Gesture recognition method for wearable sports devices based on sparse representation

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Abstract: In order to effectively solve the shortcomings of traditional gesture recognition methods for sports devices, such as high error rate and long recognition time, this paper designs a gesture recognition method for wearable sports devices based on sparse representation. A gesture model was constructed according to the gesture features of wearable sports devices, and the standard characteristic quantities of gestures were obtained. A sensor is then used to quickly collect a sample of the gesture. The sparse coefficient is obtained. Gestures were classified and processed according to the minimum residual value and sparse coefficient, so as to obtain accurate gesture recognition results of wearable sports devices. The simulation results show that the correct rate of gesture classification is always above 95.41%, the error rate of gesture recognition is always below 5.32%, and the recognition time is less than 0.8 s, which proves that the method has achieved good practical application effect.

Keywords: sparse representation; wearable sports devices; gesture recognition; characteristic; classification process.

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1 Introduction

Gestures have always been an important way of communication before language appeared. This expression has been used to this day, even in military and sports games. Promoted by the update and development of information technology, a variety of wearable devices have developed rapidly. With the continuous improvement of people's requirements for such devices, the updating speed of such devices has been accelerating (Chen et al., 2019). But so far, the human-computer interaction technology has been widely used in the field of wearable sports equipment design, because of gesture recognition technology is an important research topic in the field of human-computer interaction, so in order to promote wearable sports equipment man-machine interaction ability, needs of wearable motion equipment gesture recognition technology, in-depth study of upgrading wearable intelligent sports equipment, so you need to study a wearable sports equipment gesture recognition method has important research significance (Yuan, 2020; Liu, 2020).

Research on gesture recognition methods for wearable sports devices has made some progress at present. For example, Hui (2019) proposed a gesture recognition method for wearable devices based on deep learning algorithm. The method mainly USES wearable devices bring user gesture data of sensors and the data pre-processing, get a more complete set of sample data, on the basis of using TensorFlow build neural network (CNN), and the network was trained in order to reduce the output error of classifying data collected after finishing as neural network input samples, wearable device gesture recognition results, but the method problems of wearable devices gesture recognition error rate is higher, and the ideal accuracy has the very big disparity. Li et al. (2019) proposed a gesture recognition method for wearable sports devices based on electrical measurement. This method mainly uses the inertial sensor to collect the gesture data in real-time, and carries on the cleaning processing and fills the missing purpose from the realisation. On this basis, the cleaned data are classified, and the collected gesture information is searched and matched according to the designed gesture recognition principles, so as to get the final recognition results. Although the classification ability of this method is strong, the efficiency of the recognition process is low. Li (2018) proposed a gesture recognition method for wearable sports devices based on mixed motion data. In this method, two devices, Leap Motion and Depth Camera, are used to obtain gesture data of wearable sports devices, and two data sets are obtained. On the basis of the joint correction for the two data sets of data, and will deal with good data input to the wearable sports equipment to gesture recognition model, get the final movement of wearable devices gesture recognition results, but this method exists wearable sport equipment gesture recognition error rate is higher and recognition takes longer, the actual application effect is not ideal.

Aiming at the shortcomings of the above methods and achieving various goals such as reducing the error rate and time consuming of gesture recognition for wearable sports devices, this paper proposes a gesture recognition method for wearable sports devices based on sparse representation. The overall technical route of this method is as follows:

1) In order to improve the effectiveness of wearable sports device gesture recognition model, sensors are used to quickly collect gesture samples to improve the accuracy of wearable sports device gesture recognition model.

2) Based on reducing the error rate and shortening the recognition time of motion equipment gesture recognition methods, a sparse dictionary matrix is constructed to obtain the sparse coefficients. The gestures are classified according to the minimum residual value and sparse coefficient to reduce the recognition error rate, so as to obtain accurate gesture recognition results of wearable sports devices.

3) Experimental verification. Taking the error rate and shortening the recognition time of the gesture recognition method of sports equipment as the experimental comparison index, the proposed method is compared with Hui (2019), Li et al. (2019) and Li (2018).

2 Gesture recognition method for wearable sports devices

In this study, we build a gesture model to obtain the standard characteristic quantities of gestures. Then, based on the gesture samples quickly collected by the sensor, the samples are normalised. According to the characteristics of hand model, the recognition method of first classification and then matching is adopted and the concept of membership degree in fuzzy theory is introduced to complete gesture recognition. According to the characteristics of the data, the average standard of clustering distance is redefined to complete gesture recognition. Then, the sparse coefficient is obtained by constructing the sparse dictionary matrix. Finally, the gestures were classified according to the minimum residual value and sparse coefficient, and the accurate gesture recognition results of wearable sports devices were obtained.

2.1 Gesture modelling of wearable sports devices

Gesture modelling is the basis of gesture recognition for wearable sports devices. It is mainly a method to establish a gesture model based on gesture features and use the model to represent the whole process of gesture actions (Xing et al., 2020). Therefore, this paper mainly defines common gestures, and the results are presented in Table 1.

Table 1 Common gesture definitions

Signal types	*Knock*	*Flip*	*Switch*	*Rock*	*Draw hook*	*Cross the fork*
Specify	A single tap	Counter clockwise and clockwise flips	One way to shake	Sway from side to side	First go down and then go up	First down, then up and down again

In general, because the static gesture modelling is relatively simple, this paper mainly carries out the dynamic gesture modelling of wearable sports devices. In the spatial coordinate system, the dynamic gesture mainly refers to the moving track of the hand in space (Li, 2019). The dynamic gesture trajectory is shown in Figure 1.

In the spatial coordinate system, the gesture trajectory is composed of a set of three-dimensional spatial points arranged in an orderly manner, which is described as follows:

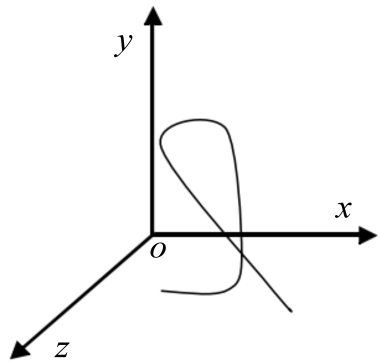
$$T = \left(p_1, p_2, \ldots, p_i\right) \tag{1}$$

where $p_1, p_2, \ldots, p_i$ represents the dimension of the sparse dictionary matrix, and its specific composition is as follows:

$$p_i = \left\{x_i, y_i, z_i\right\} \tag{2}$$

where x_i, y_i, z_i are components in the three-dimensional direction respectively.

Figure 1 Gesture trajectory



By analysing the above formula, it can be seen that the dynamic gesture has a certain spatial attribute and a certain time attribute, so the velocity attribute of the point p_i in three-dimensional space is:

$$\overline{v}_i = \left\{\overline{v}_{ix}, \overline{v}_{iy}, \overline{v}_{iz}\right\} \tag{3}$$

The dynamic gesture time attribute is differentiated with $\overline{v}_i$ to obtain the acceleration of point p_i (Wang et al., 2018). The specific calculation formula is as follows:

$$\overline{a}_i = \frac{d\overline{v}_i}{dt} \tag{4}$$

In the dynamic gesture trajectory model of wearable sports devices, the hand is generally considered as a zero-dimensional point. However, in practice, the shape of the hand is usually closer to a cuboid and this idea is also adopted in the process of gesture data acquisition that is conducive to the sensor (Wu et al., 2018; Pan et al., 2018). So, we need to introduce the attitude Angle to better describe the angular velocity of the change in the hand orientation. The specific description of attitude angle is as follows:

$$\Phi_i = \{\theta, \gamma, \varphi\} \tag{5}$$

In the above formula, θ represents the Angle between the palm plane and the x-axis, γ represents the angle between the palm plane and the y-axis and φ represents the angle between the palm plane and the z-axis. Obtaining the angular velocity of palm orientation change by attitude angle (Cao et al., 2018a):

$$\Omega = \left\{\omega_\theta, \omega_\gamma, \omega_\varphi\right\} \tag{6}$$

Among them, the calculation formulas of ω_θ, ω_γ and ω_φ are as follows:

$$\omega_\theta = \frac{d\theta}{dt} \tag{7}$$

$$\omega_\gamma = \frac{d\gamma}{dt} \tag{8}$$

$$\omega_\varphi = \frac{d\varphi}{dt} \tag{9}$$

Combined with the above analysis results, the gesture model of wearable sports devices is constructed, which is described as follows:

$$\mathrm{G} : T, V, \Phi, \mathrm{t} \tag{10}$$

where t represents time.

2.2 Extraction of gesture feature quantity

In the process of gesture recognition of wearable sports devices, gestures change dynamically, so the coordinate system of sensor devices will change constantly, which makes the result of gesture data acquisition inaccurate and affects the subsequent recognition effect. The method of gesture recognition is completed according to the orientation map of gesture key feature points. Therefore, based on the gesture model constructed above, this paper extracts the gesture feature quantity of wearable sports devices (Feng et al., 2018; Cao et al., 2018b), which lays a solid foundation for subsequent gesture recognition.

Based on the summary of previous research experience, this paper divides the gesture characteristic quantity of wearable sports devices into the following six categories, as follows:

1) *Gesture length L*: Represents the track length from the starting point to the end point during the movement of the user's palm.

2) *Gesture kinetic energy E*: The energy consumed by the user's hand in the process of displaying different gestures is called gesture kinetic energy. Gesture kinetic energy can be obtained by formula (11):

$$E = \sum_{i=1}^{L} \left(|w_{xi}| + |w_{yi}| + |w_{zi}| + |a_{xi}| + |a_{yi}| + |a_{zi} - g| \right) \tag{11}$$

where w_{xi}, w_{yi} and w_{zi}, respectively represent the angular velocity of the gesture on the *x*-, *y*- and *z*-axes; a_{xi}, a_{yi} and a_{zi}, respectively represent the acceleration of the gesture on the *x*-, *y*- and *z*-axes; g represents the acceleration of gravity.

3) *Angular velocity of the axis with the greatest energy*: Before obtaining the axis with the highest angular velocity energy, we first need to determine the angular velocity energy in each axis direction (Yang et al., 2018; Bao and Lv, 2018). The formula for calculating the angular velocity energy of *x*-, *y*- and *z*-axes is as follows:

$$E_{wx} = \sum_{i=1}^{L} \left(|w_{xi}| \right) \tag{12}$$

$$E_{wy} = \sum_{i=1}^{L} \left(\left| w_{yi} \right| \right) \tag{13}$$

$$E_{wz} = \sum_{i=1}^{L} \left(\left| w_{zi} \right| \right) \tag{14}$$

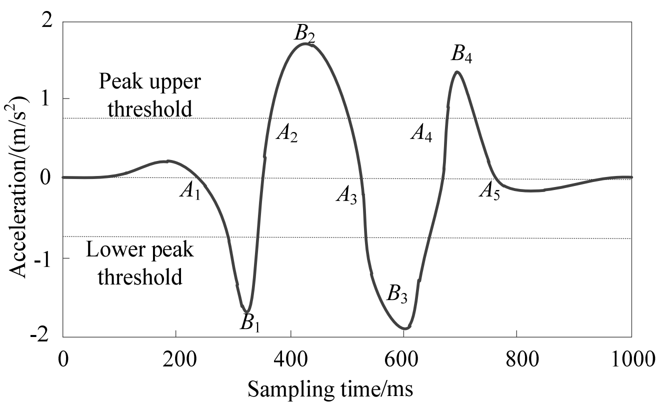
Then, the maximum angular velocity energy axis can be obtained by combining the above formula. The specific calculation formula is as follows:

$$Q = \max\left(E_{wx}, E_{wy}, E_{wz}\right) \tag{15}$$

where the maximum angular velocity energy axis is the coordinate axis Q_T where Q is located.

4) *Number of acceleration peaks*: This value is mainly the sum of the acceleration peaks of *x*-, *y*- and *z*-axes (Guo and Meng, 2018). Acceleration waveform diagram is shown in Figure 2.

Figure 2 Acceleration waveform diagram



Find out all the intersection points of all gesture acceleration data and horizontal axis, which are mainly expressed by the following formula:

$$A = A_1, A_2, \ldots, A_n \tag{16}$$

On this basis, the maximum acceleration point between any two intersection points is determined, which is mainly expressed by the following formula:

$$B = B_1, B_2, \ldots, B_k \tag{17}$$

Then the number of acceleration wave peaks can be calculated by the following formula:

$$R = n + k \tag{18}$$

1) *The change of attitude angle* $\Delta\Phi$: This index represents the sum of the difference values of attitude angles in different axial directions between the start and stop positions of gestures, and the calculation process is as follows:

$$\Delta\Phi = |\theta_B - \theta_A| + |\gamma_B - \gamma_A| + |\varphi_B - \varphi_A| \tag{19}$$

where θ_A, γ_A and φ_A, respectively represent the starting attitude angles of gestures on *x*-, *y*- and *z*-axes; θ_B, γ_B and φ_B, respectively represent the ending attitude angles of gestures on *x*-, *y*- and *z*-axes.

2) *Single-sign angular velocity* Ω_i: In the process of gesture expression of wearable sports devices, the angular velocity on each axis in the spatial coordinate system is always positive or negative, so it is called single-sign angular velocity (Wang et al., 2019; Zou et al., 2018).

In summary, the gesture characteristic quantity of wearable sports devices is extracted as follows:

$$W : L, E, Q_T, R, \Delta\Phi, \Omega_i \tag{20}$$

2.3 Gesture separation and recognition based on sparse representation

The research of sparse representation mainly appeared in the 1990s. With the vigorous development of related theories, sparse representation methods have been widely used in various fields. According to the characteristics of gesture separation, the recognition method of classification before matching is adopted, and the concept of membership in fuzzy theory is introduced. When using wearable motion sensor acquisition equipment for gesture data processing, it is very easy to be affected by many factors such as light and noise, resulting in the decline of accuracy and efficiency of gesture recognition results, Therefore, this paper introduces the sparse representation of gesture recognition in order to improve the robustness of wearable sports equipment recognition and the accuracy of the results in the recognition process.

In this paper, the sensor collects the data of gesture training samples of wearable sports devices, and normalises the training samples, so as to construct the dictionary matrix A. Assuming that the training sample $A_i = [\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{in}] \in R^{i\times m}$ consists of i types of samples, then α_{in} represents the column vector of the dictionary matrix and the following relationship exists:

$$m = \mathrm{w} \times h \tag{21}$$

where $\mathrm{w} \times h$ represents the size of the gesture training sample of the wearable sports device.

If the number of data in the training set is large enough, the test sample $\mathrm{y}_i \in R^m$ can be approximated by a linear combination of i samples, and its specific description is as follows:

$$\mathrm{y}_i = x_{i1}\alpha_{i1} + x_{i2}\alpha_{i2} + \ldots + x_{in}\alpha_{in} \tag{22}$$

When the training samples have c categories, the test samples in the training sample set can be sparsely represented by the following formula (Zhang et al., 2020):

$$\mathrm{y}_0 = \mathrm{A}x_0 \tag{23}$$

where x_0 represents the sparse vector:

$$x_0 = [0,\dots,0,x_{i1},\dots,x_{in},0,\dots,0]^T \in R^n \tag{24}$$

where n represents the total number of gesture training samples of wearable sports devices. When $n < m$, this system of equations is considered to be super-stable, that is, the sparse vector x_0 is unique. Then, one norm α in the norm set l_0 of the sparse representation in the above equation satisfies the minimum value of α_0, which can be calculated by the following formula:

$$\hat{\alpha}_0 = \mathrm{argmin}\alpha_0 \; s.t. y = A\alpha \tag{25}$$

However, it is still difficult to solve the above formula, so it is necessary to convert the above formula according to compressed sensing and coefficient representation theory, and use convex optimisation method to approximate the solution. The specific results are as follows:

$$\hat{\alpha}_1 = \mathrm{argmin}\alpha_1, s.t. y = A\alpha \tag{26}$$

where α_1 is a value in the norm set l_1, so the problem can be described by using a standard linear equation, which can be specifically expressed as:

$$\hat{\alpha}_1 = \mathrm{argmin} x_1 \; s.t. \; y - A\alpha_2 \leq \varepsilon \tag{27}$$

where ε represents the tolerance error.

The test samples are classified into the category with the highest correlation, that is, the minimum residual value combined with the sparse coefficient is used to conduct gesture classification of wearable sports devices. The results are as follows:

$$\text{if entity}(\mathrm{y}_i) = \mathrm{argmin} y - A\alpha_2 \tag{28}$$

The gesture classification results of wearable sports devices were matched according to the gesture category rules to obtain the final gesture recognition results of wearable sports devices, which are specifically expressed as follows:

$$F = \frac{\hat{\alpha}_1 (W + G)}{\text{ifentity}(y_i)} \tag{29}$$

To sum up, this study based on wearable sports equipment gesture characteristic signal model is constructed to obtain the standard characteristic, then the gestures of the collected samples normalised processing and build a sparse matrix dictionary, according to the residual error minimum and sparse coefficient classification processing of gestures, wearable sports equipment gesture recognition result is obtained.

3 Experimental test

3.1 Simulation experiment design

The following experiments are designed to verify the practical application effect of the proposed method.

1) *Experimental environment*: the simulation experiment needs to be carried out in a unified experimental environment. The technical parameters are expressed in Table 2.
2) *The experimental data came from a wearable sports equipment manufacturer*. The technical parameters and factory test data of the equipment were collected as experimental sample data for many times, and all the data were input into the simulation software, and the experimental results were obtained by running the simulation software, in order to improve the authenticity of the simulation results.
3) *Comparison method*: Method of Hui (2019); Li et al. (2019) and Li (2018) were selected as the comparison method in this study.

Table 2 Technical parameters of simulation experiment environment

Parameter	*Description*
CPU	10 Cores Intel Xeon E5-2640 CPU
Memory	64GB
Hard disk	HDD 10TB
	SSD 480GB
Network card	Broadcom NetXtreme Gigabit Ethernet
Operating system	Windows XP
Simulation software	Matlab 7.0

3.2 Experimental evaluation indexes

Experimental evaluation indexes: the accuracy of gesture classification of wearable sports devices, the error rate of gesture recognition of wearable sports devices and the time of recognition were taken as evaluation indexes.

Among them, the higher the accuracy of gesture classification of wearable sports devices, the more accurate the classification result is.

The lower the error rate of gesture recognition for wearable sports devices, the more accurate the recognition result is. The specific calculation formula is as follows:

$$Q_C = \frac{W_i - W_j}{W_i} \times 100\% \tag{30}$$

In the above formula, W_i represents the total number of gestures of wearable sports devices and W_j represents the number of correctly recognised gestures of wearable sports devices.

The shorter the time of gesture recognition of wearable sports devices is, the higher the recognition efficiency will be. The specific calculation formula is as follows:

$$E_C = \sum_{i=1}^{N} t_i \tag{31}$$

In the above formula, t_i represents the time taken for the *i*-th gesture recognition item of wearable sports devices, and N represents the total number of recognition items.

3.3 Data analysis

In this section, the accuracy of gesture classification of wearable sports devices, the error rate of gesture recognition and the time consuming of recognition are taken as evaluation indexes respectively to verify the practical application effects of the method in this paper and the three traditional methods.

3.3.1 Comparison of correct rate of gesture classification

Firstly, the accuracy of gesture classification of wearable sports equipment is compared with Method of Hui (2019); Li et al. (2019) and Li (2018) and Method of this paper. The comparison results are presented in Table 3.

Table 3 Comparison of correct rate of gesture classification (unit: %)

Number of experiments	*Method of Hui (2019)*	*Method of Li et al. (2019)*	*Method of Li (2018)*	*Method of this paper*
10	85.26	78.55	75.23	96.32
20	87.35	74.61	74.14	95.41
30	82.15	78.45	78.36	98.72
40	84.24	74.12	79.63	96.47
50	85.44	76.35	85.23	98.12
60	87.13	74.28	84.19	97.45
70	80.26	75.38	83.56	97.23
80	86.33	76.81	84.75	96.32
90	81.29	79.51	79.37	97.55
100	82.34	80.12	78.25	98.26

Analysis of the data in Table 3, Method of Hui (2019) gestures changes between 80.26% and 87.35%, classification accuracy in Li et al. (2019) gesture of classification accuracy between 74.12% and 80.12%, refer to Method of Li (2018) on the classified accuracy when using gestures changes between 74.14% and 85.23%, and the method of gesture to remain above 95.41%, classification accuracy is wearable sports equipment in the four methods gestures with the highest classification accuracy, shows that the method can realise accurate classification, wearable sports equipment gestures It can lay a solid foundation for subsequent gesture recognition.

3.3.2 Gesture recognition error rate comparison

Firstly, the error rate of gesture recognition of wearable sports devices was compared with Method of Hui (2019); Li et al. (2019) and Li (2018) and Method of this paper. The comparison results are presented in Table 4.

Table 4 Comparison of gesture recognition error rate (Unit: %)

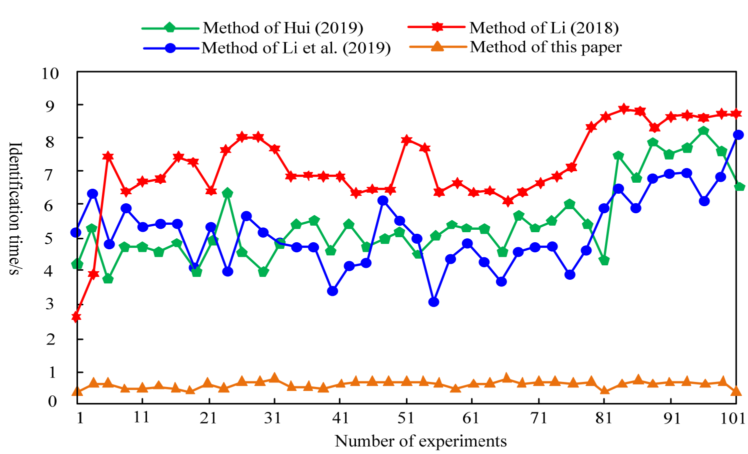
Number of experiments	*Method of Hui (2019)*	*Method of Li et al. (2019)*	*Method of Li (2018)*	*Method of this paper*
10	9.65	12.36	18.36	5.32
20	9.32	15.56	18.25	4.12
30	8.56	12.34	12.56	3.25
40	9.31	15.86	13.41	5.11
50	10.21	17.25	17.41	3.69
60	11.33	18.24	18.52	3.64
70	11.52	19.62	17.12	2.58
80	12.85	12.52	15.63	3.89
90	13.69	14.75	12.34	4.55
100	12.36	16.33	18.42	3.69

According to the data in Table 4, the error rate of gesture recognition in Hui (2019) ranges from 8.56 to 13.69%, the error rate of gesture recognition in Li et al. (2019) ranges from 12.34 to 19.62%, and the error rate of gesture recognition in Li (2018) ranges from 12.34 to 18.52%, while the error rate of gesture recognition in this method is always below 5.32%, which means that The results show that this method has lower error rate and higher recognition accuracy.

3.3.3 Comparison of identification time

Finally, the time consuming of gesture recognition for wearable sports devices was compared between Method of Hui (2019); Li et al. (2019) and Li (2018) and Method of this paper. Comparison results are presented in Figure 3.

Figure 3 Comparison of gesture recognition time



Analysis Figure 3 shows that in Hui (2019) gesture recognition method of wearable sports equipment takes between 3.7 s and 8.3 s, Li et al. (2019) gesture recognition method of wearable sports equipment takes between 3.2 s and 7.9 s, refer to the method of Li (2018) wearable sports equipment gesture recognition takes between 2.7 s and 8.9 s, and the method of wearable sports equipment gesture recognition time consuming under 0.8 s, shows that the method of identify takes shorter and more short, identification is more efficient.

4 Conclusions

1) Gesture recognition is an important function of wearable sports devices. Aiming at the problems of high error rate and long recognition time in the current gesture recognition methods of wearable sports devices, this paper designed a new recognition method based on sparse representation. In gesture characteristic building model is established on the basis of rapid acquisition wearable sports equipment gestures samples, then the signal samples normalisation processing and build sparse matrix dictionary, again according to the residual error minimum and sparse coefficient of classifying gestures to sample processing, so as to obtain accurate wearable sports equipment gesture recognition results.

2) Experimental results show that the accuracy of gesture classification is always above 95.41%, the error rate of gesture recognition is always below 5.32%, and the time of gesture recognition is always less than 0.8 s, which can achieve accurate and fast gesture recognition of wearable sports devices.

3) The next step is to optimise the gesture comprehensive performance of the wearable sports device according to the research results of this paper, so as to enhance the intelligence of the device and promote the further development of the wearable sports device manufacturing industry.

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