Big Data Fast Extraction Method of Lithium Ion Screen Exchange Feature in Cloud Computing

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Abstract. The characteristic distribution performance of big data, the exchange characteristic of lithium ion screen in cloud computing environment, quantitatively reflects the running state of lithium ion screen exchanger, in order to realize the effective monitoring of lithium ion screen exchange process. A fast extraction algorithm of Li-ion screen exchange feature big data based on big data is proposed. Big data acquisition of lithium ion screen exchange characteristics is realized in lithium ion screen exchange array, and the statistical analysis model of big data mining is constructed. In big data distribution subspace, the spectral feature extraction method is used to extract the spectral stripe feature of Li-ion screen exchange feature big data, and the extracted spectral stripe feature is fuzzy clustering and mining by adaptive neural network learning algorithm. Big data rapid extraction of exchange characteristics of lithium ion screen was realized. The simulation results show that the method has high accuracy in fast extraction of exchange features of lithium ion screen, strong resolution of exchange characteristics of lithium ion screen, and has good application value in high precision measurement of exchange characteristics of lithium ion screen.

Keywords: Cloud computing · Lithium ion screen · Exchange · Feature big data · Rapid extraction

1 Introduction

The exchange characteristic of lithium ion screen, big data, comes from the characteristic sensor of lithium ion screen exchange. The exchange characteristic of lithium ion screen is a dense, equal spacing parallel line engraving on a long strip of optical glass. The measurement data are collected and integrated by distributed lithium ion screen exchange characteristic sensor array, and big data rapid extraction of lithium ion screen exchange feature is carried out in cloud computing environment. To improve the ability of measuring information analysis of exchange characteristics of lithium ion screen, so as to improve the high precision measurement performance of exchange characteristics of lithium ion screen, the research of fast data extraction method has been paid great attention to [1].

The exchange characteristics of lithium ion screen are made of photosensitivity in optical fiber. In the rapid extraction of big data, it is easy to be interfered by the spatial

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distribution of light intensity in doped optical fiber, which leads to the poor accuracy of mining. In the traditional method [1], the rapid extraction methods of big data for lithium ion screen exchange features include HPCC (High Performance Computing Cluster) mining method, irregular spectral stripe mining method, phase lithium ion screen exchange feature transmission mining method and fuzzy frequent itemset mining method. The spectral characteristic quantity of big data in lithium ion screen exchange feature sensor is extracted, combined with information recombination and fuzzy clustering method, the rapid extraction of lithium ion screen exchange feature big data is realized, and some mining efficiency is obtained. In reference [3], a feature extraction method of lithium ion screen exchange feature big data based on inter-class closed frequent itemsets mining is proposed. The multi-level distributed array grooming model of lithium ion screen exchange feature sensor is used to realize data mining. The feature directivity of data mining is improved, but this method has a large amount of computation in fast data extraction. In reference [4], the piecewise regression test method is used to extract the exchange feature of lithium ion screen, big data is used to extract the exchange feature of lithium ion screen, and the matched filter is used to filter redundant information, so as to improve the statistical analysis ability of big data fast extraction of exchange feature of lithium ion screen. This method is greatly interfered with each other in the feature information fusion of fuzzy sets, which can easily lead to the misclassification and leakage of big data characteristics of lithium ion screen exchange characteristics. In reference [5], a fast extraction method of Li-ion screen exchange feature big data based on improved chaotic partition algorithm is proposed, which uses chaotic partition algorithm for fast extraction and data clustering. The big data feature optimization mining of big data concentrated lithium ion screen exchange feature is realized. the reflection bandwidth range and additional loss of this method are large in the fast extraction of lithium ion screen exchange feature [5].

In order to solve the above problems, a fast extraction algorithm of Li-ion screen exchange feature big data based on big data is proposed in this paper. Firstly, the exchange characteristics of lithium ion screen in lithium ion screen exchange array, big data, were collected, and the characteristic distribution sequence of big data, the exchange feature of lithium ion screen, was reorganized, and then the spectral characteristic quantity of the exchange feature big data of lithium ion screen was extracted. The adaptive neural network learning algorithm is used for fuzzy clustering and mining, and the improved design of the fast extraction algorithm is realized. Finally, the simulation experiment is carried out. The superior performance of this method in improving the fast extraction ability of exchange features of lithium ion screen is shown.

2 Data Acquisition and Big Data Sequence Analysis of Lithium Ion Screen Exchange Characteristics

2.1 Lithium Ion Screen Exchange Characteristic Sensing Data Acquisition

In order to extract the exchange characteristics of lithium ion screen quickly by big data, firstly, the network model of lithium ion screen exchanger is constructed, and the distributed lithium ion screen exchanger array is used for big data acquisition. The exchange characteristics of lithium ion screen collected by big data are mainly scale lithium ion screen exchange characteristic big data, indicating lithium ion screen exchange characteristic big data [6]. The characteristic stripe data of lithium ion screen exchange and the electric pulse data of measurement system in optical path system. The big data acquisition model of lithium ion screen exchange characteristic sensor is constructed, as shown in Fig. 1.

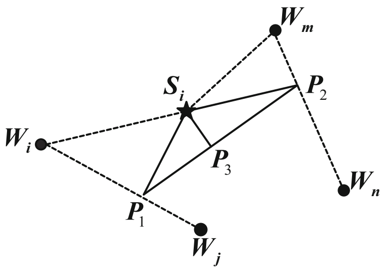

Fig. 1. Big data acquisition model of lithium ion screen exchange characteristic sensor

The big data acquisition model of lithium ion screen exchanger shown in Fig. 1 is divided into three layers: physical layer, transport layer and application layer. In the physical layer, the distributed lithium ion screen exchanger array is used to sample the lithium ion screen exchange characteristic measurement data, and the lithium ion screen exchange characteristic sensor network model is that N lithium ion screen exchanger nodes are randomly deployed in the monitoring area [7]. The running cluster head and computational cluster head of lithium ion screen exchange characteristic sensor network use chirped lithium ion screen exchange characteristics to control the periodic oscillations to improve the accuracy of data acquisition. In the lithium ion screen exchange characteristic sensor network model, each cluster has a cluster head node (SN) and several intra-cluster nodes (V0). The exchange characteristics of lithium ion screen can be divided into periodic structure and aperiodic structure. The distance between the characteristic nodes of lithium ion screen exchange is calculated by Euclidean distance formula, which is as follows:

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

Wherein, $E_{Tx}(L,d)$ represents the Euclidean distance between the two lithium ion sieve exchanger nodes, and the distance $E_{Tx}(L,d)$ between the source and the Sink node is expressed as:

$$E_{Tx}(L,d) = \begin{cases} LE_{elect} + L\varepsilon_{fs}d^2, d < d_0 \\ LE_{elect} + L\varepsilon_{mp}d^4, d > d_0 \end{cases} \tag{2}$$

The energy characteristics of the sensing array are expressed as follows:

$$E_{Rx}(L) = LE_{elect} \tag{3}$$

Where E_{elect} represents the transfer energy of lithium ion screen exchange characteristic node (intermediate node) S in the range of reflection bandwidth, d is the transmission link set of big data characteristic of lithium ion screen exchange feature. The load information transmitted in the lithium ion screen exchange array to the Sink node is expressed as follows:

$$\begin{aligned} Compution(n_j) &= (E_{elec} + E_{DF})l\delta + E_{Tx(l,d_j)} \\ &= (E_{elec} + E_{DF})l\delta + lE_{elec} + l\varepsilon_{fs}d_j^2 \\ &= [(E_{elec} + E_{DF})\delta + E_{elec} + \varepsilon_{fs}d_j^2]l \end{aligned} \tag{4}$$

According to the results of load fusion, the attribute partition characteristics of big data, the exchange characteristics of lithium ion screens, were excavated, and the exchange characteristics of lithium ion screens, big data, were collected in the exchange array of lithium ion screens. The collected data are constructed by multi-mode fusion method to form big data sequence of exchange characteristics of lithium-ion screen, and big data is used to extract the exchange feature of lithium-ion screen quickly [8].

2.2 Analysis of Big Data Sequence of Exchange Characteristics of Lithium Ion Screen

Suppose that the distribution time series of big data characteristic of lithium ion screen exchange characteristic $\{X_n\}, n = 1, 2, \cdots, N$, represents big data feature distribution set in lithium ion screen exchange characteristic sensor array, and in the finite data set distribution of lithium ion screen exchange characteristic big data, The spectrum characteristic distribution $X_N = X_n + \eta$ of big data, where η is the observation noise, is the exchange characteristic of lithium ion screen. In the big data distribution region, the directed vector quantification method is used to match the big data spectrum characteristics of lithium ion screen exchange characteristics, combined with big data output time delay [9]. The big data output time series of big data, which is the exchange characteristic of lithium ion screen, is obtained as follows:

$$X_n = \{X_n, X_{n-\tau}, X_{n-2\tau}, \cdots, X_{n-(d-1)\tau}\} \tag{5}$$

Let $R_{d\times L}$ be the matrix of $d \times L$. The average mutual information of big data, the exchange feature of lithium ion screen, is excavated in the feature space of information recombination, and the mutual information distribution matrix is obtained as follows:

$$R_1 = \{X_1, X_2, X_3, \cdots, X_d\}^T \tag{6}$$

By adopting the parallel mining method, the association rule mining of the large data characteristics of the exchange characteristic of the lithium ion screen is carried out, and the mutual information distribution matrix is decomposed, and the vector set of the characteristic decomposition is obtained as follows:

$$R_1^T R_1 = \{X_1, X_2, \cdots, X_m\}\{X_1, X_2, \cdots, X_m\}^T \tag{7}$$

The high dimensional mapping of Li ion screen exchange feature big data is carried out by using singular value feature distributed fusion method. The data structure model of Li ion screen exchange feature big data in high dimensional mapping space is described by the following two dimensional matrix model:

$$R_1^T R_1 = V_1 \sum\nolimits_1 V_1^T \tag{8}$$

Big data mining the exchange characteristics of lithium ion screen from $L+1$ to $2L$ dimension is carried out. According to the analogy of the above methods, the output eigenvalues of big data, which is the exchange feature of lithium ion screen, are obtained as follows:

$$R_2^T R_2 = V_2 \sum\nolimits_2 V_2^T \tag{9}$$

$$R_2 = \{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}^T \tag{10}$$

$$R_2^T R_2 = \{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}\{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}^T \tag{11}$$

The association rule mining method is used to reconstruct the exchange feature big data of lithium ion screen. The fuzzy eigenvector set $R^T R$ satisfies the inter-class equilibrium, and the big data sequence analysis model of exchange feature of lithium ion screen is constructed. Combined with the statistical analysis method of panel data test, big data clustering processing of lithium ion screen exchange feature was carried out to improve the rapid extraction ability of lithium ion screen exchange feature big data [10].

3 Rapid Extraction and Optimization of Exchange Characteristics of Lithium Ion Screen by Big Data

3.1 Statistical Analysis Model of Big Data for Exchange Characteristics of Lithium Ion Sieves

On the basis of big data acquisition and time series analysis of exchange characteristics of lithium ion screen, the rapid extraction algorithm of big data, which is the exchange feature of lithium ion screen, is optimized. In this paper, a fast extraction algorithm of

Li-ion screen exchange feature big data based on big data is proposed [11]. In the distributed sensor storage medium with lithium ion screen exchange characteristics, the balanced scheduling model of output load $\xi_k^w(\omega)$ is as follows:

$$\eta_k^w(\omega) = E\left(T_k^w \middle| T_k^w > \xi_k^w(\omega)\right),\ k \in R_w, w \in W \tag{12}$$

Wherein, the spectral stripe $\xi_k^w(\omega)$ of big data, the exchange characteristic of lithium ion screen, can be expressed as follows:

$$\xi_k^w(\omega) = \min\left\{\xi \middle| \Pr\left(T_k^w \le \xi\right) \ge \omega\right\} = E\left(T_k^w\right) + \gamma_k^w(\omega) \tag{13}$$

The exchange characteristics of lithium ion screen big data were linearly fitted by the generalized least square method. The multiple collinear feature matching pairs of big data, the exchange feature of lithium ion screen, $E\left(T_k^w - \xi_k^w(\omega) \middle| T_k^w \ge \xi_k^w(\omega)\right)$. The test statistic SDF for rapid extraction of big data, the exchange feature of lithium ion screen, can be expressed as follows:

$$s_h^w = E\left[\min_{k \in R_w}\left\{\mathrm{H}_{h,k}^w\right\} | \boldsymbol{\eta}^w\right] = -\frac{1}{\theta}\ln\sum_{k \in R_w}\exp\left(-\theta\eta_{h,k}^w(\omega)\right),\ w \in W, h \in H \tag{14}$$

Under the extreme learning and training, the big data feature recombination model of big data lithium ion screen exchange characteristics is constructed as follows:

$$H(S) = -\sum_{i=1}^{n} P_s(s_i)\log_2 P_s(s_i) \tag{15}$$

$$H(Q) = -\sum_{i=1}^{n} P_q(q_j)\log_2 P_q(q_j) \tag{16}$$

In big data distribution subspace, the spectral stripe feature extraction of Li-ion screen exchange feature big data is carried out by using spectral feature extraction method. The pluralistic detection statistics of Li-ion screen exchange feature big data are described as follows:

$$\xi_k^w(\omega) = t_k^w + \Phi^{-1}(\omega)\sigma_{k,t}^w,\ k \in R_w, w \in W \tag{17}$$

The empirical mode decomposition method is used to control the load balance of the samples between the two adjacent time periods of big data, and the information entropy between the centers of big data, the exchange characteristic of lithium ion screen, is recorded as follows:

$$\eta_k^w(\omega) = t_k^w + \sigma_{k,t}^w \Big/ \sqrt{2\pi}(1-\omega)\exp\left(-\left(\Phi^{-1}(\omega)\right)^2 \Big/ 2\right) \tag{18}$$

and the data link of the cluster center to the inner point of the cluster is initialized, and the average mutual information amount of the large data of the exchange characteristic of the lithium ion screen is respectively:

$$q^w = E(Q^w) = \sum\nolimits_{k \in R_w} f_k^w,\ w \in W \tag{19}$$

$$v_a = E(V_a) = \sum\nolimits_{w \in W} \sum\nolimits_{k \in R_w} \delta_{ak}^w f_k^w,\ a \in A \tag{20}$$

$$f_k^w \geq 0,\ k \in R_w, w \in W \tag{21}$$

The link random distribution method is used to equalize the big data output sensing sequence of lithium ion screen exchange characteristics. The big data characteristic decomposition subsequences of lithium ion screen exchange characteristics are obtained as follows:

$$r_1(n) = r_2(n)\exp(-j\omega_0 T_p/2),\ n = 0, 1, \ldots, (N-3)/2, \tag{22}$$

$$r_2(n) = A\ \exp[j(\omega_0 nT + \theta)],\ n = 0, 1, \ldots, (N-3)/2, \tag{23}$$

The fuzzy clustering and rapid extraction were carried out according to the extracted spectral features [12].

3.2 Data Clustering and Fast Extraction

According to the number of data processed in each batch, the fuzzy clustering of Li-ion screen exchange feature big data is carried out by using adaptive random link configuration method, and the load of Li-ion screen exchange feature big data in merged cluster is obtained as:

$$R_1(k) = R_2(k)\exp(-j\omega_0 T_p/2),\ k = 0, 1, \ldots, (N-3)/2 \tag{24}$$

$$R_2(k) = A_k \exp(j\varphi_k),\ k = 0, 1, \ldots, (N-3)/2 \tag{25}$$

Big data, the exchange characteristic of lithium ion screen, is predicted linearly. According to the global optimization results, the maximum length of the data block on each merged cluster is obtained: $\sum\limits_{i \notin I} \sum\limits_{j \notin I} p_i(k) p_{ij}(k) = p_k - \sum\limits_{i \notin I} \sum\limits_{j \in I} p_i(k) p_{ij}(k)$. Given that the solution space of objective function f is from R^n to R, the outlier $U \in R^n$ of data clustering is obtained to find a point in A, and the adaptive neural network learning algorithm is used for fuzzy clustering. When the decision threshold of data clustering is satisfied, the decision threshold of data clustering is satisfied.

$$0 \le p_{k+1} \le p_k - \sum_{i \notin I} \sum_{j \in I} p_i(k) p_{ij}(k) \le p_k \le 1 \tag{26}$$

The N data clustering centers are initialized, and the K-means algorithm is adopted to gather the q clusters to obtain a measurable set of the data continuous hierarchical structure:

$$1 \ge \lim_{k \to \infty} \sum_{s_i \bigcap s^* \ne \phi} p_i(k) \ge \lim_{k \to \infty} \sum_{i \in I} p_i(k) = 1 - \lim_{k \to \infty} p_k = 1 \tag{27}$$

Under the control of optimal convergence condition, the fast extraction model of big data, which is the exchange feature of lithium ion screen, is transformed into the following least square problem:

$$\begin{aligned} &\textit{minimize} && \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ &\textit{subject to} && y_i - (w' \Phi(x_i) + b) \le \varepsilon - \xi_i \\ & && (w' \Phi(x_i) + b) - y_i \le \varepsilon - \xi_i^* \\ & && \xi_i, \xi_i^* \ge 0, i = 1, 2, \cdots, n; C > 0 \end{aligned} \tag{28}$$

To find the optimal solution of the above formula, the adaptive neural network learning algorithm is used for fuzzy clustering and mining of the extracted spectral stripe features, and the fast extraction of lithium ion screen exchange features by big data is realized [13, 14].

4 Analysis of Simulation Experiment

In order to verify the performance of this method in the rapid extraction of Li-ion screen exchange feature big data, the simulation experiment is carried out. The hardware environment of the experiment is as follows: processor Intel (R) Core (TM) 2 Duo CPU 2.94 GHz, The software simulation tool of the experiment is Matlab 7, the exchange characteristic of lithium ion screen is Braggtype lithium ion screen exchange characteristic, and the array distribution of lithium ion screen exchange characteristic sensor is 200 * 300 type array. The sampling time length is 100 s, the data sample length is 1024, the sampling period is T = 0.12 s, the fundamental frequency of big data is 100 kHz, and the maximum length of data block is 2000. The sampling time is 100 s, the length of data sample is 1024, the sampling period is T = 0.12 s, the fundamental frequency of big data is 100 kHz, and the maximum length of data block is 2000. According to the above simulation environment and parameter setting, big data, the exchange feature of lithium ion screen, is extracted quickly, and the time domain waveform and frequency domain waveform of big data sampling of the original lithium ion screen exchange feature are obtained as shown in Fig. 2.

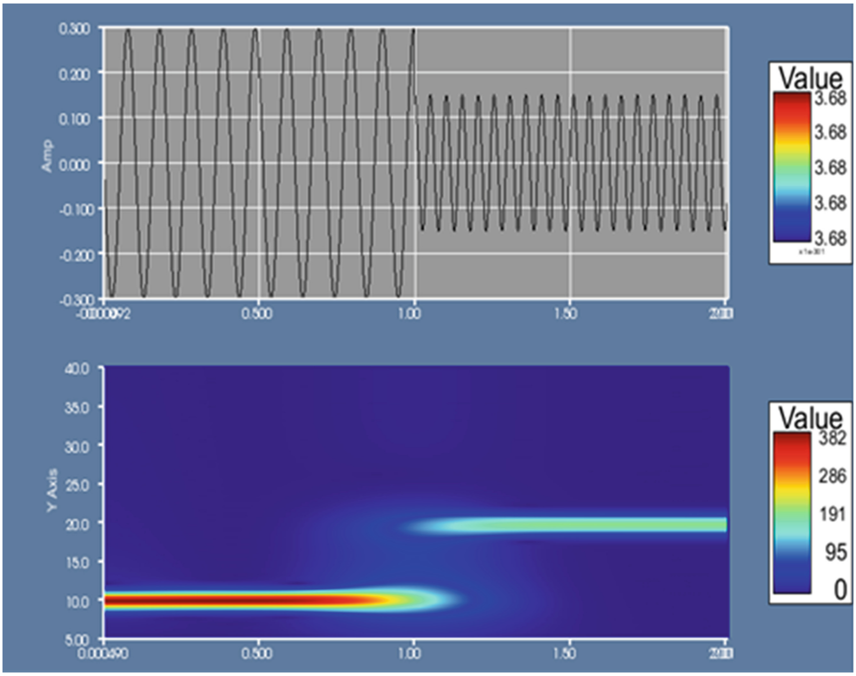

Fig. 2. Exchange characteristics of lithium ion screen big data characteristic sampling time domain and frequency domain waveforms

Taking big data, the exchange feature of lithium ion screen in Fig. 2, as the research sample, big data was used to extract the exchange feature big data of lithium ion screen in cloud computing environment, and the spectral stripe features of big data were extracted. The results are shown in Fig. 3.

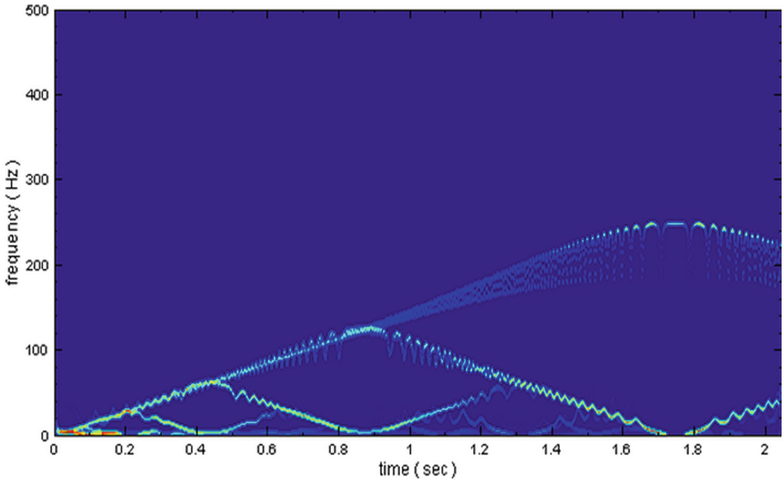

Fig. 3. Spectral stripe characteristics of big data for exchange characteristics of lithium ion sieves

Figure 3 shows that big data, a lithium ion screen exchange feature, is quickly extracted by this method, and the extracted spectral stripe features have high resolution. In order to quantitatively test the fast extraction performance of the data. The time cost of fast data extraction under different data scales is tested, and the comparison results are shown in Table 1, and the results in Table 1 show that with the increase of data size, the time cost increases. The time cost of fast extraction of Li-ion screen exchange feature big data by this method is obviously less than that by traditional method, and the real-time performance of data mining is improved.

Table 1. Comparison of time overhead (unit: s)

Data scale/Gbit	Proposed method	Spectral analysis algorithm	PSO method
20	0.345	0.632	0.532
40	0.334	0.824	0.846
60	0.423	1.056	0.954
80	0.545	1.846	1.045

5 Conclusions

In this paper, a fast extraction algorithm of Li-ion screen exchange feature big data based on cloud computing and big data is proposed. Big data collection of exchange characteristics of lithium ion screen is realized in lithium ion screen exchange array. Big data sequence of exchange characteristic of lithium ion screen is constructed by multi-mode fusion method for the collected data. The association rule mining method is used to reconstruct the structure of big data, which is the exchange feature of lithium ion screen, and the statistical analysis model of big data mining is constructed. In big data distribution subspace, the spectral feature extraction method is used to extract the spectral stripe feature of Li-ion screen exchange feature big data, and the extracted spectral stripe feature is fuzzy clustering and mining by adaptive neural network learning algorithm. Big data rapid extraction of exchange characteristics of lithium ion screen was realized. It is found that the proposed method has high accuracy, good resolution, low time cost and good fast extraction performance for lithium ion screen exchange feature big data mining.

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References

1. Zhou, S.B., Xu, W.X.: A novel clustering algorithm based on relative density and decision graph. Control Dec. **33**(11), 1921–1930 (2018)
2. He, H., Tan, Y.: Automatic pattern recognition of ECG signals using entropy-based adaptive dimensionality reduction and clustering. Appl. Soft Comput. **55**, 238–252 (2017)
3. Zhou, S.B., Xu, W.X.: A novel clustering algorithm based on relative density and decision graph. Control Dec. **33**(11), 1921–1930 (2018)
4. Zhu, Y.L., Zhu, X.X., Wang, J.M.: Time series motif discovery algorithm based on subsequence full join and maximum clique. J. Comput. Appl. **39**(2), 414–420 (2019)
5. He, W., Guo, C.J., Tian, Z.: Optimization method for multi-constellation precise point positioning performance evaluation. Comput. Eng. **45**(5), 88–92 (2019)
6. Wei, X.S., Luo, J.H., Wu, J.: Selective convolutional descriptor aggregation for fine-grained image retrieval. IEEE Trans. Image Process. **26**(6), 2868–2881 (2017)
7. Huang, X.J., You, R.Y., Zhou, C.J.: Study on optical properties of equivalent film constructed of metal nanoparticle arrays. J. Optoelectr. Laser **24**(7), 1434–1438 (2013)
8. Ma, Z.K., Chen, W.H.: Friction torque calculation method of ball bearings based on rolling creepage theory. J. Mech. Eng. **53**(22), 219–224 (2017)
9. Tu, G.S., Yang, X.Y., Zhou, T.P.: Efficient identity-based multi-identity fully homomorphic encryption scheme. J. Comput. Appl. **39**(3), 750–755 (2019)
10. Wang, Z.H., Huang, M.Y.: Integrated algorithm based on density peaks and density-based clustering. J. Comput. Appl. **39**(2), 398–402 (2019)
11. Feng, W., Wang, Y., Lin, D., et al.: When mm wave communications meet network densification: a scalable interference coordination perspective. IEEE J. Sel. Areas Commun. **35**(7), 1459–1471 (2017)
12. Matilainen, M., Nordhausen, K., Oja, H.: New independent component analysis tools for time series. Stat. Probabil. Lett. **32**(5), 80–87 (2017)
13. Hao, S.G., Zhang, L., Muhammad, G.: A union authentication protocol of cross-domain based on bilinear pairing. J. Software **8**(5), 1094–1100 (2013)
14. Liu, S, Fu, W., Deng, H., et al.: Distributional fractal creating algorithm in parallel environment. Int. J. Distrib. Sen. Networks (2013). https://doi.org/10.1155/2013/281707