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# Line Trace Effective Comparison Algorithm Based on Wavelet Domain DTW

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**ABSTRACT**
It will face a lot of problems when using existing image-processing and 3D scanning methods to do the similarity analysis of the line traces, therefore, an effective comparison algorithm is put forward for the purpose of making effective trace analysis and infer the criminal tools. The proposed algorithm applies wavelet decomposition to the line trace 1-D detection signals to partially reduce background noises. After that, the sequence comparison strategy based on wavelet domain DTW is employed to do trace feature similarity matching. Finally, using linear regression machine learning algorithm based on gradient descent method to do constant iteration. The experiment results of line traces sample data comparison demonstrate the accuracy and reliability of the proposed algorithm.

**KEY WORDS**: Line trace, Wavelet transform, Laser detection, Machine learning.

## 1 INTRODUCTION

HIGH-speed railways are being developed rapidly in China. To ensure long-term stability of infrastructure, a plenty of cables, such as leaky cables, signal cables, rail vehicle cables, and grounding wires, are distributed along the railway. The inner conductors of many cables are made of copper, a coveted target of criminals due to its high economic value. In recent years, frequent theft of cables along the high-speed railways has resulted in huge losses of state property and has caused interruption of railway signals and communication equipment power supply. This has forced failure of the respective systems leading to several railway accidents, significant loss of lives, and diminished safety of property.

Statistical data show that criminals use wire cutters, cable cutters, destroy pliers, and other large shear tools to sever cables. Line traces, which are scratches on the surface of the body, can be caused by the pressure of the line-shaped deformation and line traces of the broken ends on the surface are frequently found at the scene. Thieves use tools that cause load on the trace-bearing body, which form local material changes on the contact part. Moreover, thieves use tools to cut the cables, which form local material changes on the contact part. The tool traces reflect the external morphological structure of the contact area, and provide clues to the investigation based on the analysis of the tools used in the criminal act, thus narrowing the scope of the investigation. It possesses characteristics that are difficult to destroy or disguise, frequently occurring, and possess high identification value for investigators to determine the nature of the case and the tools used in the criminal act. These characteristics are important to confirm suspects.

Compared with the traditional methods of observation and comparison, the nonlinear shear trace quantitative examination in image recognition and 3D scanning technology. However, these detection methods are complicated because of the randomness at the crime scene. The structure of the algorithm is not well suited to engineering. The pictures and size of 3D files are too large, increasing the difficulty and making the above method unsuitable as the first approach to handling the case, which greatly reduces its practical value.

The single-point laser displacement test has advantages that include an undamaged surface of the measured object, a light-free environment, high precision, small data file size, and good frequency response characteristics. However, problems like

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signal noises reduction, signal matching and tool inference are encountered when this method is applied to analysis the traces of actual sheared scene:

From Based on previous research and in view of the requirements of efficient and rapid judgment of cutting tools in the actual scene, a fast traceability algorithm for nonlinear line trace features in the wavelet domain is designed. This algorithm uses a laser displacement sensor to detect signal characteristics and reduce noise using wavelet decomposition. Furthermore, the dynamic time warping (DTW) algorithm is used based on the wavelet features to perform a similarity matching of trace features. Finally, correct determination of the corresponding tools is quickly achieved. The practicality and effectiveness of the proposed algorithm are verified by experiments involving the use of actual trace inference shear tools.

## 2 DETECTION OF SIGNAL NOISE REDUCTION

### 2.1 Overview of wavelet noise reduction

FIRST, the single-point laser detection instrument described in literature is used to collect the non-contact data. Then, the large amount of background noise interference contained in the laser detection signal is de-noised to obtain a relatively stable coherent peak trend. Using wavelet noise reduction, the basic step is to perform a wavelet transform of the signal. The characteristics of the signal after wavelet transform are assigned to the wavelet transform coefficients of each scale. The relevant threshold is selected according to the analysis and wavelet transform coefficient, to ensure maximum suppression of background noise.

### 2.2 Noise reduction of shear trace detection signal based on wavelet decomposition

The type of wavelet must be selected prior to noise reduction. The original signal has to be decomposed into several layers in the actual noise reduction process. When more layers are decomposed, the details of data processing will also increase, leading to more details being erased to eliminate more noise. Therefore, a balanced decomposition layer must be determined.

For the trace of the current detection, the approximate signal expansion of hierarchy 1 still has more glitches. The approximate signal expansion of hierarchy 2 has been greatly improved compared to the development of hierarchy 1. Most of the glitches have been improved, while the approximate signal of hierarchy 3 improves this phenomenon further and has been very close to the desired pattern from the graphical feedback. Therefore, only the development of hierarchy 3 is necessary in general.

According to the formula:

$$f = a_n + \sum_1^n d_i \qquad (1)$$

In addition to the approximate signal, detailed data are still needed. Although the approximate data are very close to the wave style according to the naked eye at hierarchy 3, signal details are still lacking because a significant amount of low amplitude noise is lost; therefore, it can only represent the general trend but cannot accurately show the traces. The signal should be filtered and de-noised for every detail by setting a threshold:

$c_i = \begin{cases} 0, |c_i| < r \\ c_i, |c_i| \geq r \end{cases}$ , $c_i$ represents the $i$ th decomposition of the wavelet coefficients.

IA threshold needs to be set and all data under the threshold must be removed to eliminate the noise in the detail. Given that general noise exists in high-frequency irregular pattern, the value is small, which is converted to the detail part. The signal should be filtered and de-noised by setting a threshold for every detail.

$$f' = a_n + \sum_1^n d'_i \qquad (2)$$

Among them:

$d'_i$ is the detail of the data after the threshold noise reduction.

$f'$ is the trace data after the noise reduction.

Considering the characteristics of the shear line trace, the final selection is db4 or Haar as the mother wavelet through many experiments. Then, the decomposition and reconstruction of 2–5 layers are carried out according to the accuracy of the data detection. The waveform signal after the reconstruction of the removed noise is the de-noised signal. The detection signal undergoes interference by the high-frequency noise because of the influence of mechanical vibration. Noise reduction is required to make the actual trace characteristic signal clear. All high-frequency noise can be omitted after noise reduction, while the qualified data portion is uninterrupted.

## 3 SIGNAL CHARACTERISTIC MATCHING

### 3.1 Variable length and partial overlap problem

PRIOR to the matching the similarity of trace signals after noise reduction, the following two issues must be addressed:

Variable trace length. Each collection of trace detection signal length is not the same. Most of the length of the matching signal data and the signal to be matched is different. At this time, the similarity of two discrete sequences can’t be directly measured using

Euclidean distance and correlation coefficients. Thus, point-to-point operations become meaningless.

2) Parts overlap. This means that two detection signal traces may only overlap at some part by coincidence. This condition can cause significant interference to the calculation of the final coincidence.

Therefore, the problem of variable length and overlap can be optimized through a computing algorithm capable of matching. The basic steps are as follows:

1) Setting the input data of A and B, which are data that satisfy the above requirements.

2) Setting a match to the minimum length L. The two coincidences must meet the minimum overlap length by selecting the longest length to the shortest part from A and to compare with B, that is equivalent to choosing a different location for a number of matches.

3) Iteratively executing each position's contrast. Each comparison should be compared to the variance size of differences degree of the two corresponding positions. The current state is recorded if the variance size is the minimum.

4) If the function of 3) is completed, the role of A and B is exchanged, followed by completion of steps 2) and 3).

5) Calculating the variance of minimum difference degree and outputting the matching result.

### 3.2 Dynamic Time Warping overview

DTW originates from voice signal recognition. It is based on the idea of dynamic programming and focuses on the inconsistency of the matching process of the length of the signal sequence. Expanding to all discrete signal sequences, DTW is a method to measure the similarity between two discrete signal sequences. DTW can describe the time correspondence using the time warping function that meets certain conditions when the sequence length is different or the X axis could not be fully aligned. This is widely used in various types of matching tasks, such as voice recognition, dynamic gesture recognition, and information retrieval. The main concepts of DTW are as follows:

Assuming that the two discrete data sets to be matched are:

$$\begin{aligned} A &= \{A(1), A(2), \cdots, A(m)\}; \\ B &= \{B(1), B(2), \cdots, B(n)\} \end{aligned} \tag{3}$$

The element with the subscript 1 is the starting point of the sequence and the element with the subscript m is the ending point. To align sequences A and B, an m * n matrix is constructed using DTW to store the point-to-point distance between the two sequences (such as the Euclidean distance). Smaller distances result in a higher similarity between two points.

This is the core of the DTW algorithm. By considering the matrix as a grid, the algorithm aims to find an optimal path through this matrix grid. The two grid points form the ends of a path that comprises two discrete sequences after the alignment of the point pair.

The DTW algorithm defines a warp path distance (WPD) after finding the optimal path. The similarity between the two-time series is measured by summing the distances between all similar points. The path is calculated by the following formula:

$$w_{k-1} = (i, j), w_k = (i', j') \tag{4}$$

Among them, $i \le i' \le i+1,\ j \le j' < j+1$

The path needs to meet the following conditions:

1) Boundary conditions:

$w_1 = (1,1)$ and $w_k = (m, n)$ 。

2) Continuity:

If $w_{k-1} = (i, j)$ , the next point $w_k = (i', j')$ of the path needs to be satisfied: $i' - i \le 1$ and $j' - j \le 1$, which can only be aligned with their adjacent points. This ensures that each element in the sequence $A$ and $B$ appears in the warp path W.

3) Monotonicity:

If $w_{k-1} = (i, j)$, the next point $w_k = (i', j')$ of the path needs to satisfy: $i' - i \ge 0$ and $j' - j \ge 0$ . It is assumed here that the order of $A$ and $B$ is unchangeable.

The trend of path W in the matrix grid must be monotonically increasing over time. Finally, defining a cumulative distance $dist$ is needed; that is, the matching of two sequences $A$ and $B$ starts from the point $(0,0)$ and reaches each point. All the points before the calculation of the distance will accumulate. The distance describes the overall similarity of sequence $A$ and sequence $B$ after reaching the end $(n,m)$ . The cumulative distance $dist(i,j)$ can be expressed by the following formula:

$$dist(i,j) = \min \begin{cases} dist(i-1, j-1) + d(A(i), B(j)) \\ dist(i-1, j) + d(A(i), B(j)) \\ dist(i, j-1) + d(A(i), B(j)) \end{cases} \tag{5}$$

Among them, the cumulative distance $dist(i,j)$ is the distance between the current points $d(A(i), B(j))$; that is, the sum of the Euclidean distance between the two points $A(i)$ and $B(j)$ of the sequence $A$ , $A$ and the minimum distance between adjacent elements are accumulated.

### 3.3 Dynamic time warping based on wavelet features

Due to the similarity in the performance of shearing trace detection signal to random signal in time domains after noise reduction, it is difficult to directly the DTW for processing. After many experiments, it has been found that it can make similarity judgment difficult through the wavelet transform of the current signal, which is harder to deal with in the time domain than before.

The specific steps are as follows:

Performing a wavelet transform of the trace detection data after noise reduction. The original signal data is transformed to obtain the two-dimensional matrix components of the wavelet at different scales in different times.

The original signal data becomes a structure in the three-dimensional scale-time-component. A certain scale is extracted after wavelet transform or coefficients at certain scales as the characteristics of the corresponding trace signals. The corresponding coefficient series are selected on different scales to observe the size of the coefficient in the corresponding time.

The algorithm aims at tracing the shear tool to maximize the commonality between traces and maintain tool trace differences. Therefore, the intermediate coefficient is more appropriate. According to the detection device and actual experimental test, selecting the data near scale 35 is the most suitable choice. The DTW algorithm is used to measure the similarity between the sample feature and the feature to be tested after the selection of the coefficient.

Set the sample to $S = \{s_1, s_2, \cdots, s_n\}$ and the trace of the input to $T = \{t_1, t_2, \cdots, t_n\}$. Thus, a two-dimensional matrix $A$ of size $N * M$ can be constructed. The element $a_{(i,j)}$ in the two-dimensional matrix represents the distance between the samples $S = \{s_1, s_2, \cdots, s_n\}$ and the element j in $I = \{i_1, i_2, \cdots, i_m\}$.

Among Thus, the matrix $a_{(i,j)}$ is calculated as follows:

$$a_{(i,j)} = e^{-(s_i - t_j)^2} \tag{6}$$

Equation (6) is a nonlinear equation. When the matching distance between the two is relatively close, its computational similarity can be kept at a high level where it tends to infinity when the distance exceeds a certain level. The similarity can be controlled in a lower range, and the distance similarity calculation does not appear inaccurate in this situation.

When the distance between $s_i$ and $t_j$ is the minimum, the highest degree of similarity is 1. As the distance increases, the degree of similarity becomes lower. The value can be infinitely close to 0. The DTW method is used to find the best matching path after obtaining the similarity degree between different points to obtain the maximum similarity value $sims(n, m)$ at the end of the destination $(n, m)$.

The similarity of the dynamic programming equation is:

$$sims(i, j) = \max \begin{cases} sim(i-1, j) + a(i, j) \\ sim(i, j-1) + a(i, j) \\ sims(i-1, j-1) + 2 \times a(i, j) \end{cases} \tag{7}$$

The core idea of the dynamic local optimal method (greedy method) to give the new match a higher weight. In the DTW, whether the sample data at a certain position or input trace detection data at a certain position, has the same weight of the match of the first occurrence then it is given 1/2 or two, as long as it appears to match the other side of a number of locations. It can achieve the optimal matching when the condition of the two signal lengths is inconsistent.

As shown in Fig. 1, Data17 (blue) and Data18 (red) are repetitive detection signals of the same trace. The difference in the case of the smallest difference between the two data is shown in the third column. The two overlapped signal overlay is shown in the fourth column when the match is completed. Visual observation shows that the signal has a high degree of overlap. During the process of detection, some errors would inevitably be produced as the two cannot exactly be the same. The test results show that the similarity is 90%, which means that the two have been effectively aligned during matching.

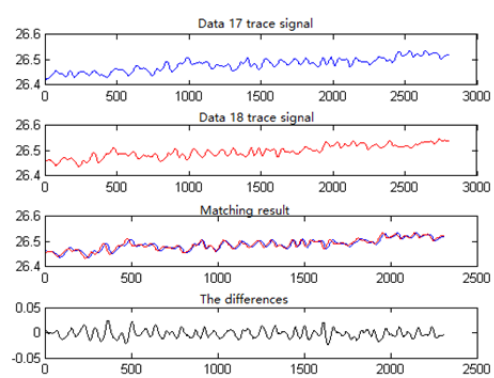


**Figure 1.** Signal difference matching.

The weight of the feature also affects the accuracy of recognition; therefore, performing specific parameter training can reduce the probability of failure. Parameter training involves the following basic steps:

1) Ensure that the steps complement the building of a sample library. The samples are sufficiently representative and distinguishable.

2) The gradient descent method is used for machine learning of parameters and constructing the corresponding cost function, reducing the costs of the cost function to a minimum by constant iterations.

3) Completing the parameter training while acquiring learning parameters.

4) When the sample library changes or the scene of usage changes, a more targeted training is recommended to continue parameter training.

The sample trace detection signal gradient is used as an input, to calculate the degree of similarity, to identify corresponding groups of tools, to infer the possible attribution of the tool after calculation, and to obtain the degree of similarity of the data. The calculation of similarity needs to calculate the similarity degree between the sample and the input sample. The degree of similarity can be mapped to a range of 0 to 1. The minimum value of 0 represents completely different, while the maximum value of 1 represents exactly the same.

The entire process of tool traceability is shown below:

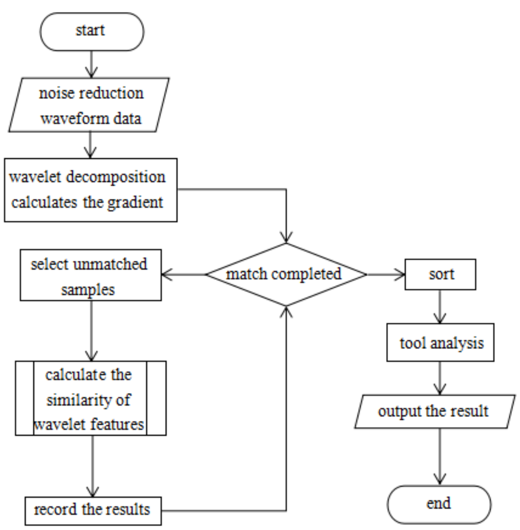


**Figure 2.** Flowchart of tool tracing.

## 4 EXPERIMENTAL VERIFICATION

THE effectiveness of this algorithm is verified through the actual shear tool source experiment. The experimental set up is as follows:

Three tools were selected: wire cutters (A), destroy pliers (B), and steel wire clamp (C). A copper bar of 1 cm diameter was cut by shear breakage. The sample parameter setting involved: a laser pot diameter of 2.5 μm, a subdivided figure for 3200 steps/s, sample frequency pulse of 1000, sampling interval of 50 ms, sampling frequency of 20 Hz, the sampling points being determined according to the cross-sectional area of the broken end. The related algorithms that match the program were written in Python upon verification by Matlab 2015b. The program was run on a ThinkPad laptop with Intel Core i5 2.9GHz CPU with 8G DDR3 memory.

The 29 sets of data labeled T16–T45 (T26 and T27 being substantially the same data) were used as test data. There were 500 data sets containing data on shearing by 10 different tools in the sample library. Excluding the data in the sample library, the results show the first five ranking values.

There were 3 sets of data in T16–T45. T16–T25 were from the traces formed by tool A, T26–T38 were from the traces formed by tools B1 and B2, and T39–T45 were from the traces formed by tool C. B1 and B2 are two tools that belong to the same tool B.

To make the simulation of the data collection in the crime scene more realistic, each group of test data was required to be tested again after shifting from the position based on the benchmark trace data and form the new data. The data in A mainly contained lateral displacement, that is the data moving on a straight line of the original traces. Some data coincided with the original data after the movement. At the same time, the data in A, B, and C, all had U-direction (up) and D-direction (down) movement and had a certain degree of dislocation with the original benchmark traces.

The definitions of tool traceability are as follows:

Backtrack precisely for the same trace (or tool). There is a certain deviation because of the location of detection, the length of the data, and many others. The sorting is more on the front and it has differentiated between the similarity degree of other types of tools.

Backtrack failed: Data not associated with the original trace.

The calculation takes 15 s, with an 88.9% matching success rate and 11.1% failure rate.

To draw a comparison with the technology proposed in this study, the literature algorithm which proposed by Nan Pan, et.al. (2015) is applied using the same sets of data labeled T16–T45. The results are shown in Table 2.

The calculation takes 18 s, with a matching success rate at 51%, the failure rate at 49%.

Compared to the method which proposed by Nan Pan, et.al. (2015), the traceability technique of proposed in this study has obvious advantages in the operation precision and stability order. Although there are no obvious differences in the speed of operation, the proposed method is more applicable to test the traces data in actual scene detection.

**Table 1. The sample matching results by the algorithm proposed in this study**

| Tool number | Highest matching | Accurate traceability rate | Data description |
|---|---|---|---|
| T16 | T17 | 100% | Group A benchmark data |
| T17 | T16 | 100% | Group A benchmark data duplicate detection |
| T18 | T20 | 100% | Group A benchmark data displacement 1/6 |
| T19 | T20 | 100% | Group A benchmark data displacement 1/3 |
| T20 | T21 | 100% | Group A benchmark data displacement 1/3 |
| T21 | T20 | 100% | Group A benchmark data displacement 1/2 |
| T22 | T23 | 100% | With the end of broken A another line |
| T23 | T18 | 100% | T22 based on the direction D of translation of 1/6 of the other line |
| T24 | T39 | 40% | T22 based on the direction U of translation of 1/6 of the other line |
| T25 | T41 | 40% | Dislocation 1/3 and deletion of 2/3 based on T22 |
| T26 | T27 | 100% | Group B benchmark data |
| T27 | T26 | 100% | Group B benchmark data duplicate detection |
| T28 | T27 | 100% | Group B benchmark data duplicate detection |
| T29 | T30 | 100% | Group B based on the direction D of translation of 1/10 of the other line |
| T30 | T29 | 100% | T29 duplicate detection |
| T31 | T32 | 100% | Group B based on the direction U of translation of 1/10 of the other line |
| T32 | T31 | 100% | T31 duplicate detection |
| T33 | T34 | 100% | Group B similar tools, different ends |
| T34 | T33 | 100% | T33 duplicate detection |
| T35 | T36 | 100% | T33 based on the direction D of translation of 1/10 of the other line |
| T36 | T35 | 100% | T35 duplicate detection |
| T37 | T38 | 80% | T35based on the direction D of translation of 1/10 of the other line |
| T38 | T37 | 80% | T38 duplicate detection |
| T39 | T40 | 80% | Group C benchmark data |
| T40 | T39 | 80% | Group C benchmark data duplicate detection |
| T41 | T25 | 60% | Group C based on the direction D of translation of 1/10 of the other line |
| T42 | T43 | 80% | T41 duplicate detection |
| T43 | T42 | 80% | T41 duplicate detection |
| T44 | T45 | 80% | Group C based on the direction U of translation of 1/10 of the other line |
| T45 | T44 | 80% | T44 duplicate detection |

**Table 2. The sample matching results by the algorithm proposed by Nan Pan, et. al. (2015)**

| Tool number | Highest matching | Accurate traceability rate | Data description |
|---|---|---|---|
| T16 | T17 | 100% | Group A benchmark data |
| T17 | T16 | 100% | Group A benchmark data duplicate detection |
| T18 | T20 | 100% | Group A benchmark data displacement 1/6 |
| T19 | T20 | 100% | Group A benchmark data displacement 1/3 |
| T20 | T21 | 100% | Group A benchmark data displacement 1/3 |
| T21 | T20 | 100% | Group A benchmark data displacement 1/2 |
| T22 | T24 | 80% | With the end of broken A another line |
| T23 | T17 | 100% | T22 based on the direction D of translation of 1/6 of the other line |
| T24 | T40 | 0% | T22 based on the direction U of translation of 1/6 of the other line |
| T25 | T19 | 20% | Dislocation 1/3 and deletion of 2/3 based on T22 |
| T26 | T27 | 100% | Group B benchmark data |
| T27 | T26 | 100% | Group B benchmark data duplicate detection |
| T28 | T27 | 100% | Group B benchmark data duplicate detection |
| T29 | T30 | 100% | Group B based on the direction D of translation of 1/10 of the other line |
| T30 | T29 | 100% | T29 duplicate detection |
| T31 | T32 | 100% | Group B based on the direction U of translation of 1/10 of the other line |
| T32 | T31 | 100% | T31 duplicate detection |
| T33 | T34 | 60% | Group B similar tools, different ends |
| T34 | T33 | 60% | T33 duplicate detection |
| T35 | T19 | 20% | T33 based on the direction D of translation of 1/10 of the other line |
| T36 | T35 | 80% | T35 duplicate detection |
| T37 | T38 | 60% | T35based on the direction D of translation of 1/10 of the other line |
| T38 | T37 | 60% | T38 duplicate detection |
| T39 | T40 | 80% | Group C benchmark data |
| T40 | T39 | 80% | Group C benchmark data duplicate detection |
| T41 | T45 | 60% | Group C based on the direction D of translation of 1/10 of the other line |
| T42 | T43 | 80% | T41 duplicate detection |
| T43 | T42 | 80% | T41 duplicate detection |
| T44 | T45 | 80% | Group C based on the direction U of translation of 1/10 of the other line |
| T16 | T17 | 100% | T44 duplicate detection |

## 5 CONCLUSION

IN this study, an effective traceability algorithm for non-linear shear traces in the wavelet domain was proposed. The proposed algorithm combines the dynamic time regularization algorithm based on wavelet features to perform similarity matching of trace features and realize the rapid inference of corresponding tools. The complexity of the algorithm presented in this study is relatively low. The algorithm can be programmed directly using the Python language, and the generated executable file can be run on mid-range computers. Through actual tests by an expert from the trace testing works in the Ministry of Public Security, the algorithm is proved to be effectively applicable to the shear tools backtrack based on line trace and provide a reliable reference for subsequent identification. To simulate actual working environments more realistically, improve the operation speed of larger magnitude data, and perform comparative and traceability studies of serial criminal offenders in the cross-region faster are avenues for future research.

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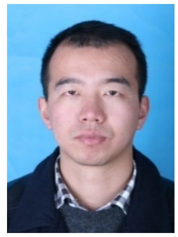
## 8 NOTES ON CONTRIBUTORS



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