



SIMILARITY ANALYSIS OF DYNAMIC TEMPERATURE MEASUREMENTS

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Abstract

Different temperature sensors show different measurement values when excited by the same dynamic temperature source. Therefore, a method is needed to determine the difference between dynamic temperature measurements. This paper proposes a novelty approach to treating dynamic temperature measurements over a period of time as a temperature time series, and derives the formula for the distance between the measurement values using uniform sampling within the time series analysis. The similarity is defined in terms of distance to measure the difference. The distance measures were studied on the analog measurement datasets. The results show that the discrete Fréchet distance has stronger robustness and higher sensitivity. The two methods have also been applied to an experimental dataset. The experimental results also confirm that the discrete Fréchet distance performs better.

Keywords: dynamic temperature, temperature time series, similarity measure, distance measure.

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1. Introduction

Temperature measurement is divided into static temperature measurement and dynamic temperature measurement. Dynamic temperature measurement means that the temperature is not constant during the measurement period but changes [1]. For the same dynamic temperature excitation source, whether it is to measure with multiple sensors, or use the multiple measurements of a single sensor, it is necessary to process multiple groups of similar dynamic temperature measurements, and distinguishing them poses is a serious problem.

Temperature measured with a sensor over a period of time is a group of time series data, so time series analysis is the most appropriate. Therefore, we regard dynamic temperature measurement values as a temperature time series [2] and distinguish them by calculating the similarity. And for temperature time series, the similarity between them is mainly measured by the Euclidean distance [3], but it only applies to data with the same sampling frequency [4].

Therefore, we also provide the Fréchet distance as an alternative method on this basis, and we study the Euclidean distance and Fréchet distance on the analog measurement datasets through

simulation. Then the same procedure is applied to an experimental dataset. The results show to distinguish multiple groups of similar dynamic temperature measurements that the Fréchet distance is more suitable for indicating temperature difference than the Euclidean distance.

2. Related work

The Euclidean distance is applied to measure the similarity between dynamic temperature measurements. Kunt *et al.* [3] used the Euclidean distance to measure the similarity between the two response curves. Mukherjee *et al.* [5] studied the arrangement of temperature sensors based on K-means clustering with a microprocessor. The Euclidean distance was used as the similarity function of measuring distance, and the average accuracy was improved by 19%. Guo *et al.* [6] used the Euclidean distance as a nonlinear operator to obtain a better model effect when monitoring the temperature trend of a wind turbine. Ortega *et al.* [7] designed an intelligent detector based on temperature modulation, and took the Euclidean distance as the similarity measure in cluster analysis.

However, the Euclidean distance is a one-to-one measure, which is only suitable for data with the same sampling frequency, so the application is not satisfactory. The Fréchet distance seeks the best time alignment matching, which can better indicate the difference between similar dynamic temperature measurements. Driemel *et al.* [8] studied the time series clustering problem with the application of the Fréchet distance, and proposed a clustering algorithm based on it which resulted in a better clustering result. Jiang *et al.* [9] raised a trajectory compression method based on the Fréchet distance, which brought a better geometric similarity between the compressed trajectory and the original trajectory. Fan *et al.* [10] proposed a long-term intuitive fuzzy time series prediction model based on vector quantization and a curve similarity measure, which replaced the Euclidean distance by the Fréchet distance, making it more suitable for vector matching. Hadi *et al.* [11] developed a data diagnosis method based on the Fréchet distance to diagnose outliers in data and verify the method in two groups of data.

Dynamic temperature measured with a sensor over a period of time can be treated as a temperature time series. Temperature time series can be analyzed through a data-driven method. This paper presents simulation of analog dynamic temperature measurement datasets, and analysis of the similarity of temperature time series with Euclidean Fréchet distances. These methods are also applied to the experimental dataset. The results show that Fréchet distance can indicate the difference between dynamic temperatures, and is more suitable than the Euclidean distance.

3. Theoretical background

3.1. Temperature time series analysis

Temperature time series is based on time- or space-transformed datasets generated on the basis of time domain observations. Processing temperature time series data has difficulties such as huge data volume, high-dimensional datasets, and noise.

There are four kinds of time series analyses [12]:

- Discrete analysis considers only part of the information in the sequence and assumes that the observed eigenvalues have no regularity in time or ignores their regularity in time.
- Point set analysis regards the time series as an unordered feature point set which can be represented by a distribution function.

- Uniform sampling analysis differs from the point set analysis in that it considers the order of points in the feature point set. Usually, the analyzed time series can be described by vectors, but it is difficult for uniform sampling to distinguish time inconsistencies.
- Time domain modeling allows time distortion and does not limit the length of the sequence. Considering temperature time series to be sequential, this paper adopts uniform sampling analysis and uses distance to measure the difference between the dynamic temperature measurements.

3.2. Measures of dynamic temperature measurements similarity

The similarity between dynamic temperature measurements is usually defined in terms of distance. The distance between any two points in the metric space ψ is defined as:

$$d: \psi \times \psi \rightarrow d(a, b) \in \mathbb{R}. \quad (1)$$

The distance needs to meet the following three conditions:

(1) It is non-negative:

$$d(a, b) \geq 0, \quad \forall a, b \in \psi. \quad (2)$$

(2) It is symmetric:

$$d(a, b) = d(b, a), \quad \forall a, b \in \psi. \quad (3)$$

(3) It satisfies the triangle inequality:

$$d(a, b) \leq d(a, c) + d(c, b), \quad \forall a, b, c \in \psi. \quad (4)$$

However, distance can only describe the similarity qualitatively, so it is difficult to analyze similarity with different methods on a unified scale. Therefore, the similarity is quantified with a similarity measure.

A similarity measure involves weighing the degree of similarity between individuals. In contrast to the distance measure, the larger the similarity measure, the greater the individual similarity and the smaller the difference.

Given function $similarity(\cdot, \cdot)$ as a normalized similarity, then it satisfies properties as follows:

$$similarity(a, b) \in [0, 1],$$

$$similarity(a, b) = 1 \Leftrightarrow a = b,$$

$$similarity(a, b) = 0 \Leftrightarrow a \text{ and } b \text{ are completely different.}$$

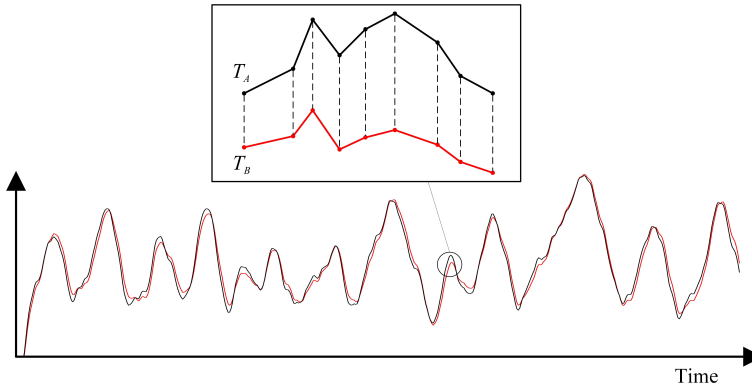
The similarity can be defined in terms of distance measure as:

$$similarity(a, b) = \frac{1}{1 + dist(a, b)}, \quad (5)$$

where $dist$ represents the distance measure and $similarity$ represents the normalized similarity.

3.2.1. Euclidean distance

The Euclidean distance is defined in a Euclidean space to calculate the overall dissimilarity. It compares samples at the same time and is a one-to-one metric [13]. Figure 1 shows the Euclidean distance between two discrete dynamic temperature measurements T_A and T_B .

Fig. 1. Euclidean distance between T_A and T_B .

Given two discrete dynamic temperature measurements T_A and T_B ,

$$T_A = \{a_k \mid k = 1, 2, 3, \dots, n\} \in \psi, \quad (6)$$

$$T_B = \{b_k \mid k = 1, 2, 3, \dots, n\} \in \psi. \quad (7)$$

In the metric space, the Euclidean distance is defined as:

$$d_E(T_A, T_B) = \sqrt{\sum_{k=1}^n (a_k - b_k)^2}, \quad (8)$$

The Euclidean distance is parameter-free [14]. However, it has the drawbacks of high sensitivity to noise and inability to reflect the morphological characteristics of the sequence. Furthermore, the Euclidean distance cannot deal with the time drift; that is, it cannot align two series in a feature-to-feature form (peak-to-peak, trough-to-trough) [4].

3.2.2. Fréchet distance

Maurice René Fréchet proposed the Fréchet distance to describe the similarity of space paths [15]. Fréchet distance considers the similarity on the curve space path, which makes it more efficient to deal with time series curves. Suppose A and B are two continuous curves in a metric space, $A: [0, 1] \rightarrow \psi$, $B: [0, 1] \rightarrow \psi$. Then, we define continuous increasing functions $\alpha(t)$ and $\beta(t)$, where $\alpha: [0, 1] \rightarrow [0, 1]$, $\beta: [0, 1] \rightarrow [0, 1]$. The Fréchet distance between A and B is defined as:

$$d_F(A, B) = \inf_{\alpha, \beta} \max_{t \in [0, 1]} \{d(A(\alpha(t)), B(\beta(t)))\}, \quad (9)$$

where, d represents the distance metric function on metric space ψ . $A(\alpha(t))$ and $B(\beta(t))$ represent the spatial positions of continuous curves A and B at time t , respectively.

From (9), for each group of $\alpha(t)$ and $\beta(t)$, we can always find the maximum distance of two curves A and B on the whole path. By changing the variables $\alpha(t)$, $\beta(t)$ and t , the maximum distance between the curves will also change. The Fréchet distance is to find a set of appropriate functions $\alpha(t)$ and $\beta(t)$ to minimize the maximum distance between the curves.

In 1994, Eiter et al. discretized the two continuous curves and expressed them as two sequences on the basis of the Fréchet distance [16]. Then, the discrete Fréchet distance was proposed by

them. As the curves are discretized, only the node distance needs to be considered. This makes it easier to find an optimal route between them. The discrete Fréchet distance is often used to describe a similarity between two curves at different travel speeds. Figure 2 shows two dynamic temperature curves and with different response speeds, where r_1 represents the discrete Fréchet distance between two dynamic temperature series T_A and T_B .

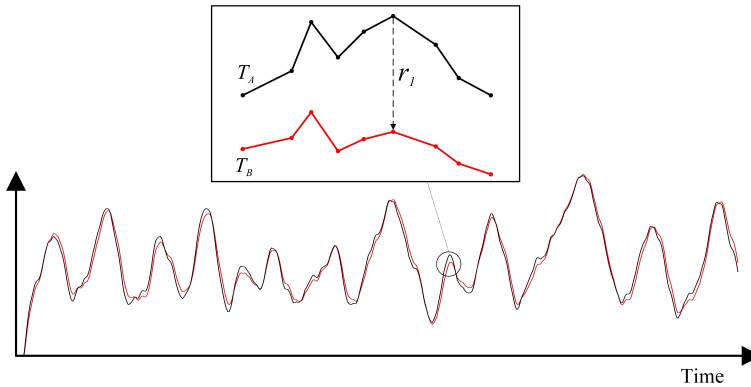


Fig. 2. Discrete Fréchet distance between T_A and T_B .

Given two discrete dynamic temperature measurements T_A and T_B from (6) and (7), and both of them are composed of n sampling points, that is, $T_A = \{a_1, \dots, a_i, \dots, a_n\}$, $T_B = \{b_1, \dots, b_j, \dots, b_n\}$. We use $u(T_A)$ and $u(T_B)$ to represent the sequential set of T_A and T_B , respectively. Then, $u(T_A) = \{a_i, \dots, a_n\}$ and $u(T_B) = \{b_i, \dots, b_n\}$, at the same time, sequence point pairs τ can be obtained $\tau = \{(a_1, b_1), \dots, (a_i, b_j), \dots, (a_n, b_n)\}$. The distance of the sequence pairs between T_A and T_B can be defined as:

$$d_{DF}^{\tau}(T_A, T_B) = \max_{(a,b) \in \tau} d(a, b). \quad (10)$$

The discrete Fréchet distance between T_A and T_B is defined as in [17]:

$$d_{DF}(T_A, T_B) = \min_{\tau} d_{DF}^{\tau}(T_A, T_B). \quad (11)$$

It can be seen from (11) that the definition of discrete Fréchet distance satisfies the nonnegativity, symmetry and trigonometric inequality of distance measures.

4. Dataset

4.1. Numerical simulation dataset

Zimmerschied and Isermann [18] applied an amplitude-modulated pseudo-random binary sequence to the study of dynamic characteristics of a temperature sensor, which can better reflect the variation of dynamic temperature than the step signal and the pseudo-random binary sequence. So, we used an amplitude-modulated pseudo-random binary sequence as excitation temperature. The time length of the whole sequence is 200 s, the data length n studied in this paper ranges from 1001 to 10001. As shown in Fig. 3, it is an amplitude-modulated pseudo-random binary

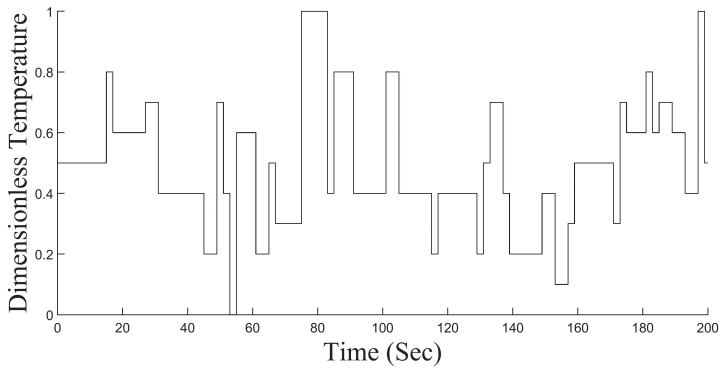


Fig. 3. Excitation signal.

sequence with data length n of 2001 and a time interval of 0.1 s. Data length n could be changed by changing the time interval between adjacent points.

As can be seen from Fig. 3, the x -axis represents the sampling time and the y -axis represents the dimensionless temperature. The dimensionless temperature is a dimensionless value between 0 and 1, where 0 represents low temperature excitation, 1 represents high temperature excitation, and the value between 0 and 1 corresponds to the temperature excitation between low temperature and high temperature. Following Tagawa [19], we simulated a temperature sensor with a time constant of 0.04 s. Its transfer function is

$$G(s) = \frac{1}{0.04s + 1}. \quad (12)$$

The amplitude-modulated pseudo-random binary sequence in Fig. 3 was used as the excitation temperature for the sensor represented by (12), and the theoretical measurement values of the temperature sensor were obtained, as shown in Fig. 4.

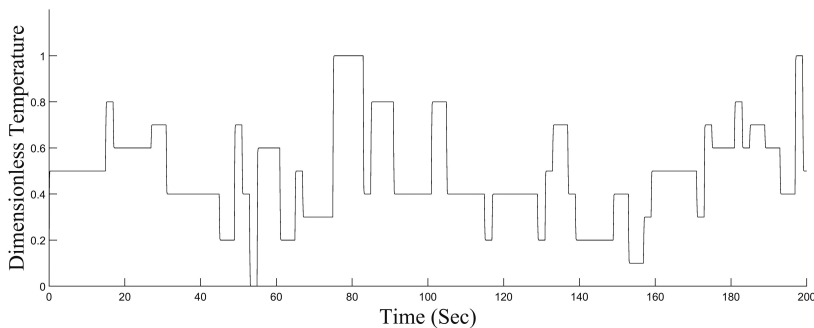


Fig. 4. Temperature sensor output.

Fig. 5 shows the zoomed characteristics of the temperature sensor input and response in the one-coordinate system (75–83 s).

As can be seen from Fig. 5, the dynamic response of the temperature sensor lags behind the input. Gaussian noise was added to these values to obtain the analog measurement values of the

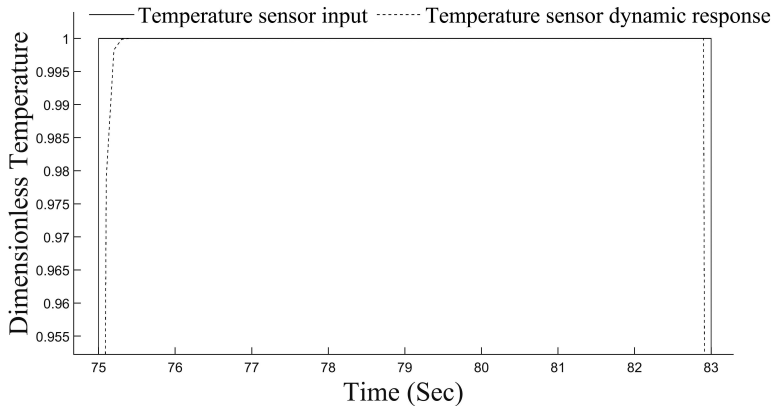


Fig. 5. Input and response of the temperature sensor (75–83 s local amplification).

temperature sensor. The intensity of the added noise was controlled using the signal-to-noise ratio (SNR), which is defined as:

$$\text{SNR} = 10 \log \left(\frac{PS}{PN} \right), \quad (13)$$

where PS and PN are the effective powers of the signal and noise, respectively.

By changing the SNR, many groups of analog measurement values can be obtained. Following Li [20], we set an SNR range of 20 dB to 70 dB and obtained several groups of analog measurement values. A small SNR indicates a large measurement error, while a large SNR indicates a small measurement error.

We also define the time constant ratio τ_r as follows:

$$\tau_r = \frac{\tau_A}{\tau_B}, \quad (14)$$

where τ_r represents the time constant ratio, τ_A and τ_B are the time constants of two temperature sensors, respectively.

For a comparison, we also simulated multiple temperature sensors according to the definition of time constant ratio τ_r . Its transfer function is defined as:

$$G(s) = \frac{1}{0.04\tau_r s + 1}. \quad (15)$$

The time constant ratio range studied in this paper is 1–2.5 and the step size is 0.5. Using a similar method, we obtained the analog measurement values of temperature sensors.

4.2. Experimental measurement dataset

In order to validate the effectiveness of the two similarity measures in the experimental data, an experimental setup for measuring dynamic temperature was built for the purpose of this paper. The system mainly included four segments: dynamic temperature measurement segment, mechanical drive segment, data acquisition segment and control segment, as shown in Fig. 6.

The temperature sensors used in the experiment were K-type NiCr/ NiSi thermocouples with wire diameters of 0.15 mm (thermocouple A), 0.15 mm (thermocouple B) and 0.1 mm

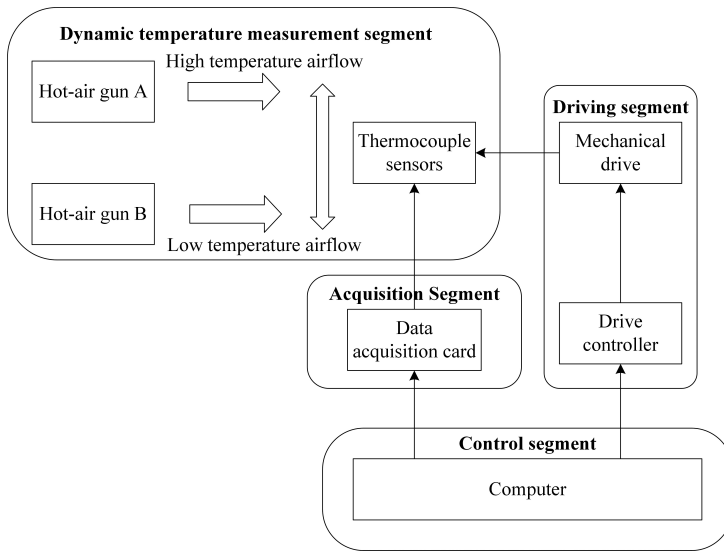


Fig. 6. Dynamic temperature measurement experimental setup.

respectively (thermocouple C), and the accuracy of the sensors is $\pm 1.5^\circ\text{C}$. The thermocouple was statically calibrated by a measuring furnace, a multi-channel thermometer and a second-class standard platinum rhodium thermocouple in the temperature range of 323 K–923 K. The data acquisition card was a USB-2408 (24-bit AD resolution), hot-air guns A and B were QUICK2008, and the programmable controller was an OMRON CPM1A.

First, two hot-air guns A and B produced high- and low-temperature airflows respectively as the temperature excitation of the thermocouples, and then the mechanical driving device was controlled by the driving controller to realize the swing of the thermocouple measuring point between the two temperature sources. Finally, the dynamic temperature data collected by the data acquisition card was returned to the controller for storage and processing, and the TracerDAQ software output the data in real time.

Table 1 shows the parameters of the experimental setup.

Table 1. Experimental parameters.

Sampling frequency/Hz	Data length	High-temperature airflow/K	Low-temperature airflow/K
50	10001	633	323

With parameters in Table 1, the experimental dataset of three thermocouples was obtained. Figure 7 shows the dynamic response of the three thermocouples under 323 K low-temperature airflow and 633 K high-temperature airflow, with the data length of 10001.

The three thermocouples are all bare wire thermocouples, and the smaller the wire diameter of the bare wire thermocouple, the smaller the time constant and the greater the speed of response. In addition, it can be seen from Fig. 7 that thermocouple A (wire diameter of 0.15 mm), thermocouple B (wire diameter of 0.15 mm) and thermocouple C (wire diameter of 0.1 mm) show good

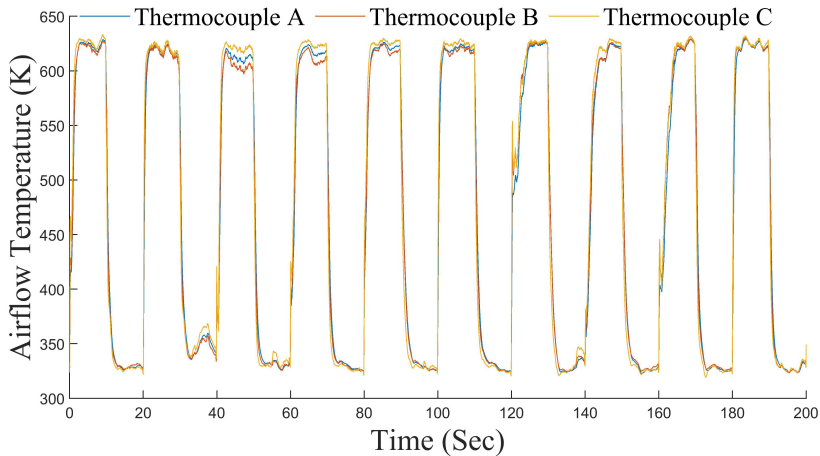


Fig. 7. Thermocouple experimental measurement data (low-temperature airflow at 323 K and high-temperature airflow at 633 K).

consistency for the same dynamic temperature excitation, and their experimental measurement values are similar and difficult to distinguish.

5. Result

5.1. Numerical simulation result

5.1.1. SNR

Firstly, considering that the time constant ratio $\tau_r = 1$, the similarity between the analog measurement values of dynamic temperature in different noise environments is studied. The analog measurement values of sensors were obtained for SNR = 20 dB, the Euclidean distance and the discrete Fréchet distance between the two groups of measurements were calculated. Then, the SNR was increased in 5 dB steps to get the analog measurement values and calculate the two distances at each step. The results are shown in Fig. 8a. The similarity between the analog measurement values can be calculated from these two distances according to (5), as shown in Fig. 8b.

Fig. 8 shows that when the SNR increases, so do the two kinds of similarity (as abscissa values increase). However, the sensitivities of the two kinds of similarities to the variation in SNR are different, with the similarity based on the Euclidean distance being the most sensitive. This means that the result given by the Euclidean distance in the analog measurement values with noise is not reliable, and it will misjudge the two groups of similar temperature data. Moreover, the robustness of the method itself is not strong and it can be easily affected by a variety of factors including noise, so it is difficult to indicate the difference between dynamic temperatures. The discrete Fréchet distance shows stronger robustness in the case of the analog measurement values of temperature sensors with noise and is more suitable than the Euclidean distance.

However, owing to the effects of fabrication technology and sensor structure and size, the time constants of two temperature sensors are not completely equal in practical application. In the following, the Euclidean distance and the discrete Fréchet distance between the two groups of measurements were calculated after we assumed the time constant ratio $\tau_r = 1.5$ and also obtained

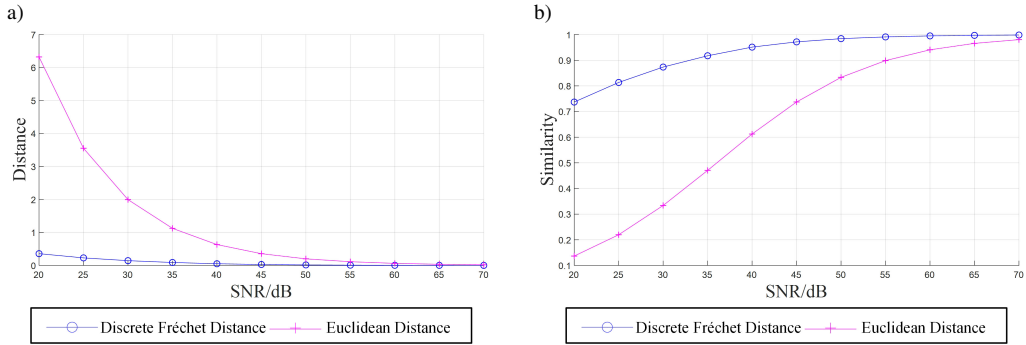


Fig. 8. Distance between analog measurement values (a); Similarity between analog measurement values (b), of the temperature sensors with the same time constant of 0.04 s.

the analog measurement values of sensors for SNR = 20 dB. Then, the SNR was increased in 5 dB steps to get the analog measurement value and calculate the two distances at each step. The results are shown in Fig. 9a. The similarity between the analog measurement values can be calculated from these two distances according to (5), as shown in Fig. 9b.

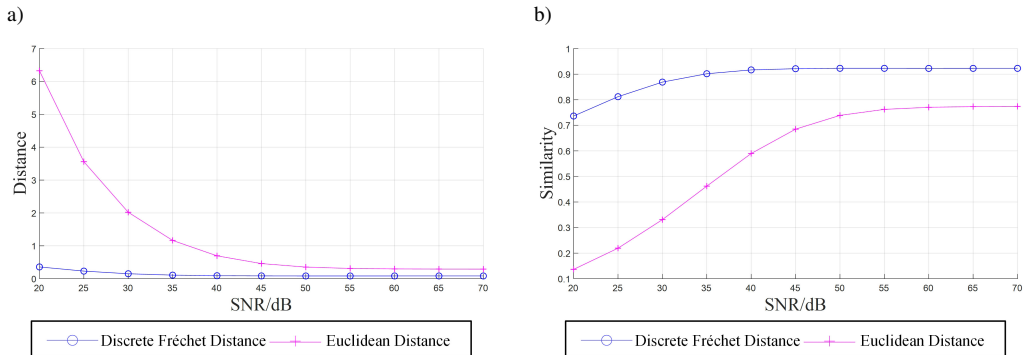


Fig. 9. Distance between analog measurement values (a); Similarity between analog measurement values (b), of the temperature sensors with different time constants of 0.04 s and 0.06 s.

Fig. 9 shows that when the sensors have different time constants, the similarities based on the Euclidean and discrete Fréchet distances sensitively measure the difference. Table 2 shows the distance and similarity between the analog measurement values of the Euclidean distance and the discrete Fréchet distance with two time-constant ratios of 1 and 1.5 respectively at different SNRs.

The results in Fig. 8, Fig. 9 and Table 2 combined show that the discrete Fréchet distance can better indicate the temperature difference between the analog measurement values of two temperature sensors with different time constants than the Euclidean distance. In the noise environment with high SNR, taking SNR of 70 dB as an example, the influence of the time constant ratio τ , increases the Euclidean distance varies from 0.0200 to 0.2920, and the discrete Fréchet distance varies from 0.0016 to 0.0836. The discrete Fréchet distance is more sensitive to the variation of the time constant of the temperature sensor, that is, it can indicate the difference between two groups of similar dynamic temperature measurements. In the noise environment with low SNR, the robustness of the Euclidean distance is poor, and it is more vulnerable to noise interference.

Table 2. Distance and similarity between analog measurements of two temperature sensors.

SNR/dB	τ_r	Euclidean distance		Discrete Fréchet distance	
		Distance	Similarity	Distance	Similarity
20	1	6.3213	0.1366	0.3568	0.7370
	1.5	6.3245	0.1365	0.3582	0.7363
25	1	3.5525	0.2197	0.2294	0.8134
	1.5	3.5594	0.2193	0.2317	0.8119
30	1	1.9959	0.3338	0.1449	0.8734
	1.5	2.0213	0.3310	0.1508	0.8690
35	1	1.1252	0.4750	0.0900	0.9175
	1.5	1.1641	0.4621	0.1091	0.9016
40	1	0.6328	0.6124	0.0513	0.9512
	1.5	0.6960	0.5896	0.0909	0.9167
45	1	0.3563	0.7373	0.0292	0.9716
	1.5	0.4601	0.6849	0.0854	0.9213
50	1	0.2000	0.8333	0.0160	0.9842
	1.5	0.3537	0.7387	0.0835	0.9229
55	1	0.1128	0.8986	0.0092	0.9909
	1.5	0.3119	0.7662	0.0835	0.9229
60	1	0.0631	0.9407	0.0051	0.9949
	1.5	0.2980	0.7704	0.0839	0.9226
65	1	0.0355	0.9658	0.0029	0.9971
	1.5	0.2933	0.7742	0.0837	0.9228
70	1	0.0200	0.9804	0.0016	0.9984
	1.5	0.2920	0.7740	0.0836	0.9228

5.1.2. Time constant ratio

This section focuses on the influence of time constant ratio τ_r on the similarity between dynamic temperature measurements. As shown in Fig. 10, the distance between the analog measurement values of two temperature sensors with time constant ratios of 1, 1.5, 2 and 2.5 under different noise environments was calculated with the Euclidean distance and the discrete Fréchet distance respectively.

The similarity between the analog measurement values can be calculated from these two distances according to (5), as shown in Fig. 11.

In order to further analyze the sensitivity of the two distance measures to the difference caused by the variation of the time constant of the temperature sensor, we introduce variation ratio v_r as the evaluation metric, which is defined as follows:

$$v_r = \frac{d(T_{0.04\tau_r}, T_{0.04}) - d(T_{0.04}, T_{0.04})}{d(T_{0.04}, T_{0.04})}, \quad (16)$$

where τ_r represents the time constant ratio, $T_{0.04}$ and $T_{0.04\tau_r}$ represent the dynamic temperature analog measurement values of the temperature sensors with the time constants of 0.04 s and $0.04\tau_r$ s, respectively, $d(,)$ represents the distance measure. Table 3 shows variation ratio v_r of the temperature sensors with time constant ratios τ_r of 1.5, 2 and 2.5 under different noise environments.

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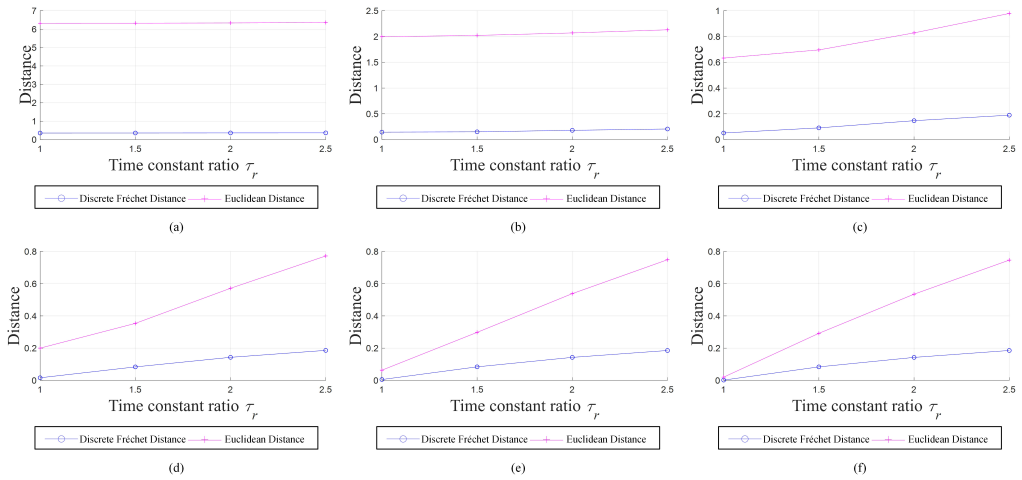


Fig. 10. Distance between analog measurement values of the temperature sensors for an SNR of 20 dB (a); 30 dB (b); 40 dB (c); 50 dB (d); 60 dB (e); 70 dB (f)

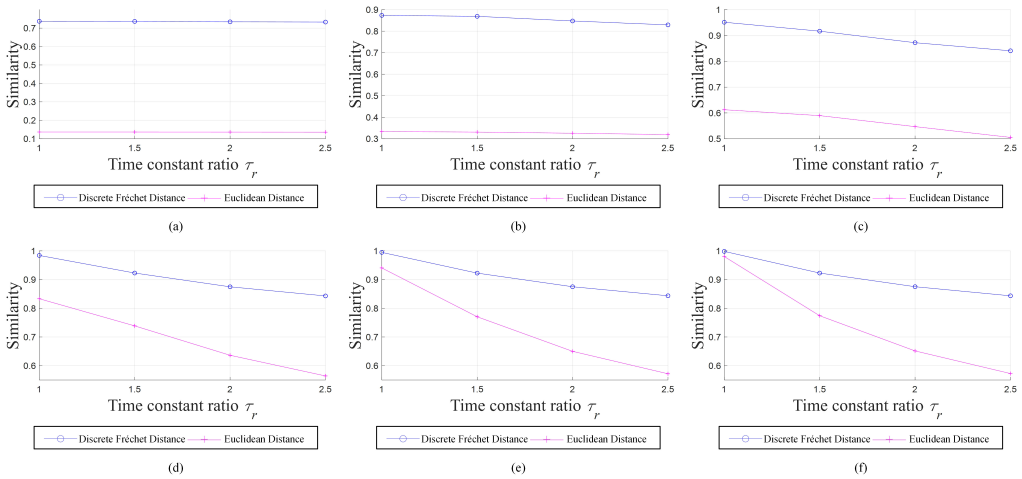


Fig. 11. Similarity sensitivity against the degree of variation of the time constant ratio for an SNR of 20 dB (a); 30 dB (b); 40 dB (c); 50 dB (d); 60 dB (e); 70 dB (f)

Table 3. Variation ratio v_r of two distance measures.

SNR/dB	Euclidean distance			Discrete Fréchet distance		
	$\tau_r = 1.5$	$\tau_r = 2$	$\tau_r = 2.5$	$\tau_r = 1.5$	$\tau_r = 2$	$\tau_r = 2.5$
20	0.0005	0.0024	0.0064	0.0039	0.0154	0.0219
30	0.0127	0.0370	0.0673	0.0407	0.2422	0.4210
40	0.0999	0.3086	0.5469	0.7719	1.8616	2.6959
50	0.7685	1.8585	2.8615	4.2188	7.9375	10.6375
60	3.7227	7.5325	10.8685	15.4510	26.9804	35.3629
70	13.6000	25.755	36.325	51.3125	88.1250	114.9375

The results in Fig. 10 and Fig. 11 show that both Euclidean distance and discrete Fréchet distance can measure the difference of temperature sensor caused by the variation of time constant ratio τ_r , and with the increase of time constant ratio τ_r , the distance between analog measurement values increases and the similarity decreases.

The results in Table 3 show that the sensitivity of the discrete Fréchet distance is significantly stronger than that of the Euclidean distance under different noise environments. In addition, with the decrease of SNR, the sensitivity of the two distance measures decreases. The main reason for this phenomenon is that the robustness of the method decreases, and it is more vulnerable to noise interference, resulting in a decrease in sensitivity. Nevertheless, the robustness of the discrete Fréchet distance is still stronger than that of the Euclidean distance, which is more suitable for processing dynamic temperature data with noise.

5.1.3. Data length

Data length represents the number of time series elements. In this section, the data length studied ranged from 1001 to 10001 and noise environment SNR ranged from 20 dB to 70 dB. Two groups of temperature sensors with time constant ratio τ_r of 1 and 1.5 were taken as the research objects. Figure 12 shows the Euclidean distance and the discrete Fréchet distance between analog measurements with data length n of 1001, 2001, 4001 and 10001 respectively.

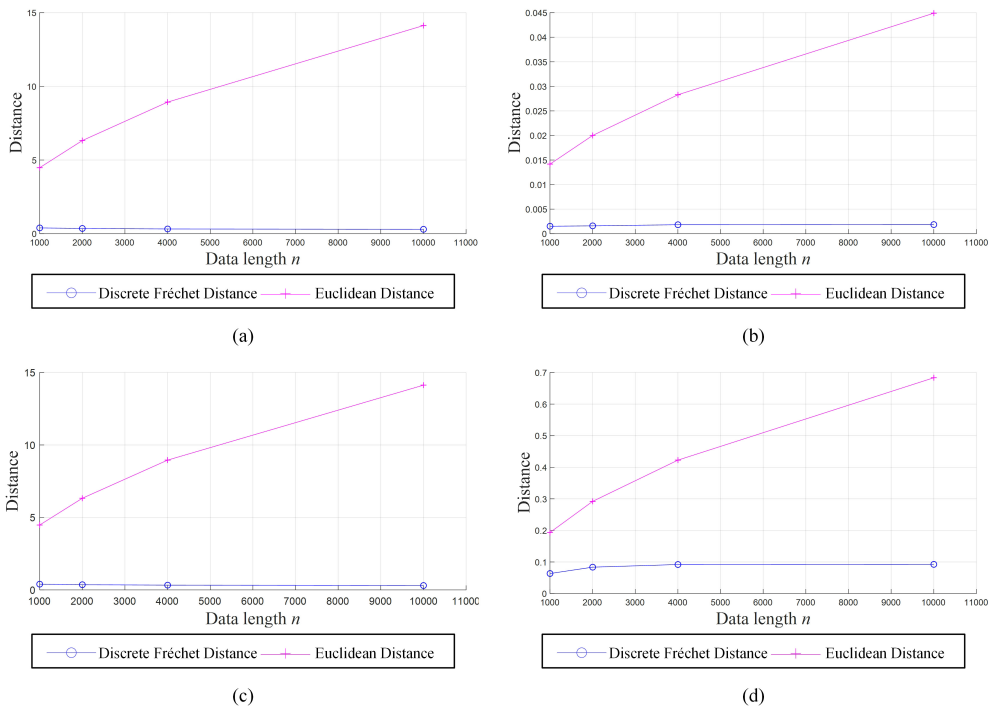


Fig. 12. Distance between analog measurement values of the temperature sensors for $\tau_r = 1$, SNR = 20 dB (a); $\tau_r = 1$, SNR = 70 dB (b); $\tau_r = 1.5$, SNR = 20 dB (c); $\tau_r = 1.5$, SNR = 70 dB (d).

The similarity between analog measurement values was calculated following (5) and the results are shown in Fig. 13.

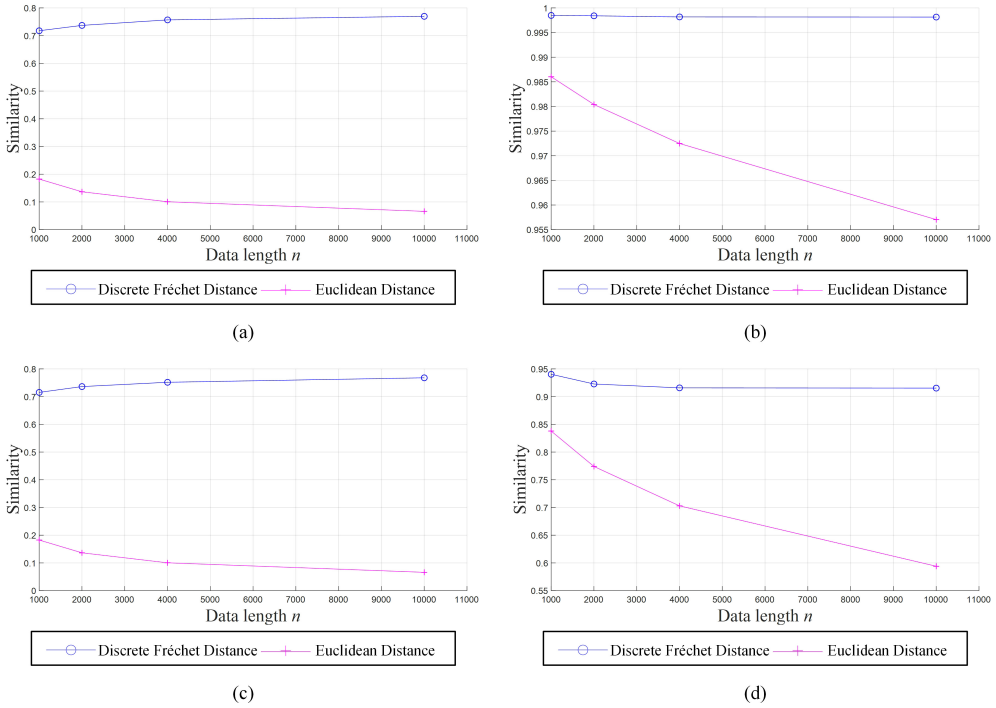


Fig. 13. Similarity sensitivity against the degree of variation of data length n for $\tau_r = 1$, SNR = 20 dB (a); $\tau_r = 1$, SNR = 70 dB (b); $\tau_r = 1.5$, SNR = 20 dB (c); $\tau_r = 1.5$, SNR = 70 dB (d).

The results in Fig. 12 and Fig. 13 combined show that with an increase in data length, the Euclidean distance between the analog measurement values of the temperature sensor increases rapidly, while the discrete Fréchet distance varies little. Due to the difference of large order of magnitude between the Euclidean distance and the discrete Fréchet distance, it is difficult to analyse the impact of the data length only with the numerical variation trend. Therefore, v_l is introduced as an evaluation metric to represent the variation rate of the two distances with data length. A smaller v_l means that the distance is less affected by the data length, which is defined as follows:

$$v_l = \frac{\left| d\left(T_{0.04\tau_r}^l, T_{0.04}^l\right) - d\left(T_{0.04\tau_r}^{1001}, T_{0.04}^{1001}\right) \right|}{d\left(T_{0.04\tau_r}^{1001}, T_{0.04}^{1001}\right)} \quad (l = 2001, 4001, 10001), \quad (17)$$

where $T_{0.04}^l, T_{0.04\tau_r}^l$ represent the analog measurement values of the temperature sensors with data length of l and time constants of 0.04 s and $0.04\tau_r$ s, respectively. $T_{0.04}^{1001}, T_{0.04\tau_r}^{1001}$ represent the analog measurement values of the temperature sensors with data length of 1001 and time constants of 0.04 s and $0.04\tau_r$ s, respectively. The values of v_l are shown in Table 4.

The results in Table 4 show that, compared with Euclidean distance under the conditions of different SNRs and different time constant ratio τ_r , v_l of each data length of the discrete Fréchet distance is less than the Euclidean distance, which means that the discrete Fréchet distance is less affected by data length n . Therefore, discrete Fréchet is insensitive to the variation of data length,

Table 4. v_l for the two distance measures.

SNR/dB	τ_r	Euclidean distance			Discrete Fréchet distance		
		$l = 2001$	$l = 4001$	$l = 10001$	$l = 2001$	$l = 4001$	$l = 10001$
20	1	0.4110	0.9935	2.1531	0.0930	0.1833	0.2394
	1.5	0.4126	1.0004	2.1557	0.1002	0.1706	0.2409
70	1	0.4085	0.9930	2.1620	0.0667	0.2000	0.2000
	1.5	0.5098	1.1851	2.5341	0.3145	0.4450	0.4528

has a wider applicability, and as such, is more suitable for processing dynamic temperature data than Euclidean distance.

5.2. Experimental results

Section 5.1 analyzed the performance of the Euclidean distance and the discrete Fréchet distance on multiple groups of analog measurement datasets by simulation. In order to verify the numerical simulation results, the two distance measures were further analysed with the experimental dataset presented in this paper. The experimental dataset was acquired by thermocouple A, thermocouple B and thermocouple C. Before calculating the similarity, the experimental dataset was normalized. Based on the normalized experimental dataset, the Euclidean distance and the discrete Fréchet distance were used to measure the similarity of performance of the three thermocouples under the same dynamic temperature excitation, as shown in Table 5.

Table 5. Euclidean and discrete Fréchet distances between the three thermocouple sensors.

Euclidean distance	Thermocouple A		Thermocouple B		Thermocouple C	
	Distance	Similarity	Distance	Similarity	Distance	Similarity
Thermocouple A	/	/	0.9784	0.5055	2.1779	0.3147
Thermocouple B	0.9784	0.5055	/	/	1.4428	0.4094
Thermocouple C	2.1779	0.3147	1.4428	0.4094	/	/
Discrete Fréchet distance	Thermocouple A		Thermocouple B		Thermocouple C	
	Distance	Similarity	Distance	Similarity	Distance	Similarity
Thermocouple A	/	/	0.1180	0.8945	0.2052	0.8297
Thermocouple B	0.1180	0.8945	/	/	0.1429	0.8750
Thermocouple C	0.2052	0.8297	0.1429	0.8750	/	/

The results in Table 5 show that the distance between the experimental measurement value measured with the Euclidean distance is significantly greater than the discrete Fréchet distance. This is because the Euclidean distance involves the distance between points and is highly sensitive to variation of each dynamic temperature measurement sampling point. At the same time, the discrete Fréchet distance focuses more on the structure and spatial similarity between dynamic temperature measurements. Under the excitation of the same dynamic temperature, with three thermocouples with of response speeds caused by different wire diameters, the discrete Fréchet distance can better grasp the structural similarity. The discrete Fréchet distance is more suitable for distinguishing between multiple groups of similar dynamic temperature measurements.

6. Conclusions

In dynamic calibration, values measured with a high-precision temperature sensor are used to approximate the real temperature, and the point of interest is how to convert into a comparison between two temperature sensors. This paper has analyzed the similarity between the dynamic temperature measurements of temperature sensors. Aiming at solving the problem of how to distinguish multiple groups of similar dynamic temperature measurements, it is proposed to calculate the similarity through the distance measures to distinguish the similar dynamic temperature measurements. Simulations show that the discrete Fréchet distance can distinguish the dynamic temperature measurement values more accurately than the Euclidean distance, and the performance is better in the noise environment with low SNR. We have built an experimental setup for measuring dynamic temperature with thermocouples and acquired the experimental dataset. The experimental results are consistent with the simulation results. The main reason why the discrete Fréchet distance is better than the Euclidean distance is that the Euclidean distance is sensitive to noise and is a step-locked measure. In contrast, the discrete Fréchet distance can allow time distortion, adapt to a local time shift, has low sensitivity to noise and as such, it is more suitable to process dynamic temperature data as a similarity measure.

In future research, we can also study thermocouples of different materials and different types of temperature sensors. The combination of deep learning algorithms and denoising algorithms is also considered to better deal with the dynamic temperature measurements in strong noise environment.

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