Forensic Retrieval of Striations on Fired Bullets by using 3D Geometric Data

Atsuhiko Banno, Tomohito Masuda and Katsushi Ikeuchi
Institute of Industrial Science, The University of Tokyo
4-6-1 Komaba, Meguro-ku, Tokyo 153-8505, Japan
Email: {vanno, tom, ki}@cvl.iis.u-tokyo.ac.jp

Abstract

Currently, optical devices, such as microscopes and CCD cameras, are mainly utilized for identification of bullets and tool marks in the field of forensic science. While these optical methods are easily manageable and effective, they are under great influence of illumination condition. Besides these appearance-based approaches, we can utilize 3D geometric data of tool marks that are free from lighting condition. Nevertheless, a perfect correspondence of two striation patterns is rarely encountered, even if the two bullets have been fired from the same firearm. Therefore, more robust methods are required. In this study, we propose a two-stage comparison method focused on 3D geometric. At first, we have aligned global shapes and evaluated a global shape similarity. Then small elevations are compared by neural networks; that is local matching. In this stage, rendered images under a unified lighting condition are utilized. By using 2-stage comparison, we have developed a robust method that searches for similar striation patterns.

1. Introduction

Many striation and impression marks caused by various ordinary tools, such as a screwdriver, a crowbar and a hummer, are left at crime scenes. These marks are significant evidences. In particular, striation marks on a fired bullet are important for identifying the suspicious firearm (Fig.1). Forensic scientists identify these striations mainly by using optical tools such as comparison microscopes, CCD cameras and photos. The surfaces of striation have three-dimensional roughness intrinsically. By using optical devices, we compare reflectance images instead of 3D shapes. Appearances of striations through these devices, however, depend on location of light and viewpoint[8]. In other words, it is possible that the same striation has will look different under different lighting conditions. Besides these appearance-based methods[5], we are also able to exploit 3D geometric data of striations. That is model-based methods. The measurement of small elevations on a striation had been difficult in aspect of hard ware. However many sophisticated 3D measurement devices are developed recently and we can easily obtain fine 3D maps of striation surfaces. The shape of striation surface is expected to be printed intrinsic shapes of the tool that caused the striation marks. Moreover, 3D data are independent of lighting condition.

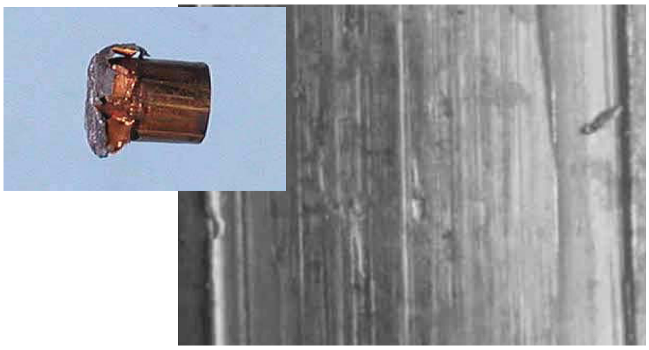

Figure 1. A bullet and a striation mark

In addition, there is another difficulty in identifying striations. That is, a perfect correspondence of two striation patterns is rarely encountered, even if the two are on non-deformed bullets and have been fired from the same firearm (Fig.2). We, therefore, need an algorithm which is robust with respect to minute changes of patterns.

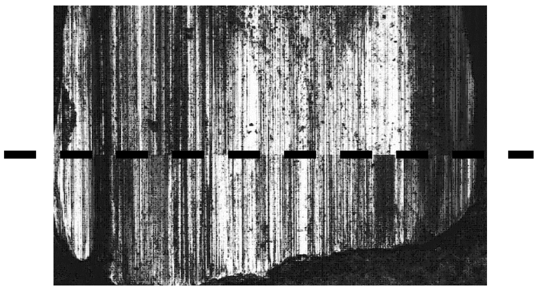

Figure2. An image by a comparison microscope. The correspondence of two striations is "pretty" good

Although there are some researches on 3D surfaces of bullets and tool marks [4][6], they had not led to shape comparisons by using 3D surface data directly. In the field of Japanese archaeology, Masuda et al. [9] have analyzed shape difference of ancient bronze mirrors with a method of computer vision. In this study, we apply this method to identification of bullets, especially landmark impressions. Moreover, by using neural networks, we have developed a robust identification algorithm[1]. Neural networks [11] are modeled after the structure of the human brain, and the human brain has an advantage over a computer in terms of pattern recognition [7]. In this study, neural networks have appeared to overcome minute changes of striation patterns.

At first, we acquired 3D data of striations surfaces and compared global 3D shapes numerically. The distance of two surfaces is calculated for the evaluation of global shape matching. Then neural networks compare local elevation patterns. This two-stage method enabled us to construct a robust identification algorithm of striation patterns.

2. Global shape comparison

2.1 Alignment of 3D data

We obtained 3D data of striations surfaces by a confocal microscope. To compare two shapes, we must move one shape in order to coincide two surfaces better. If the two striations are derived from the same origin, the shapes will be similar. Furthermore, if we could calculate the distance of the two shapes' difference, similarity of two shapes would be estimated according to the distance.

We adopted the alignment method [8], which is a kind of ICP method [1] for shape matching. If two shapes have the same origin, a point on one shape has the corresponding point on the other shape. The location of the corresponding point, however, is usually unknown. Then, we resolve this correspondence problem by iterative method. The objective function, which should be minimized for the alignment, is defined as:

$$f(\mathbf{R},\mathbf{t}) = \sum_{i,j} \left\| \mathbf{R}\mathbf{x}_{\mathrm{i}} + \mathbf{t} - \mathbf{y}_{ji} \right\|$$

$$\begin{aligned} \textit{where} \quad & \mathbf{R}: \text{rotation matrix} \\ & \mathbf{t}: \text{translation vector} \\ & \mathbf{x}_{\mathrm{i}}: i\ th \text{ point in one data} \\ & \mathbf{y}_{\mathrm{ji}}: \text{the corresponding } j\ th \text{ point in} \\ & \qquad \text{the another data for } \mathbf{x}_{\mathrm{i}} \end{aligned}$$

This objective function indicates the summation of distances between all pairs of corresponding points. When the function converges under a threshold, we decide two shapes are similar[2].

We use quaternion to minimize the objective function. By substituting quaternion **q** to rotate matrix R, motion vector **p** can be found as follows.

$$p = \arg\min_{\mathbf{R},\mathbf{t}} f(\mathbf{R},\mathbf{t}) = \arg\min_{\mathbf{q},\mathbf{t}} f(\mathbf{q},\mathbf{t})$$

$$\textit{where} \quad q = [u \quad v \quad w \quad s]$$

Motion vector **p**, that is **q** and **t**, is solved by the conjugate gradient method and line minimization with golden section search [10]. The solutions are the ones that minimize the objective function.

2.2 Shape Difference

Above alignment determines the relationship of corresponding points. Therefore, the distance between each pair of corresponding points can be calculated. We regard these distances between the corresponding points will be a cue of shape matching. If the distance of a pair is less than a threshold, the correspondence is regarded as right. Otherwise, the pair does not have correspondence, namely two shapes do not match at this part.

In terms of shape matching of two surfaces, wide region of non-matching indicates that two shapes are different.

3. Local shape comparison

3.1. Character extraction

The shape of a striation is usually uniform along the direction of the scratch. To input into neural networks, elevations on the surface should be converted into a binary signal. The method of binarization is simple (Fig.3); at first, gradients of all patches are calculated. Then, shapes of striation are converted into binary images by a threshold for these gradients. Finally, we derive a binary signal from a binary image by using morphological processings.

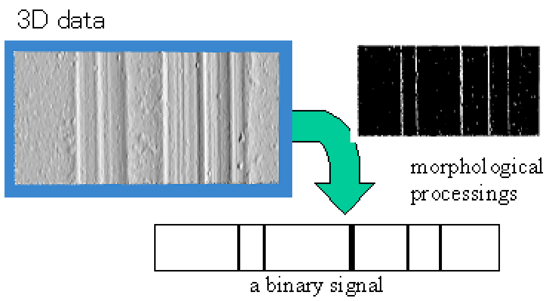

Figure 3. The binarization method, which converts a surface shape into a binary signal

3.2 Neural Network Model

In this study, a multi-layer network that contains three layers is used (Fig.4). There are 96 neurons in the input layer, 15 neurons in the middle layer and only 1 neuron in the output layer. The neurons in the input layer are divided into two blocks: input blocks A and B. Each input block contains 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.

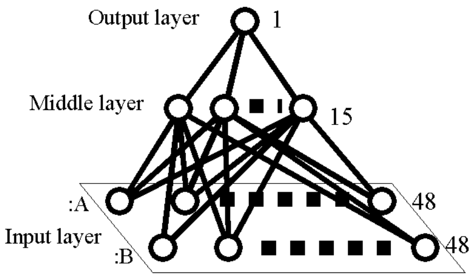

Figure 4. The structure of the three-layer network model with two input block

3.3 Learning

Two training patterns to be compared are inputted into each block, which contains 48 neurons. The training patterns are binary signals with a 48-bit length. Each signal consists of only one element with a value of "1" and forty-seven elements with a value of "0". Namely, 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.

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

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

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.

4. Experiments

4.1 Shape difference

The shape difference is visualized according to the distances of corresponding pairs (Fig.5). If the distances are within a threshold (in this study, it is 0.015mm), the area is displayed in pink region. While the distances are further than it, the area is colored blue. In the left side of Fig.5, almost all part of overlapped region is colored dark gray. It indicates that the two shapes are matched well because two images in the left side are results of comparisons that compare two pairs from the same origins.

On the other hand, a result, which compares two shapes in different origin, is shown in the right side. Blue region are wider than in the left side. It indicates the number of corresponding pairs is fewer even in overlapped region. In addition, the shape of non-coincide region spreads out along the direction of the scratch (a blue region sandwiched between pink regions). This is an obvious feature when two shapes have different origins.

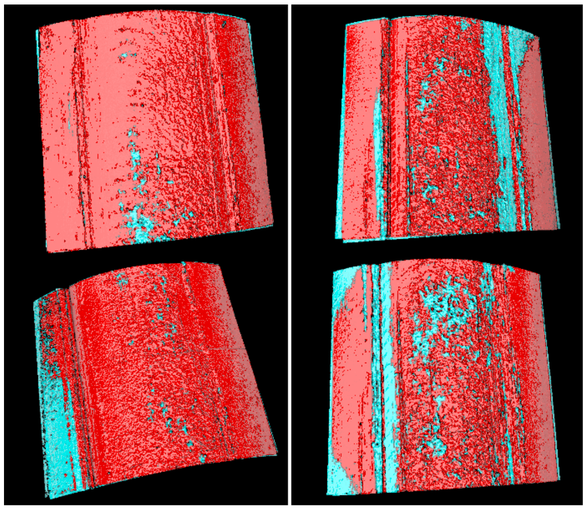

Figure5. Shape differences of landmark impressions. The left side pairs are comparisons of impressions by the same landmarks, and the right side pairs are by different ones

4.2 Simulation by Neural Networks

The neural network was used to identify 300 artificial patterns produced at random. 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 Neural Network 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 4 systems;

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

The results of the simulation are also shown in Fig.6. In deformed systems (A), (C) and (D), over 91% of the original patterns were ranked within the top 5. Over 96% of the patterns were ranked within the top 10. 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, we should be able to find the answer with a probability of more than 98%.On the other hand, the accuracy was worse for the deformed system (B) than for the others. Only 85% of the original patterns were ranked within the top 10 and 7% patterns failed to be included in the top 20. In many cases, many excited neurons corresponding to failure patterns are located in the erased part.

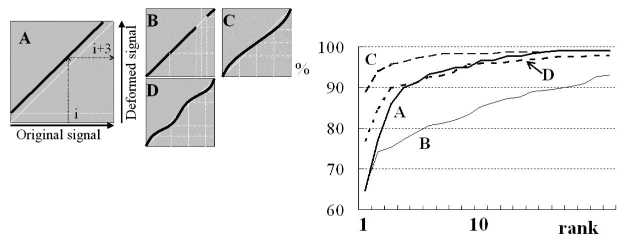

Figure 6. The 4 deformation systems and the result of query simulation with 300 artificial patterns

4.3 Two-stage evaluation

Finally, we want to calculate a combined evaluation that contains both global and local shape similarities. We then introduce a combined score. When two data Z_1 (database striation shape) and Z_2 (unidentified striation shape) are given, a score that presents two striation shapes have the same origin is defined as follow,

$$S(Z_1, Z_2) = S_{local}(Z_1, Z_2) \cdot S_{global}(Z_1, Z_2)$$

The similarity score about global shape matching S_{global} is represented as the area ratio defined by

$$S_{global} = \alpha \cdot \frac{\text{area of pink regions}}{\text{Overlapped area}}$$

Here, α is a coefficient that takes a low value (in this study 0.5) when there are any non-coincide regions spreading out along the direction of the scratch. Otherwise, it takes 1.

On the other hand, we regard the local shape similarity score S_{local} as the score by the neural networks. The score S_{local} is the averaged score evaluated in eight local regions chosen among the whole surface at random.

We have compared 100 pairs of real striations on fired bullets. Figure 7 shows the results. Ten pairs of them have the same origins and others have different ones. This 2-stage method shows a good performance, since the result clearly shows the difference between by the same origins and by different origins. All pairs of same origins have scores over 0.4, while pairs of different ones have under 0.3. We could consider that a value of a threshold for identification is between 0.3 and 0.4.

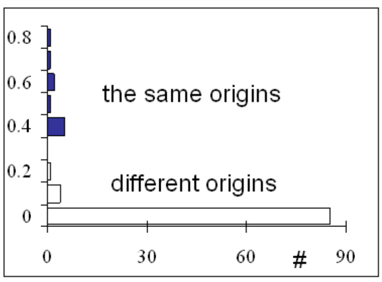

Figure 7. Experimental results

5. Conclusion

In this paper, we presented a 2-stage algorithm for a shape comparison of impressions on bullets, by using 3D shape data. Firstly, we measured surface topography and compared the global shapes of two impressions. Neural networks were used for similarity evaluation of local elevations.

Our goal is to propose a 3-Dimensional identification method. To extend this method into rigid bullet identification, we have to compare numerous pairs of bullets to determine the rigid parameters. This is one of the most important future works about this method.

We used striations on fired bullets mainly. It is not to say that this algorithm can be applied to other tool marks and other shapes.

At present, we compared two shapes by global curvatures and by local small elevations. Since elevations on striations of bullets are very small, it takes much time to measure striations. Moreover, it takes huge memory to store many striation shape data. Next, we are going to compress huge 3D data and build a practical system for tool mark identification.

References

[1] A.Banno, T.Masuda and K.Ikeuchi, "Three dimensional visualization and comparison of impressions on fired bullets", Forensic Science International, vol.140, pp.233-240, 2004.

[2] A.Banno, "Estimation of bullet similarity by using neural networks", Journal of Forensic Sciences, vol.49, pp.500-504, 2004,.

[3] P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes", IEEE Transactions on Pattern Analysis and Machine Intelligence, 14(2), pp.239-256, 1992.

[4] Z. Geradts, D. Zaal, H. Hardy, J. Lelieveld, I Keereweer and J. Bijhold, "Pilot investigation of automatic comparison of striation marks with structured light", Proceedings of SPIE, vol.4243, pp.49-56, 2001.

[5] M. Heizmann and F. P. León, "Imaging and analysis of forensic striation marks", Optical Engineering, 42(12), pp.3423-3432, 2003.

[6] J. D. Kinder and M. Bonfanti, "Automated comparisons of bullet striations based on 3D topography", Forensic Science International, 101(2), pp.85-93, 1999.

[7] C. Kingston and D. Crim, "Neural Networks in Forensic Science", Journal of Forensic Science, 37(1), pp.252-264, 1992.

[8] F. P. León, "Enhanced imaging by fusion of illumination series", Proceedings of SPIE, vol.3100, pp.297-308, 1997.

[9] T. Masuda, S. Imazu, T. Furuya, K. Kawakami and K. Ikeuchi, "Shape difference visualization for old copper mirrors through 3D range images", Proceedings of the 8th International Conference on Virtual Systems and Multimedia, pp.942-951, 2002.

[10] K. Nishino and K. Ikeuchi, "Robust simultaneous registration of multiple range images", Proceedings of the 5th Asian Conference on Computer Vision, vol.2, pp.454-461, 2002.

[11] D. E. Rumelhart and J. L. McClelland, "Parallel Distributed Processing", The MIT Press, New York, 1986.