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Study on Rapid Archival Technology of Bullets Based on Graph Convolutional Neural Network

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Abstract. *Traditional gun archiving methods are mostly carried out through bullets' physics or photography, which are inefficient and difficult to trace, and cannot meet the needs of large-scale archiving. Aiming at such problems, a rapid archival technology of bullets based on graph convolutional neural network has been studied and developed. First, the spot laser is used to take the circle points of the bullet rifling traces. The obtained data is filtered and noise-reduced to make the corresponding line graph, and then the dynamic time warping (DTW) algorithm convolutional neural network model is used to perform the processing on the processed data. Not only is similarity matched, the rapid matching of the rifling of the bullet is also accomplished. Comparison of experimental results shows that this technology has the advantages of rapid archiving and high accuracy. Furthermore, it can be carried out in large numbers at the same time, and is more suitable for practical promotion and application.* © *2022 Society for Imaging Science and Technology.*
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1. INTRODUCTION

The rifling traces of bullets refer to the scratches formed by the rubbing of the bullets and the rifle barrel when the bullet is fired. The purpose of detecting the rifling traces of the bullets is to determine the match between the gun and the bullet. It is necessary to identify the bullets left at the scene with the shell fired by the gun [1–3], the bullet marks of the bullet fired by the same gun can reflect the details of the rifling of the gun, and by identifying these details, the responsible gun can be determined [4, 5]. Common rifling trace identification of bullets generally uses a comparison microscope, through two-dimensional image comparison, line docking, segmented photography, stylus detection and other visual observation methods. These methods are inefficient, lengthy matching time, low accuracy, and cannot be used in large-scale many-to-many comparison situations [6–9]. Moreover, the fast filing of a large number of official guns is also a major problem that plagues public security agencies, the army and prisons [10, 11]. The public security agencies need an efficient and precise rifling recognition method and an efficient data-based filing solution.

Researchers at home and abroad have made significant achievements in data analysis and comparison of rifling traces. Literature review [12] provided a new idea for evaluating the state of the tube hole and its degree of wear to predict the applicability reserve and the value of the spray gun; recent studies [13] used wavelength-dispersive X-ray fluorescence spectroscopy to match the characteristics of rifle bullets. The use of chemometric analysis and comparison of rifle bullets has certain practical significance; Literature review [14] prompted an algorithm to automatically search for the same trajectory, taking into account the structure of the trace and the number of overlapped trajectories, and simultaneously analyze the dependence of the trajectory offset. A recent study [15] analyzes bullet traces by extracting multi-dimensional features of bullet data and combining the advantages of multi-dimensional features, and achieving certain results in the experimental stage. Similarly, the study [16] chosen to analyze the bullet traces through the depth texture information of the bullet traces, also provides insights for this article.

After the advancement of deep learning in 2012, academic communities began to investigate the combination of graph models and neural networks, and research on Graph Convolutional Neural Networks (GCN) has also progressed with it [17, 18]. The processing power of spatial data, graph convolutional neural network is used by many researchers in many fields, such as label recognition and power load recognition [19, 20]. In this paper, the graph convolutional neural network model is selected for feature extraction and identification of the gun rifling data curve graph. Through a large amount of data training, the graph convolutional neural network model can quickly process a large number of rifling data line graphs, which is the gun rifling data behind. The unified filing offers a solution.

This study presents the analysis and development of a rapid archival technology of bullets based on graph convolutional neural network. First, point lasers are used

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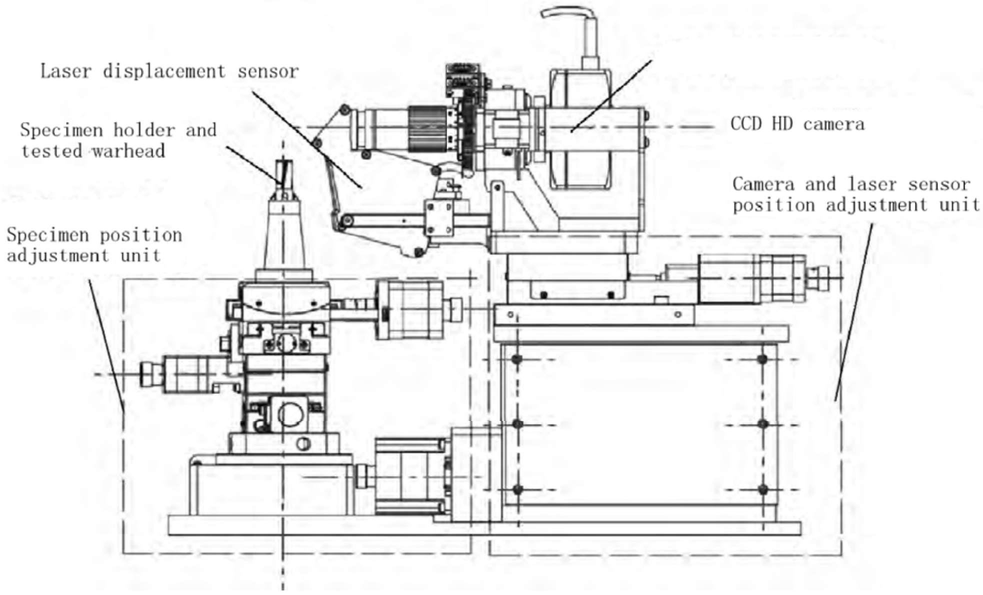


Figure 1. Bullet traces laser detector.

to take the points of the bullet firing rifling traces in a circle, and the obtained data is filtered and denoised to make a corresponding line graph, and then combined with the dynamic time warping DTW algorithm and graph convolutional neural network to perform similarity check to the processed data. Based on the degree of match, rapid comparison of rifling traces of bullets, while supporting one-to-one, one-to-many comparison; some one-to-one, some one-to-many comparison and other comparison methods can be achieved.

2. DESCRIPTION OF THE PROBLEM

In many criminal cases, bullets are obvious evidence to identify criminal suspects, but the matching of bullets and shooting guns is a big obstacle in actual implementation. In order to determine which gun from which the bullets were fired, it is necessary to scan and extract the rifling trace features of the bullet, translate these rifling features into a broken line graph, and use the corresponding model for similarity analysis.

3. MODEL ESTABLISHMENT

3.1 *Testing Equipment*

The single-point laser detection device for bullet traces used in the experiment was independently developed by Kunming Xinnuo Laibo Technology Co., Ltd., as shown in Figure 1.

During detection, the electric rotating table drives the measured bullet to revolve at a uniform speed, and the laser sensor collects the distance change data on the bullet surface here. After the tested bullet rotates a circle, the stage will be raised or lowered, and the distance between the laser sensor and the tested bullet will be modified to collect the next circle data. Repeatedly, the laser sensor collects multiple sets of data to complete the rifling trace data collection link of the point laser.

3.2 *Data Preprocessing*

The data preprocessing is divided into two parts, data weighted average and interference data filtering, the specific process is shown in Figure 2.

3.2.1 *Data Eighted Average Processing*

The collected data is the distance between the surface of the bullet and the laser head obtained by the laser sensor continuously detecting a circle on a bullet revolving at a constant speed of 360°. The specific data is shown in Figure 3. Fig. 2 is a graph of the rifling trace data of a 9 mm pistol bullet without any processing. It is evident from the picture that there are 6 undulations, corresponding to 6 rifling traces.

Since a point laser sensor is used as a collection tool, when collecting data with uneven surfaces such as bullet rifling traces, a single piece of data cannot accurately retrieve the features of its rifling traces. Therefore, multiple detections are required to ensure the accuracy and reproducibility of the original data. After numerous tests, we finally chose to collect 1020 raw data points of rifling traces within a certain distance of the tested bullet axis. After weighted average of these data, more accurate average curve data of rifling traces can be obtained, as shown in Figure 4.

3.2.2 *Interference Data Filtering Processing*

The obvious rifling traces in the average curve of rifling traces can quickly distinguish the types of shooting guns. As shown in Fig. 3, there are 6 obvious rifling traces, which proves that this bullet cannot be fired by a 95-style rifle. But this kind of obvious trace is meaningless for the identification of similar guns. The rifling traces of bullets fired by similar guns are very similar. There is no distinguishing point, which will only

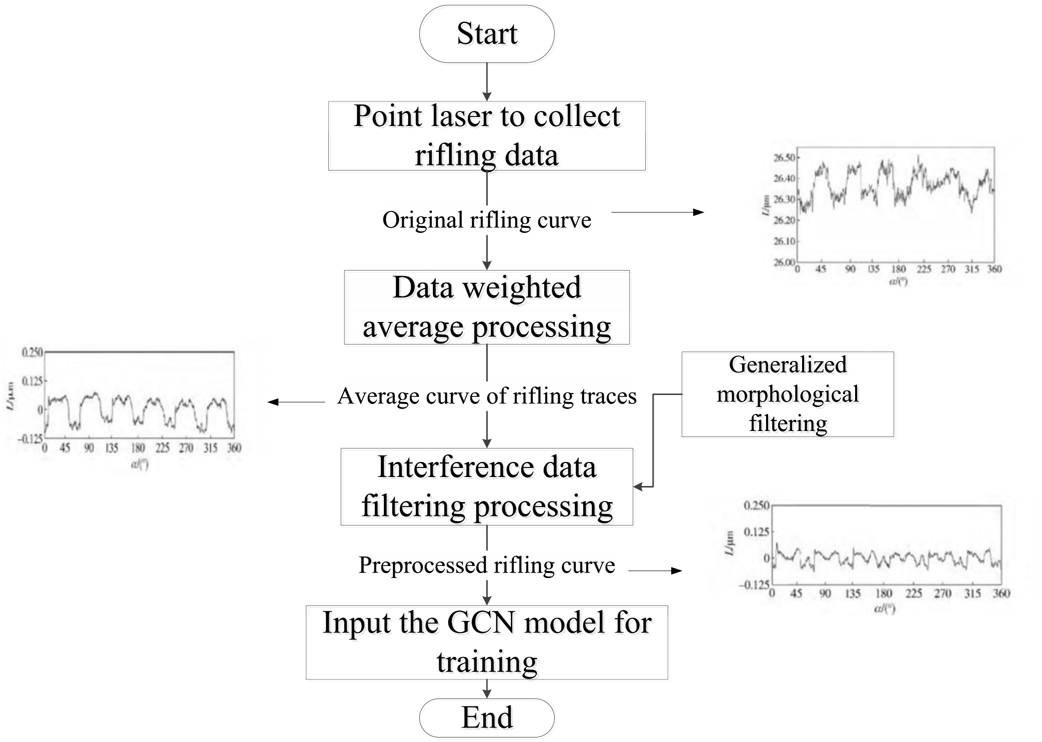


Figure 2. Data preprocessing flow chart.

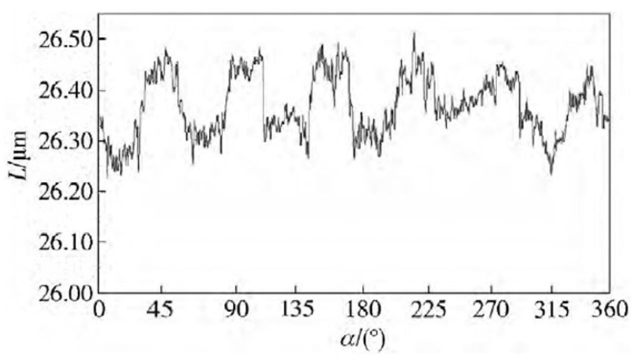


Figure 3. Original curve of the rifling traces of the 9 mm bullet.

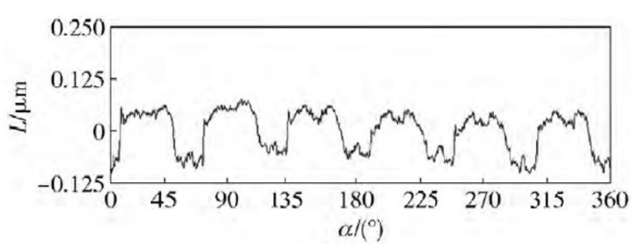


Figure 4. Average curve of rifling marks of 9 mm bullets.

increase the workload of identification and matching, so the rifling traces need to be removed. The main traces in the data are filtered out, and then the follow-up feature comparison is performed.

Commonly used image filtering algorithms include mean filtering, median filtering, Gaussian filtering and generalized morphological filtering. These methods have their own advantages and disadvantages. Mean filtering is simple to implement and fast, but the denoising effect is not ideal. Median filtering is the most common image preprocessing method, which is very suitable for smoothing impulse noise. Gaussian filtering is suitable for eliminating Gaussian Noise. In the generalized morphological filtering, not only is the selection accuracy and robustness good, the difficulty of implementation is low, and the running speed is faster.

This study utilizes the peak signal-to-noise ratio (PSNR) and running time to evaluate the above filtering methods, and selects the most suitable filtering method for creating the line graph of rifling data. The test sample uses 20 rounds of 92 9 mm pistol bullets. The final PSNR value is the arithmetic mean of the PSNR values of the 20 filtered images. The specific examination results are as follows:

It can be seen from Table I that generalized morphological filtering has better filtering ability for rifling data line graphs than other methods, and it runs faster. Therefore, generalized morphological filtering is used to process the rifling data line graph.

Let the signal $f(n)$ be defined in an integer array $A = [0, 1, \ldots, N-1]$ discrete signal, where N is the number of data to be filtered, and the grading elements of the filtered data are $a_1(n)$ and $a_2(n)$ respectively. The open-close filter of the generalized morphological filter is defined as:

$$GOC(f(n)) = f(n) \circ a_1(n) \bullet a_2(n). \tag{1}$$

Table I. Comparison of various filtering methods.

Filtering method	Peak signal-to-noise ratio/dB	Running time/s
Mean filter	23.424	2.1 s
Median filter	27.577	3.3 s
Gaussian filtering	22.976	3.1 s
Generalized morphological filtering	30.677	1.6 s

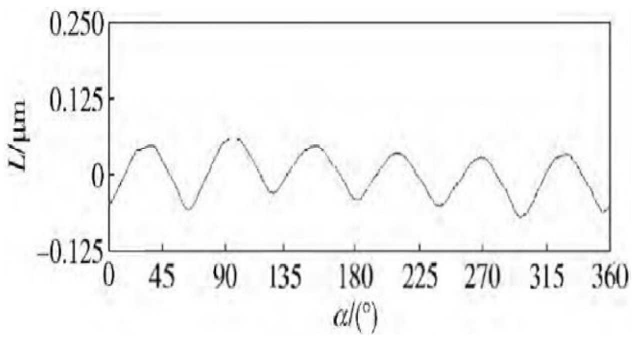


Figure 5. The main trace of rifling produced after morphological filtering (inverted phase).

The closed-open filter of the generalized morphological filter is defined as:

$$GCO(f(n)) = f(n) \bullet a_1(n) \circ a_2(n). \tag{2}$$

In the above formula, $\bullet$ is the closed operation, and $\circ$ is the open operation. In actual filtering, these two filters need to be weighted and combined to ensure the accuracy of the filter, as shown in formula (3):

$$\frac{GOC[f(n)] + GCO[f(n)]}{2}. \tag{3}$$

The generalized morphological filter using weighted combination can retain the signal shape characteristics for generalized morphological waves, and the specific amplitude of the filter needs to be changed according to the actual situation. In actual operation, it is necessary to reverse the phase of the main traces of the rifling traces in the rifling traces curve, and then add them to the average curve to remove the main traces, as shown in Figure 5.

The data preprocessing obtains the curve chart of the characteristic traces of the rifling which filters out the main rifling waves, as shown in Figure 6.

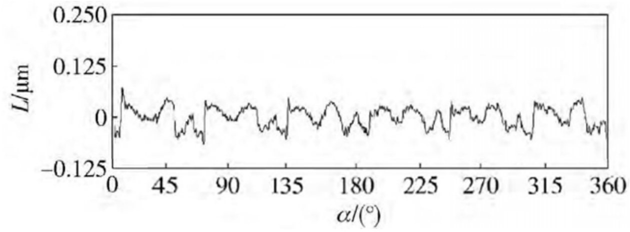


Figure 6. Rifling trace curve after data preprocessing.

3.3 *Comparison and Matching of Rifling Traces*

Classical similarity comparison generally uses Euclidean distance comparison, K-means algorithm, and others. Through many experiments, in order to meet the requirements of one-to-one, one-to-many comparison and some one-to-one, some one-to-many comparisons, the graph convolutional neural network model (GCN) was introduced in the comparison and matching parts. While GCN is used for one-to-one and one-to-many comparisons, DTWis used for incomplete one-to-one and partial one-to-many comparisons. The specific flow of the matching algorithm is shown in Figure 7.

3.3.1 *One-to-one, one-to-many comparison: GCN model*

This article mainly uses the spectrum method in the mainstream GCN method. The GCN operator is defined in the Fourier domain. The key is to calculate the eigenvalue decomposition of the discrete Laplacian. The basis function of the Fourier transform corresponds to the eigenvector of the Laplacian matrix. The traditional Fourier transform and Convolution uses the Laplacian operator as a bridge to connect to the Fourier transform of the graph domain, and then uses the convolution theorem to realize the process from the Fourier transform of the graph domain to the graph convolution. The definition of graph convolution is formula (4):

$$g\theta * x = Ug\theta(\Lambda)U^T x. \tag{4}$$

Where x is the graph signal, $g\theta$ is the filter, U is the matrix composed of the eigenvectors of the normalized Laplacian matrix, Λ is the diagonal matrix composed of all the eigenvalues, and θ is equal to the trainable convolution kernel parameter.

The spectral method uses the convolution theorem to define the graph convolution operator from the spectral domain. Specifically, the Fourier function of the signal x is $\hat{x} = U^T x$, and the inverse transform is $x = U\hat{x}$. According to the Fourier change and the inverse change, the calculation can be given based on the convolution theorem:

$$x *_g y = U((U_T x)\Theta(U_T y)). \tag{5}$$

In the above formula, $*_g$ is the convolution operator, and x and y each represent the signal of the node domain, and $*_g$ represents the multiplication of two vector elements.

The rifling trace curve graph is partitioned and pooled according to the convolution operator defined by the above-mentioned spectral method, the network hierarchical structure is distinguished, and the corresponding convolution model is constructed. The Laplacian matrix needs to be added, and the derived formula is (6):

$$L = I_M - C^{\frac{1}{2}}, HD^{1/2} \in R^{N\times N}. \tag{6}$$

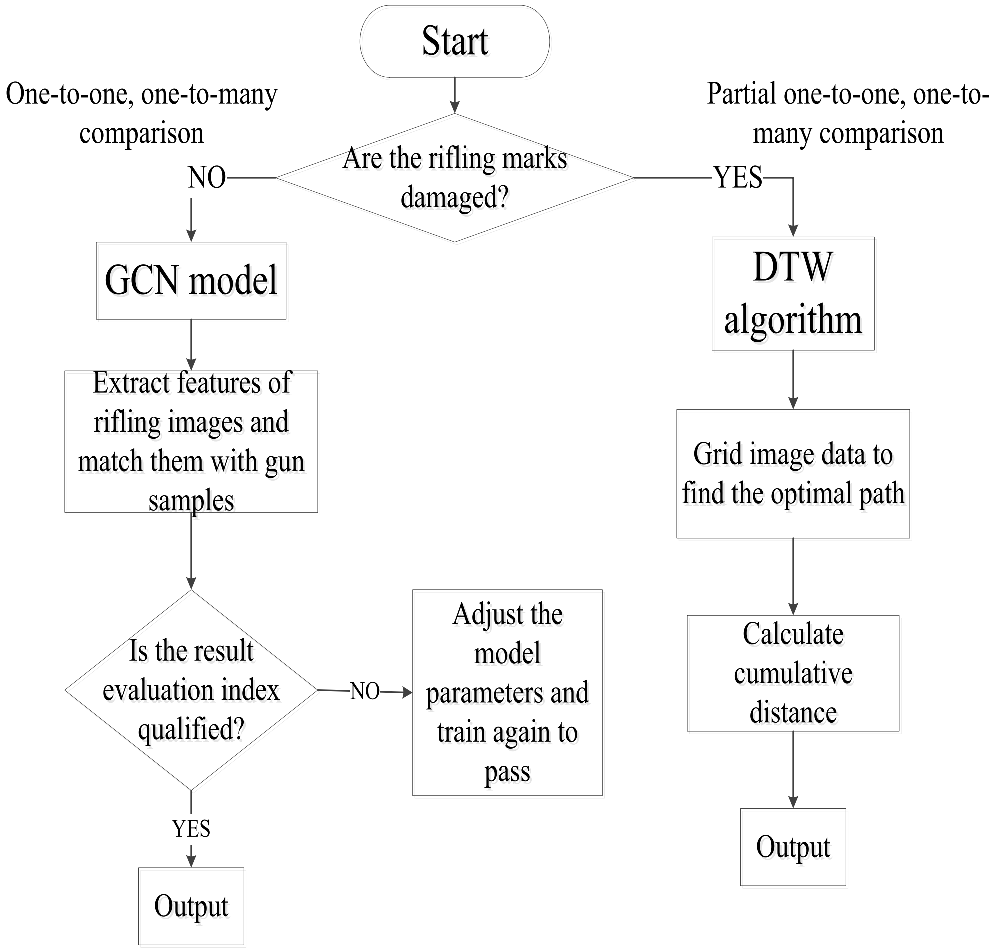


Figure 7. Flow chart of matching algorithm.

Where I_M is the identity matrix, C is the pair angle matrix, and H is the adjacency matrix. The eigenvalue decomposition of L has $L = U \Lambda U^T$, $\Lambda \in R^{N \times N} U \Lambda U^T$ is a diagonal matrix composed of the eigenvalues of L, and U is the Fourier basis. That is, the eigenvector matrix of L. The data $x \in R^N$ in the node is regarded as the signal on the graph, and $*_g$ is used to denote the convolution operation.

After the construction of the Laplacian matrix is completed, the convolution kernel Θ is used to convolve the signal on the graph as formula (7):

$$\Theta(\Lambda) \approx \sum_{K+0}^{K-1} \theta_K T_K(\tilde{\Lambda}) = \frac{2\Lambda}{\lambda_{max}} - I_N. \tag{7}$$

This completes the convolution operation of defining one-dimensional data $x \in R^N$ in the figure above.

The neural network model is composed of an input layer, a hidden layer, and an output layer. Due to the high accuracy of the data that needs to be identified, this model creates 2 convolutional layers and divides them as hidden layers. The number of nodes N is set to 2870. To meet the characteristics of the extracted rifle data, set W^0 as the weight matrix from the input layer to the hidden layer, which has H feature maps; set W^1 the weight matrix from the hidden layer to the output layer, and W^0 and W^1 in the network are trained through gradient descent. For each "training iteration", the complete data set is used to perform "batch gradient descent", randomness introduced in the training process through Dropout, and finally "sparse-dense matrix multiplication" is used for operation.

Figure 8 is the result of a one-to-one comparison. The red curve is the measured data, and the blue curve is the data in the library file. It can be seen that only half of the waveforms overlap, and the similarity is only 72.83%.

After the model is built, it is necessary to input a large number of rifling trace curves as the test set, and train the GCN model until the model meets the accuracy index requirements and enter the test set into the experiment.

3.3.2 *Part one-to-one, part one-to-many comparison: DTW algorithm*

The DTW algorithm adopts the idea of dynamic programming, which is mostly used in signal comparison when the signal length is inconsistent. The core is that when the sequence lengths are not uniform or the X-axis cannot be totally aligned, a time warping function that satisfies certain conditions is used to describe the time correspondence between the two. Using this feature, when the bullet rifling

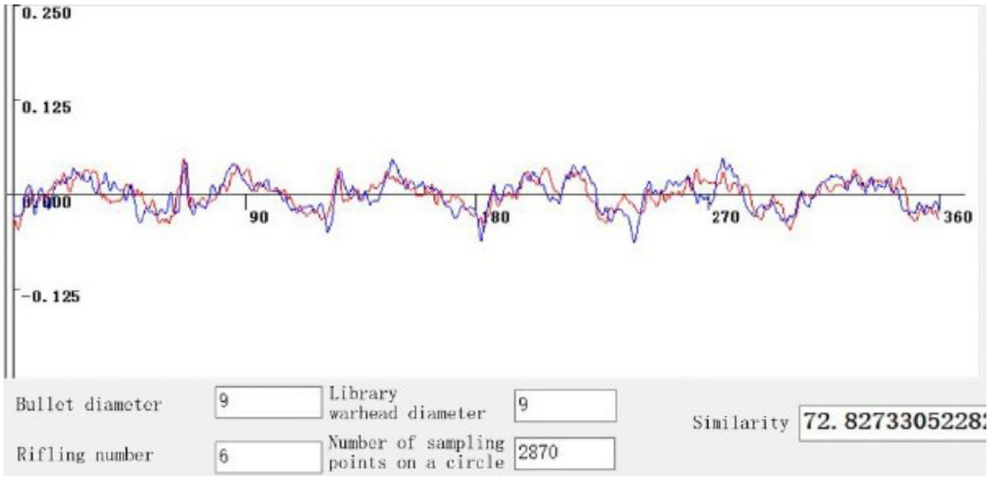


Figure 8. One-to-one comparison experiment.

traces are damaged and only a small part of the collected data can be used, a partial comparison method can be adopted. Here the warhead rifling trace damage refers to the missing and incomplete rifling traces caused by friction, cutting and corrosion of the warhead. The feature data required for the experiment cannot be extracted, and the neural network model cannot be used for matching.

The so-called incomplete comparison refers to only taking 1/5 of the usual rifling trace collection points for comparison. The above-mentioned GCN model does not have an advantage in comparison experiments with several test sets, so DTW algorithm is required for this special case comparison.

The core of the DTW algorithm is to treat the matrix as a grid. The purpose of the algorithm can be summarized as finding an optimal path through the matrix grid. The grid points passed by the path are the points where two discrete sequences have been aligned.

Path calculation formula of DTW algorithm (8):

$$w_{k-1} = (i, j), \quad w_k = (i', j'). \tag{8}$$

Where $i \leq i' \leq i+1, j \leq j' < j+1$. At the same time, there are corresponding restrictions on boundary conditions, continuity, and monotonicity. At the same time, a cumulative distance dist is defined, starting from (0,0) to match the two sequences of A and B, to a point, all previous points are calculated. The distance will be accumulated, and the accumulated distance $dist(i, j)$ obtained after reaching the end point represents the overall similarity between A and B. The calculation can be expressed as the following formula (9):

$$dist(i,j) = \min \begin{cases} dist(i-1, j-1) + d(A(i), B(j)) \\ dist(i-1, j) + d(A(i), B(j)) \\ dist(i, j-1) + d(A(i), B(j)). \end{cases} \tag{9}$$

For part of the rifling trace comparison experiment, when using DTW, it is necessary to replace the time series with the most complete 1/5 phase sequence in the rifling trace curve. As shown in Fig. 8, some one-to-one curves require fewer points than a full one-to-one comparison, and some one-to-one comparisons have a lower accuracy than a complete data one-to-one comparison.

In the DTW model, the input data are set as A and B respectively. Both of them have undergone data preprocessing and are feature data extracted from the partially damaged warhead of the rifling. A minimum length that satisfies when the two overlap is set. From A, the part from the longest length is selected to the shortest length in B for comparison, and multiple matches from different positions are performed to get the minimum length. Iteratively performing the comparison of each position to obtain the variance of the corresponding position difference between A and B, and then exchanging the roles of A and B to be compared again in order to obtain the variance of B versus A, and finally calculating the variance with the smallest variance, and matching result image is considered as the output.

4. SIMULATION EXAMPLES

4.1 *Environmental Description*

In order to fit the actual application and meet the subsequent file-building requirements, the experiment considered the use of a large number of 92-type 9 mm pistols, 59-type 9 mm pistols, and 77-type 7.62 mm pistols for comparison and matching experiments. Among them, a provincial public security bureau and a town's public security bureau provided a total of 72 92-type 9 mm pistols, firing 864 rounds, and each gun shot 12 rounds; one of the city's public security bureau provided a total of 57 59-type 9 mm pistols, firing 513 rounds of bullets. Each gun fired 9 rounds; the 77-type 7.62 mm pistols provided by the public security bureau of a major city totaled 35, firing 315 rounds of bullets, and each gun fired 9 rounds.

In this experimental design, based on the methods described in Sections 3.2.1 and 3.2.2, the round traces of the bullet surface were collected and data pre-processed. The data collected from a total of 3 types of guns, 164 guns, and 1692 bullets were processed to form a training set for GCN and the model was trained. Finally, the extracted data of 3 types of guns, 62 guns, and 392 rounds of bullets were selected as the test set and input into the GCN model.

The experimental environment is as follows: a single computer, configured as Intel(R) Core(TM) i5-8300H CPU @ 2.30 GHz, Windows 10 operating system, 16.0 GB RAM, and programming environment used is PyCharm Community Edition 2020.1.3 ×64.

4.2 *Evaluation Index*

There are many evaluation indicators for deep learning, among which accuracy, precision rate, recall rate, F1 value, etc. are commonly used evaluation indicators based on preference and use by many scholars. Accuracy, precision, and recall rate,F1 value and running time are used to comprehensively evaluate the GCN model. The physical meaning of accuracy is the proportion of samples that are accurately decomposed in all decomposed samples; the physical meaning of accuracy is the proportion of samples that are classified properly among the samples whose classification results are positive; the physical meaning of recall is in all samples. Among the positive samples, the proportion of samples that are correctly classified; the F1 value is the harmonic average of the precision rate and the recall rate, which can be regarded as a comprehensive index of the recall rate and the precision rate. The calculation formula is as follows:

$$P_a = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{10}$$

$$P_b = \frac{T_P}{T_P + F_P} \tag{11}$$

$$P_c = \frac{T_P}{T_P + F_N} \tag{12}$$

$$F1 = \frac{2P_b P_c}{P_b + P_c}. \tag{13}$$

In the above formula, P_a is the accuracy, P_b is the precision rate, and P_b is the recall rate. This experiment stipulates bullets with a similarity of more than 90% are matched with this gun, and less than 90% is a mismatch. T_P is the predicted match, and the actual proportion of the match; F_P is the predicted match, but the actual proportion of the match; F_N is the predicted mismatch, and the actual proportion of the match; T_N is the predicted mismatch, and the actual proportion is the percentage of mismatches.

4.3 *Comparison of Experimental Results*

This experiment will be compared with the methods used in previous studies [1]. Literature review indicates [1] that the same point laser is used for rifling data collection, and the matching part of the Pearson correlation coefficient is compared for similarity comparison calculation. Since the method in the study [1] is not deep learning, the above evaluation indicators cannot be used for evaluation. The accuracy of pure use cannot be used as a good indicator to measure the results when the sample is not balanced. Therefore, the F1 value will be used as the GCN model. The comprehensive accuracy rate of is finally compared with the accuracy rate obtained in the literature [1].

Table II. Matching results of 3 kinds of pistols (the algorithm of this paper).

Match result	Accuracy/%	Precision rate/%	recall rate/%	F1 value/%	Running time/s
Type 92 9 mm pistol	94.68%	92.4%	78.28%	85.79%	2.8 s
Type 59 9 mm pistol	95.58%	87.08%	78.92%	85.53%	2.0 s
Type 77 7.62 mm pistol	95.14%	84.36%	77.86%	84.98%	2.0 s

There are 62 guns and 392 bullets in the test set data input to GCN. Among them, 20 type 92 9 mm pistols fired 140 rounds; 16 type 59 9 mm pistols fired 96 rounds; 26 type 77 7.62 mm pistols fired a total of 156 rounds. The matching results of the GCN model are shown in Table II.

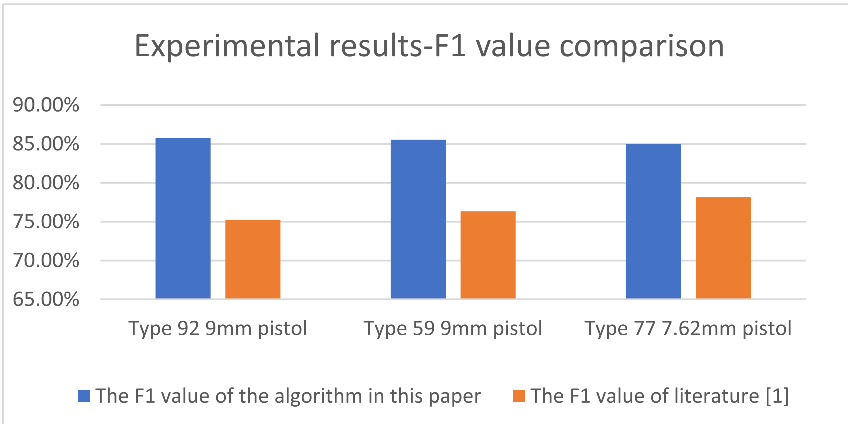
From the data comparison in Table III, it can be seen that the accuracy of the method in this study is significantly improved compared with the method in [1], which can reach more than 80%, which has certain advantages; there is a slight gap in operating speed. However, as the data increases, from 0.2 s for the 59-type 9 mm pistol with the smallest sample to 0 s for the 92-type 9 mm pistol with the most sample, the gap is gradually decreasing. In the one-to-many comparison of a large amount of rifling data, the algorithm presented in this study is likely to be better than this study's [1] algorithm.

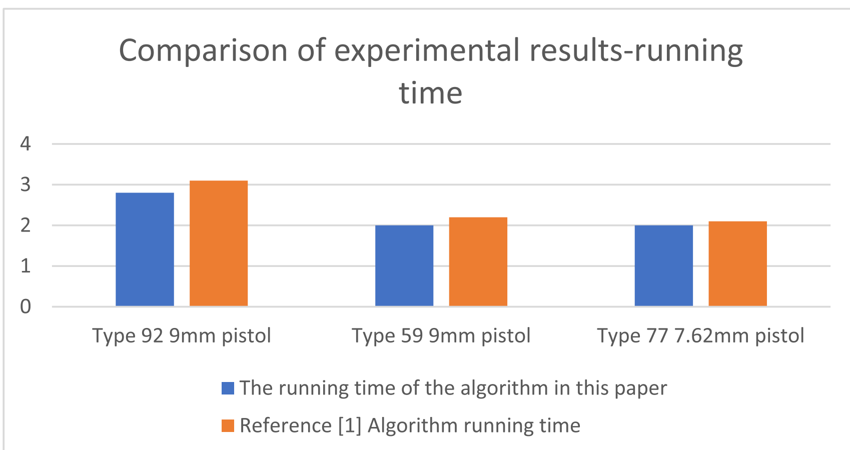
5. CONCLUSION

This paper presented a rapid archiving technology of bullets based on graph convolutional neural network, which uses a point laser to take the points along the rifling traces of the bullet nose, weighted average the obtained data, filtered and reduced noise to make the corresponding line graph. The processed data is fed into the graph convolutional neural network model for comparison and matching to quickly determine the correlation between the tested warhead and the guns in the sample library, and the DTW algorithm can also be used to perform part of the test when the rifling traces of the tested warhead are damaged match. In the verification stage of the experiment, a total of 3 types of guns were collected. The rifling trace data of the 392 bullets of the 62 guns were matched with the guns in the sample library and compared with the method described in literature [1]. The experimental results show that the method in this paper has high accuracy and fast matching speed. In the matching experiments of the three guns, the pass rate is more than 88% and the excellent rate is more than 25%, and the F1 value is about 85%. Compared with studies done earlier the algorithm in [1] has obvious advantages,

Table III. Comparison between the algorithm in this paper and the algorithm in literature [1].

Compare results	F1 value-accuracy rate comparison/%		Run time comparison /秒	
	algorithm in this paper	algorithm in literature [1]	algorithm in this paper	algorithm in literature [1]
Type 92 9 mm pistol	85.79%	75.25%	2.8 s	3.1 s
Type 59 9 mm pistol	85.53%	76.32%	2.0 s	2.2 s
Type 77 7.62 mm pistol	84.98%	78.13%	2.0 s	2.1 s





and it runs faster than the algorithm in [1]. In addition, DTW algorithm can be used for one-to-one comparison, one-to-many comparison; some one-to-one comparison, some one-to-many comparison. It can be used in the case investigation and gun filing operations where the actual pistol bullet matches the pistol. Future work will focus on improving the accuracy rate, optimizing the program, reducing the running time, and adding the bullet trace data of the remaining firearms into the database, so that the program can compare and match more firearms.

For practical applications, the following issues need to be studied:

(1) Further improve the accuracy of the experiment, increase the pass rate to more than 95%, and the excellent rate to more than 35% to ensure that there will be no misjudgments in actual use.
(2) For the partial comparison of the rifling traces of the bullet, considering that the bullet may be maliciously damaged, it is necessary to improve the requirement of 1/5 of the points that must be collected in a circle in the original method, so that part of the collection can be carried out with fewer points. ratio.
(3) Compared with the number and types of official guns in our country, the samples provided in this experiment are

too few, which can only verify the matching accuracy of a small number of pistols, and cannot prove that there are still equivalent matching effects for other rifles and guns.

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