2). One of the most important functions of an automated rifling mark identification system is the time spent by the forensic scientist. In the case of an auto-system, some bullets can be selected for inspection by a comparison microscope. Thus, it is not the auto-system but a forensic scientist that makes the final decision in a forensic identification. An ideal algorithm could be used to eliminate bullets that do not need to be compared, and could select likely candidate bullets that have striation patterns that are similar to the striations on the target bullet.

The question arises as to how to estimate these similarities. A number of attempts have been made to view the estimation as a probability and a statistics problem (3,4). The objective of the present paper is to utilize neural networks to estimate similarities of striations.

Another reason to adopt a neural network is that it is robust with respect to changes of patterns. In actual cases, bullets are sometimes deformed by collision that might cause a small deformation in the striation. In addition, a perfect correspondence of two striation patterns is rarely encountered, even if the two are on nondeformed bullets and have been fired from the same firearm, because a minute difference in illumination conditions or the position of the bullet on a stage causes an apparent change in the striation pattern. As described later in this paper, neural networks appear to overcome these obstacles.

A commercial auto-system for bullet identification, IBIS is currently available, but the algorithm proposed here using neural networks bears no relation to IBIS.

Character Extraction

The data inputted directly into neural networks are not an image but a numerical signal, which is derived from the striations on a bullet. The input signal should reflect some characteristics of the striation. This means the identification of the signals serves for that of the striation itself. In this section, the method used to produce the signals is explained. The procedure involves character extraction.

An image of a striation is recognized as a set of bright and dark lines. Fortunately, the texture of a striation is usually uniform along the direction of the scratch. To reduce the influence of noise, the brightness values of pixels along the scratch direction are averaged. Consequently, although an examiner perceives depth/contour variations through gradations in brightness caused by side lighting, in the case of a neural network analysis, two-dimensional information (an image) is converted into a one-dimensional signal. This signal is then converted into a suitable signal for neural networks; the length of the signal is shortened and converted into a binary signal. The length of the original signal equals the number of pixels on an image (about 1200 pixels in this study). On the other hand, as described later, neural networks deal with signals of a 128-bit length. Therefore, the original signal is divided into 128 blocks. If a block has a total brightness value over a threshold, the block is given a score of "1." If the total value of the block is below the threshold, the block is given a score of "0." The threshold is defined empirically. This

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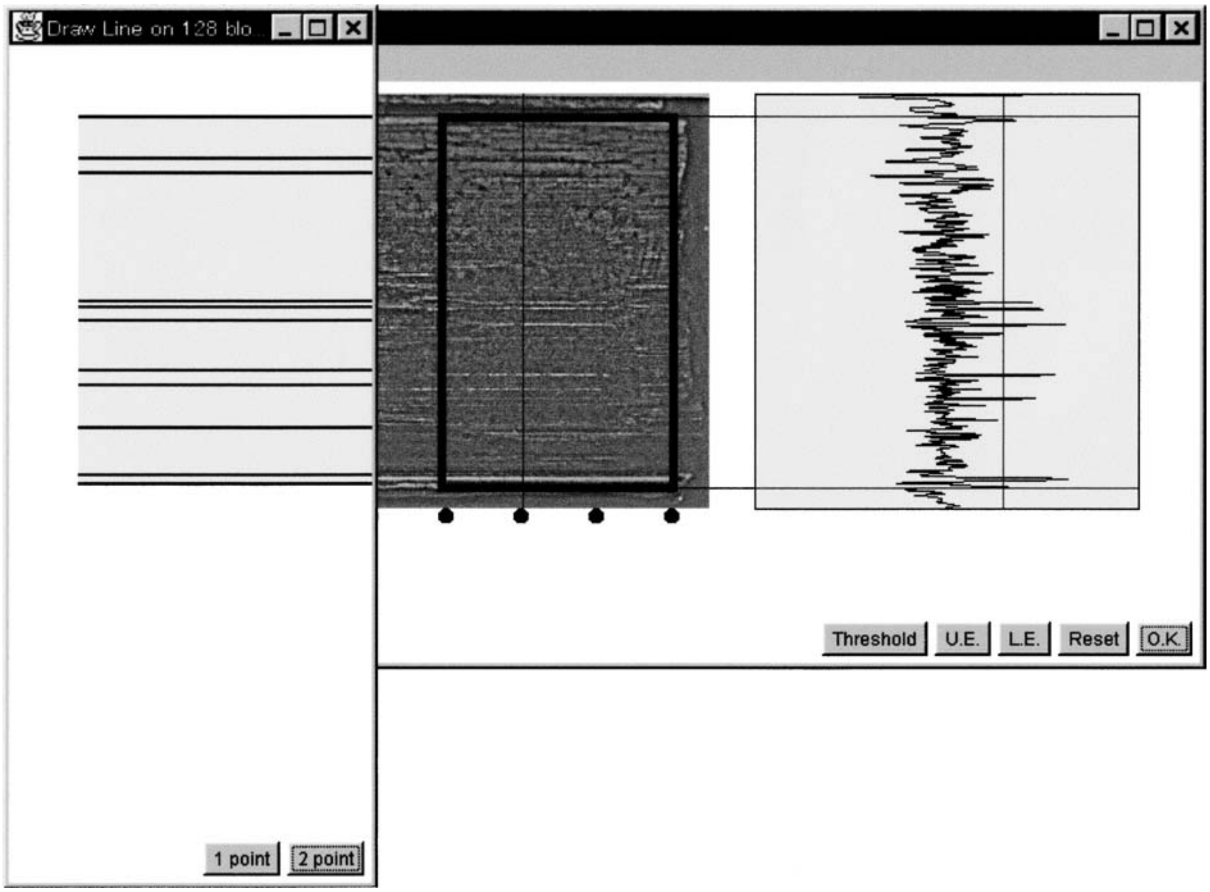

FIG. 1—*PC screen of character-extraction software that derives a binary signal with a 128-bit length from an image of a striated bullet land impression.*

process converts the original signal into a binary signal of 128-bit length.

Figure 1 summarizes the above procedure and shows a computer screen image from the character-extraction software. A digital image of a striation is initially displayed on the background window on the screen. A high-pass filter (5) is applied to the digital image. By observing the screen and dragging the mouse, the examiner creates a rectangle on the striation image. The software then averages the brightness values of the pixels included in the rectangle along the horizontal direction. The averaged brightness value forms a one-dimensional wave signal. The signal is displayed graphically at the right side on the window.

The one-dimensional wave signal is then converted into a binary signal that has a 128-bit length. This converted signal is shown as stripes in the foreground window in Fig. 1.

Here an original image of a land impression can be converted into a binary signal suitable for a neural network.

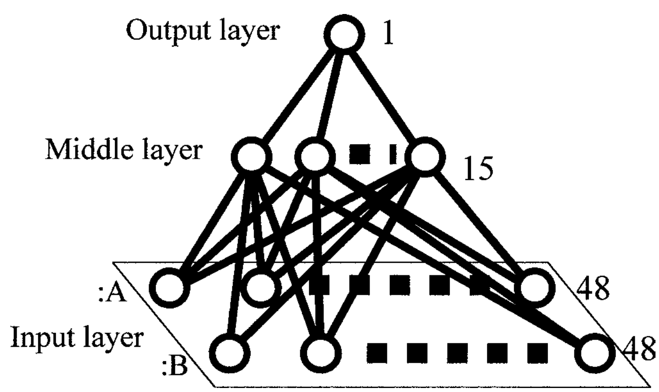

FIG. 2—*Structure of the multi-layer network model with two input layers.*

Neural Networks Model

Generally, there are two types of neural networks: a Hopfield network and a multilayer network (MLN). In this paper, the latter is used. The MLN has a structure of several layers. Each layer consists of a number of nodes called neurons. Each neuron in a layer connects to all neurons of the next layer, and no one neuron connects to any other neurons in the same layer.

The structure of the MLN model is illustrated in Fig. 2. The model used in this study contains three layers where the bottom layer is the input layer and the top layer is the output layer. There are 96 neurons in the input layer, 15 neurons in the middle layer, and only one neuron in the output layer. The neurons in the input layer are divided into two blocks: input blocks A and B. Both input blocks contain 48 neurons.

There are two patterns to be compared in terms of their similarity. Two patterns are inputted into the two input blocks A and B separately. During a learning process, the network is modified so that it outputs a value of near 1 with similar input patterns and a value of near 0 with nonsimilar patterns.

Figure 3 describes the function of a neuron. All neurons of the middle and output layers have the same function. Assuming that a layer (the bottom or middle layer) has N neurons and the output value of each neuron is x_n(n = 1,2...N), the inputted vector of a

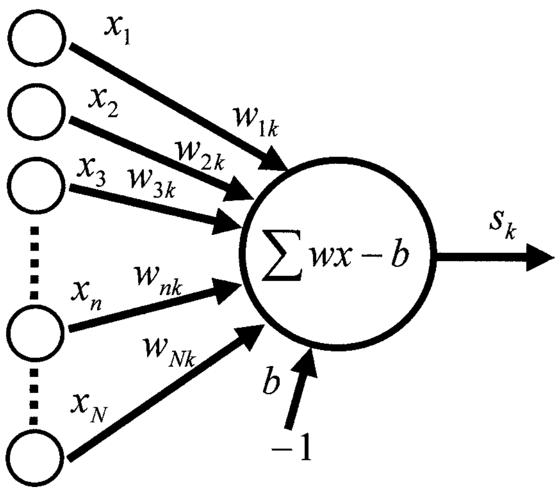

FIG. 3—*Function of a neuron. A neuron in the middle (output) layer is connected to all neurons in the input (middle) layer.*

neuron in the next layer (the middle or top layer respectively), $\vec{x}_k$, can be described as

$$\vec{x}_k = (x_1, x_2, \ldots\ldots, x_N, -1)$$

Each element of $\vec{x}_k$ is multiplied by a coefficient. A set of these coefficients is defined as a weight vector described as

$$\vec{w}_k = (w_{1k}, w_{2k}, \ldots\ldots, w_{Nk}, b_k)$$

b_k denotes "bias." The output value of the neuron, s_k, can then be described as

$$s_k = f(\vec{w}_k \vec{x}_k) = f\left(\sum_{i=1}^{N} w_{ik} x_k - b_k\right)$$

Generally, the sigmoid function is used as the above function f:

$$f(a) = \frac{1}{1 + e^{-a}}$$

The output value of the neuron in the output layer represents the output value of the neural network.

Learning

Learning involves modifying all weight vectors in order to output a desired value at the neuron in the output layer. This desired value is referred to as a "teaching signal."

For defining the teaching signals, the input layer consists of two blocks as described above. The two patterns to be compared are inputted into each block, which contains 48 neurons. Learning patterns are binary signals with a 48-bit length. Each signal consists of only one element with a score of "1" and 47 elements with a score of "0." That is, in the learning process, only one neuron in each block has an input value of "1" (this neuron is referred to as an "excited neuron"), and the other 47 neurons in each block have an input value of "0." A teaching signal is given in the following form $T(i, j)$:

$$T(i, j) = \exp\left\{-\frac{(i-j)^2}{\sigma^2}\right\}$$

$$\text{for} \quad \begin{array}{l} x_k = 1 \text{ (if } k = i\text{)}, x_k = 0 \text{ (if } k \neq i\text{) at the input block A} \\ x_k = 1 \text{ (if } k = j\text{)}, x_k = 0 \text{ (if } k \neq j\text{) at the input block B} \end{array}$$

That is, if two patterns are the same, the output value of this network is "1." In addition, the closer together two positions of the excited neurons are, the closer to "1" the output value will be. On the other hand, the further apart the two positions are, the closer to "0" is the value (Fig. 4).

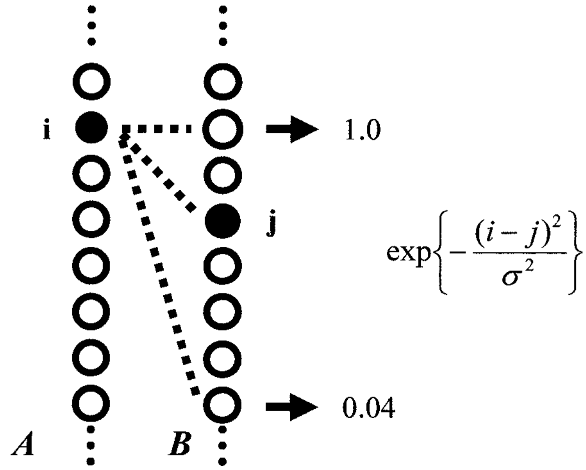

FIG. 4—*Definition of a teaching signal. The exponential function gives high score if two positions of excited neurons are close, and low score if two are not close.*

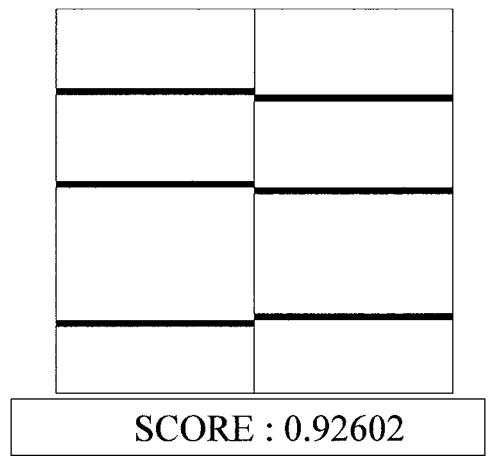

FIG. 5—*Example of comparison of patterns with three excited neurons. Although the MLN learned the pattern with only one excited neuron, it can afford an appropriate score in comparison with multi-excited neurons.*

In conclusion, the goal of this MLN is to output a high score with similar signals and to output a low score with nonsimilar signals.

Two questions arise: Is learning with only one excited neuron suitable for the recognition of striations? Can this algorithm function with several excited neurons? The answer is indicated in Fig. 5. This is a result of a comparison of patterns with three excited neurons in both input blocks. The identical neural network with the above learning gives the score of 0.926.

Simulation

The validity of the MLN is discussed in this section. Before using actual bullets, the MLN was used to identify a number of artificial patterns produced at random by a PC. The artificial patterns have 128 elements. In the previous section, the MLN model has only 48 input elements. On the other hand, a characteristic signal derived from a striation image has 128 elements, as shown in the character extraction section. A signal with 128 elements is then divided into five parts (Fig. 6). Consequently, the MLN outputs the scores of the

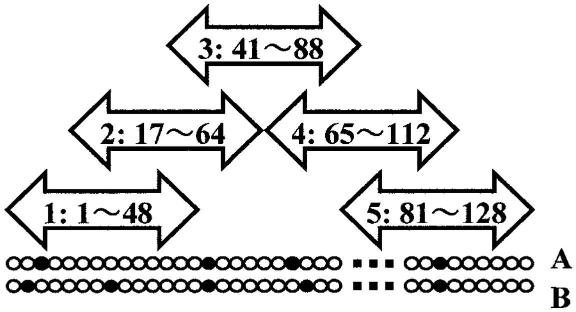

FIG. 6—*Division of whole pattern for the MLN. A 128-bit signal is divided into five blocks.*

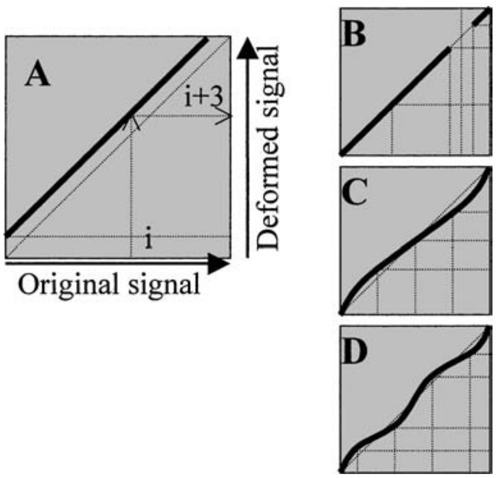

FIG. 7—*Four systems to produce deformed patterns.* (A) *All elements transfer to 3-element backward.* (B) *Elements on a certain part (=20%) disappear.* (C) *Elements tend to gather around the center.* (D) *Elements transfer on a sine wave.*

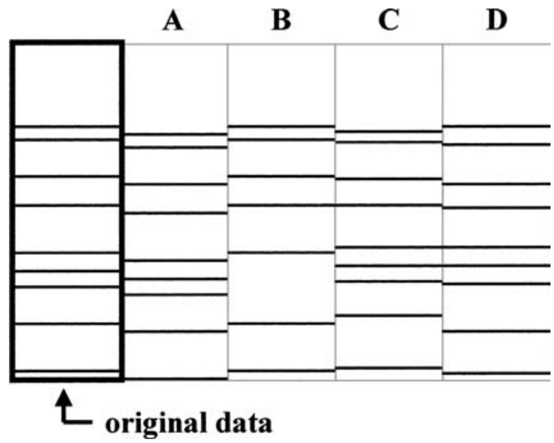

FIG. 8—*Example of original patterns. Deformed patterns by the four systems are shown.*

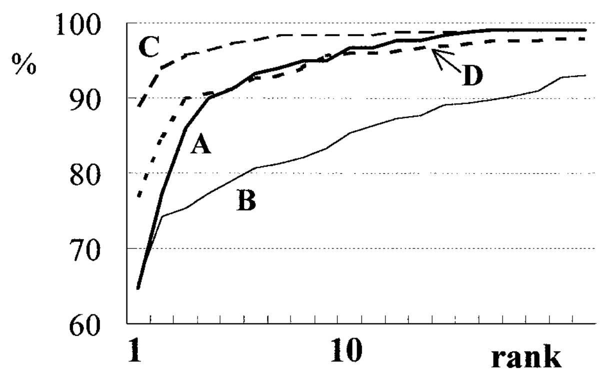

FIG. 9—*Result of simulation with 300 artificial patterns. In the deformation system (A), (C) and (D), over 90% of the original patterns were ranked within the top five. On the other hand, only 85% of the original patterns were ranked within the top ten.*

five parts independently. The final score for similarity is defined as the summation of the five output values.

A PC is used to produce 300 artificial patterns. These patterns are stored as a database. Unidentified patterns are slightly deformed database patterns. The deformed patterns are compared with the database. According to the output score, the MLN determines the ranking of all patterns in the database. A deformed pattern resembles the original. Therefore, if the original pattern ranks high, this simulation is proved successful.

The deformed patterns are produced on the following four systems (Fig. 7);

(A) All elements transfer to 3-element backward.
(B) Elements on a certain part (= 20%) disappear.
(C) Elements tend to gather around the center.
(D) Elements transfer on a sine wave.

A sample of an original pattern and its deformed patterns is shown in Fig. 8. The results of the simulation are also shown in Fig. 9. The latter figure shows the ranking of the original patterns when the MLN is used to compare deformed patterns with the database. In deformed systems (A), (C) and (D), over 91% of the original patterns were ranked within the top five. Over 96% of the patterns were ranked within the top ten. The percentage of the patterns that failed within the top 20 was only 2%. This indicates that if an examiner searches at least 20 striations in the 300 database striations, he should be able to find the answer with a probability of more than 98%.

On the other hand, the accuracy of the MLN was worse for the deformed system (B) than for the others. Only 85% of the original patterns were ranked within the top ten and 7% patterns failed to be included in the top 20. The deformed system (B) erased 20% of the elements of a pattern (= 26 elements). In many cases, many excited neurons corresponding to failure patterns are located in this erased part.

In this simulation, the use of only one striation was the cause of the above results. In fact, the probability of bullet identification will be higher, because a bullet typically contains several striations. This simulation brings validity to the MLN and the learning process. In addition, the MLN, which can shorten the run-time of an inquiry, is robust in terms of identifying changes of patterns.

Experiments

In this section, the retrieval of actual bullets using the MLN is demonstrated. Ten firearms (9 mm Ruger) were used in this experiment, and two bullets were fired from each firearm. One of each pair is reserved as the database (Bullets A′ ∼ J′) and the other was assumed to be an unidentified bullet (Bullets A ∼ J). Bullets A and A′ are fired from the same firearm. Similarly, B and B′ are fired from the same firearm.

TABLE 1—*All results of experiments which identified ten bullets with the ten database bullets. Diagonal elements are the scores with two bullets from the same firearm. A score at the diagonal is the highest in each row.*

	A′†	B′	C′	D′	E′	F′	G′	H′	I′	J′
A*	**1.97**	0.88	1.00	0.97	0.88	0.65	1.43	1.27	0.83	1.25
B	0.81	**3.24**	0.94	1.09	0.74	0.67	1.15	0.91	0.86	1.02
C	1.53	1.20	**2.02**	1.06	1.24	1.07	0.85	1.05	0.90	1.05
D	1.04	1.30	0.84	**1.96**	0.60	0.92	1.19	0.55	0.65	1.22
E	0.94	0.62	1.13	0.39	**1.78**	0.96	0.50	0.48	0.69	1.38
F	0.72	0.50	0.45	0.37	1.15	**2.43**	0.68	1.10	0.59	1.24
G	0.86	1.02	0.83	0.78	0.73	0.58	**2.68**	0.73	0.60	0.92
H	0.83	0.83	0.81	0.53	1.44	0.58	0.62	**2.01**	0.55	0.90
I	1.34	0.85	1.05	1.13	1.13	0.96	0.85	0.89	**2.65**	1.28
J	0.67	0.76	1.14	0.61	1.03	1.17	0.72	0.58	0.81	**3.76**

* A ∼ J: Unidentified bullets.
† A′ ∼ J′: Database bullets.

Each bullet has six land impressions. Therefore, the total score of the six impressions is used as the index of similarities of a bullet. All the results are given in Table 1.

Considering the unidentified bullet "A," all scores of Bullet A compared with the database can be found in row A in Table 1. The neural network afforded the highest score in comparison with A′. The neural network judged that Bullet A′ is the most similar to Bullet A in the database.

Considering other unidentified bullets, it can be seen that the diagonal components in Table 1 provide the highest score in each row. The diagonal component represents a pair of bullets from the same firearm. The results show that the neural network selected the right bullet from the database.

Conclusions

Neural networks are easily used to identify binary signals. The algorithm developed here was effective for the identification of bullets and was able to identify deformed striations. Moreover, it is not necessary to adjust strictly the location of bullets obtained from an image of a land impression, indicating that this could significantly shorten the time needed for an inquiry. Naturally, this algorithm can be used for non-firearm-related striation toolmarks as well. It would also be interesting to see if neural networks could be used effectively in the analysis of nonstriated compression/impression toolmarks.

However, further investigation concerning the use of a neural network for identifying striated toolmarks will be needed. The main goal of this study was to develop a new method for estimating similarity. A much higher number of bullets will be needed for the validation of this algorithm. If the database contains more bullets, there is no guarantee that the MLN will be able to select the right answer correctly.

Finally, a decision on a bullet identification must be made by a forensic scientist. The aim of an automated comparison system is to reduce the labor involved for a scientist. Based on this, a number of algorithms should be used, and these should be part of an automated system.

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