Anomaly Detection Algorithm Based on FCM with improved Krill Herd

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ABSTRACT The anomaly detection algorithm plays an important role in the field of network security. Among them, the most representative method is anomaly detection based on fuzzy C-means (FCM). FCM relies heavily on the initial clustering center and is prone to local extremum. Therefore, the detection effect of the FCM-based anomaly detection algorithm is not ideal in some cases. The herd intelligent optimization technology has a strong global search capability and is widely used in various fields. As a herd intelligence technology, the krill herd algorithm has a relatively simple optimization function structure, which has strong global search ability and is easy to integrate with other optimization strategies. Therefore, a KH algorithm with strong global search capability is introduced, and a hybrid KH-FCM algorithm is proposed. In the hybrid KH-FCM algorithm, the randomly generated initial population will be divided into two subpopulations containing the same number of individuals.

1. Introduction
Cluster analysis is one of the classic methods often used in machine learning. The basic idea is to analyze some invisible relationship which is based on data samples, and then divide these samples into different clusters. This remarkable feature is very suitable for detecting anomalous features [3]. Among them, fuzzy C-means clustering algorithm (FCM) is one of the most classic algorithms in unsupervised machine learning algorithms. Its most notable feature is that it does not need to mark the category information of data records in advance [4] and has been widely used in the field of anomaly detection [5]. However, FCM is highly dependent on the initial value and is prone to fall into local minima. Moreover, it usually requires more iterations [6]. To this end, people have adopted a variety of optimization measures to improve it [7], as the literature [8] combines FCM with genetic algorithm (GA), proposed GA-FCM, the algorithm first selects the best individual and it crosses and mutates the operation, and iteratively generates new optimal individuals until the optimal initial clustering center is generated to improve the FCM’s high dependence on the initial value and easy to converge to the local minimum. Xiao Mansheng et al. [9] proposed a spatially correlated FCM, and designed its influence value according to the spatial distribution characteristics of the data set to improve the clustering center, thus reducing the sensitivity to noise.

Chen Haipeng et al. [10] introduced a soft partitioning method, using different clustering numbers to perform multiple clustering analysis. Finally, using the information about membership degree obtained by optimization, the correlation matrix was constructed to obtain the final result.
2. RELATED WORK

2.1 FCM-based Anomaly Detection Algorithm

Anomaly detection automatically detects and detects various abnormal behaviors by monitoring various events in the system in real time. The basic model is shown in Figure 1 [11]. FCM-based anomaly detection incorporates the idea of clustering. According to the nature of normal and abnormal features, they are divided into different clusters as much as possible and no intersection occurs [17].

![Fig. 1 Basic model of anomaly detection](image)

The FCM-based anomaly detection method is widely used. In the field of medical application, the literature [12] applied the FCM-based anomaly detection to the brain nuclear magnetic resonance image segmentation and corrected the intensity non-uniformity by the FCM algorithm, thus improving the accuracy of the algorithm for tissue segmentation. In [13], FCM-based anomaly detection is applied to brain tumor segmentation nuclear magnetic resonance images, and artificial bee colony algorithm is introduced to reduce the influence of noise and help to identify brain tumors. In the application of power system, the literature [14] introduces the cross-section and cross-over algorithm to optimize the FCM anomaly detection algorithm, effectively compensates for the shortcomings of the single algorithm, and achieves a comprehensive and accurate refinement of the major power customers. Literature [15] combines FCM with adaptive fuzzy reasoning to improve the detection accuracy of the system. The model can quickly detect abnormal conditions and fault level conditions of the distribution network.

1) Mahalanobis Distance

Let \( A \) be an \( n \times 1 \) input matrix, which contains \( n \) samples, \( n_i \in A(1,2,\ldots,n) \). The Mahalanobis distance between \( n_i \) and \( A \) can be defined as follows:

\[
d_M = (n_i - \bar{n})^T C^{-1} (n_i - \bar{n}) .
\]

(1)

\( \bar{n} \) is the sample mean and \( C \) is the covariance matrix, expressed as:

\[
C = \frac{1}{n} \sum_{i=1}^{n} (n_i - \bar{n})(n_i - \bar{n})^T .
\]

(2)

Xiang et al. [22] can adaptively adjust the set distribution of data by using Mahalanobis distance, and apply it to fuzzy clustering, and obtain better results. Therefore, this paper will use the Mahalanobis distance to measure the difference between samples.

2) FCM algorithm based on Mahalanobis distance

Its objective function can be expressed as:

\[
J(U, V, C) = \sum_{i=1}^{C} \sum_{j=1}^{m} u_{ij} m (n_j - \bar{n})^T C^{-1} (n_j - \bar{n}) .
\]

(3)

\( U \) is the membership matrix, and \( V \) is the cluster center matrix. The goal of the FCM algorithm based on the Mahalanobis distance is to obtain a minimum value for the equation. The constraint is:

\[
\sum_{i=1}^{C} u_{ij} = 1, \quad u_{ij} \in [0,1] .
\]

(4)

Then use the Lagrange multiplier method to get the following formula:

\[
\bar{n}_i = \frac{\sum_{j=1}^{m} u_{ij} m n_j}{\sum_{j=1}^{m} u_{ij} m} .
\]

(5)
\[ T_l = \frac{\sum_{j=1}^{n} u_{ij}^m (n_j - \overline{n}) (n_j - \overline{n})^T}{\sum_{j=1}^{n} u_{ij}^m}, \]  
(6)

\[ d_{ij} = (n_j - \overline{n})^T \left[ \overline{T} \right]^{-1/2} \left[ \overline{T} \right]^{-1} (n_i - \overline{n}) \]  
(7)

\[ u_{ij} = \frac{1}{\sum_{k=1}^{c} (d_{ij} - d_{kj})^{2/m-1}}. \]  
(8)

among them, \(1 \leq i \leq c, 1 \leq j \leq n\), \(c\) is the number of cluster centers.

FCM algorithm based on Mahalanobis distance requires 3 parameters: Iterative termination error \(\varepsilon\) and Fuzzy weighted index \(m\) among them, \(c\) is given in advance. According to the literature [23], the optimal value interval of \(m\) is, in general, the median value of the interval, \(\varepsilon\) Usually set to 10-5.

KH algorithm is a new heuristic intelligent optimization algorithm, which is mainly based on the simulation study of the survival process of the Antarctic krill herd in the marine environment. For each krill particle, its location update is mainly affected by three factors:
1) induced exercise (induction of surrounding krill);
2) Foraging activities;
3) Random diffusion;

The speed update formula for krill individuals uses the following Lagrangian model:

\[ \frac{dx_i}{dt} = \dot{N}_i + F_i + D_i \]  
(9)

Among them, \(N_i,F_i,D_i\) represent induced movement, foraging movement, and random diffusion, respectively.

The formula for the three factors is constructed as follows:

\[ N_i = N_{\text{max}} \alpha_i + \omega_n N_{\text{old},i}. \]  
(10)

\[ F_i = v_f \beta_i + \omega_f F_{\text{old},i}. \]  
(11)

\[ D_i = D_{\text{max}} \left( 1 - \frac{t}{t_{\text{max}}} \right) \delta. \]  
(12)

\(N_{\text{max}},v_f,D_{\text{max}}\) represent the maximum induction speed, maximum foraging speed and maximum diffusion speed, respectively; \(\alpha_i,\beta_i,\delta\) represent induction direction, foraging direction and diffusion direction, respectively; \(\omega_n, \omega_f\) represent the induced weight and the foraging weight, respectively; \(t, t_{\text{max}}\) are the current number of iterations and the maximum number of iterations. \(N_{\text{max}}=0.01, v_f=0.02, D_{\text{max}}=0.005\).

The position of the krill individual in the interval \(t\) to \((t + \Delta t)\) is updated as follows:

\[ x_i(t + \Delta t) = x_i(t) + \left( \frac{dx_i}{dt} \right)(\Delta t). \]  
(13)

\[ \Delta t = C_t \sum_{j=1}^{N_v} (B_{u,j} - B_{L,j}). \]  
(14)

\(\Delta t\) is the scaling factor of the velocity vector; \(C_t\) is the step size scaling factor, taking a constant between \([0, 2]\); \(N_v\) represents the number of variables; \(B_{u,j}, B_{L,j}\) are the upper and lower bounds of the \(j\)th variable, respectively.

To further improve the performance of the algorithm, the genetic operator (crossover or mutation) is executed in the algorithm. After testing, the crossover operator is more effective.

\[ x_{i,m} = \begin{cases} x_{r,m} & \text{if } a_{i,m} < C_r; \\ x_{i,m} & \text{else,} \end{cases} \]  
(15)

\[ x_{i,m} = \begin{cases} x_{g,\text{best},m} + \mu (x_{p,m} - x_{q,m}), & a_{i,m} < M_u, \\ x_{i,m} & \text{else.} \end{cases} \]  
(16)

\(C_r\) is the crossover operator; \(M_u\) is the genetic operator; \(\alpha\) is a uniformly distributed random number on \([0,1]\); \(\mu\) is a constant in \([0,1]\).
3. IMPROVED ANOMALY DETECTION ALGORITHMS FOR KRILL HERD FCM

The algorithm mainly includes three parts: the improved krill herd is proposed, and then applied to FCM. Finally, an anomaly detection algorithm based on improved krill herd FCM is proposed.

3.1 Improved Krill Herd Algorithm

According to the standard KH algorithm, since the particle motion is random during the iterative process, when the algorithm moves to a poor position, that is, when the krill herd moves to the harsh environment of the predator, if the krill individual cannot be timely The information transmission makes a dangerous warning, the krill herd is easy to be preyed, and there are a large number of invalid iterations, which makes the algorithm not complete the local search well; Especially when dealing with multi-peak optimization problems, the solution of the algorithm is more likely to fall into local optimum, and the phenomenon of “premature maturity” appears. Based on this, an improved krill herd algorithm based on mutual benefit symbiosis and survival of the fittest is proposed.

3.1.1 Mutual benefit symbiosis strategy of krill herd

Living creatures in nature form a stable ecosystem, and there is a direct or indirect relationship between different species. This relationship can be roughly divided into three categories: mutual benefit and symbiosis, that is, mutual benefit to both parties; symbiosis, only beneficial to one of them, but harmless to the other; parasitic, beneficial to one of them, but harmful to the other. Mutual benefit symbiosis summed up as follows: Individuals of different species live together, and the mutual relationship between the two sides can also refer to the organisms that can survive normally even if they leave each other. Krill will escape from the danger of predators, causing the entire krill herd to move in different directions. In this process, a mutual benefit symbiosis strategy is introduced to enable the krill individuals to communicate with each other and transmit dangerous signals, for other krill warnings. Krill individuals will move toward the krill with good fitness value by comparing the advantages and disadvantages of their respective positions, that is, the difference in the fitness value of the current position, to avoid the predator. Record the current position safety factor level $X_{\text{current}}$, the global safety factor level $X_{\text{global}}$, and the global krill average safety factor level $X_{\text{average}}$. Use the following formula to indicate the movement of each krill after the hazard warning issued by the world's safest krill to all krills:

$$X' = X + r_i \times (X_{\text{global}} - \lambda X_{\text{average}}) \quad (17)$$

$$\lambda = \text{round}[1 + a(0,1)] \quad (18)$$

$r_i$ is a random number between [0,1], $\lambda$ is an early warning factor, and the value of $\lambda$ is 1 or 2. If $X'_k$ is better than $X_k$, then update $X_k$; Update $X_{\text{best}}$ if $X'_k$ is better than $X_{\text{best}}$.

At this point, after receiving the global warning danger signal, the krill herd will transmit dangerous signals to each other. So randomly select two krills $p$ and $q$, and $X_p \neq X_q$. The mutual symbiosis of this strategy is represented by:

$$X''_p = \begin{cases} X'_p + r_i (X'_p - X'_q), f(X'_p) < f(X'_q); \\ X'_p + r_i (X'_q - X'_p), f(X'_q) < f(X'_p) \end{cases} \quad (19)$$

$r_i$ is a random number between [0,1]; $X'_p$ and $X'_q$ represent the safety factor level of krill $p$ and krill $q$ before exchange, respectively; If $X''_p$ is better than $X'_p$, update $X'_p$; If $X''_p$ is better than $X'_q$, update $X'_q$.

3.1.2 Survival of the fittest

On the basis of the above improvements, this paper also added the idea of survival of the fittest, and finally obtained the improved krill herd algorithm (MASFKH) based on mutual benefit and survival of the fittest.

The basic idea of survival of the fittest is that the basic idea of survival of the fittest is to maintain the diversity of particles in the population. The specific operation method of the “survival of the fittest”
strategy is: after generating a new generation of populations, the newly generated populations will be evaluated for fitness values, that is, sorted according to fitness values, and the worst R particles will be discarded in the algorithm. And randomly generate R new particles in the search space. If the value of R is larger, the newer particles are generated, which is beneficial to maintain the diversity of the population and avoid the algorithm falling into local optimum. However, if the value of R is large, the algorithm tends to search randomly; if the value of R is smaller, it is not conducive to the algorithm to maintain the individual diversity of the particles, and the entire search ability of the algorithm becomes weak. Hence, R here takes NP/10, where NP is the population size.

3.1.3 MASFKH algorithm specific process
Step 1: Determine the size of the population and initialize the settings of the population and related parameters;
Step 2: The objective function value is used as the fitness value to evaluate the fitness of each particle in the population, and the current position and fitness value of the krill herd are stored in the \( P_{\text{best}} \) of each body, and all \( P_{\text{best}} \) are optimally stored in \( G_{\text{best}} \);
Step 3: Calculating the velocity component of the krill individual using equations (2)-(4);
Step 4: Adopting the formulas (9)-(11) to implement the "mutually beneficial symbiosis" strategy for the krill herd;
Step 5: For each body, compare the position it experiences and the objective function, update \( P_{\text{best}} \) and \( G_{\text{best}} \);
Step 6: Sort new populations according to fitness values and carry out the strategy of “survival of the fittest”, and keep \( P_{\text{best}} \) and \( G_{\text{best}} \) unchanged;
Step 7: Determine whether the algorithm satisfies the termination condition. If it is satisfied, output \( P_{\text{best}} \) and \( G_{\text{best}} \); Otherwise, return to Step 3 to continue searching.

3.2 FCM Algorithm Based on Improved Krill Herd
Based on the FCM algorithm of improved krill herd, MASFKH-FCM, the advantage of MASFKH can be well utilized to solve the problem that the FCM algorithm is too dependent on the initial value and is easy to fall into the local extremum. The algorithm idea is to use MASFKH to iteratively calculate the optimal solution of the problem. Then the solution is used as the initial clustering center of FCM, and iterative clustering analysis is carried out to classify different types of samples into different cluster classes. The algorithm flow is shown in Figure 2:
Fig. 2 Flow chart of MASFKH-FCM

The algorithm has two key points: problem space coding and fitness function determination.

1) Coding: The algorithm encodes sample data based on the initial clustering center's encoding format, that is, n initial cluster centers form the position information of each krill herd. Let s be the dimension of the problem space, then the position of the krill is the n×s dimension variable:

\[ P_n = (c_{11}, c_{12}, \ldots, c_{1s}, \ldots, c_{m1}, \ldots, c_{ms}, \ldots, c_{n1}, \ldots, c_{ns}) \]  

(20)

2) Fitness function: In the FCM algorithm, the minimum value of the objective function \( J \) (calculated by equation (3)) is the optimal clustering result. The smaller the value, the more obvious the clustering effect. Therefore, the following formula is set as the fitness function of the algorithm:

\[ f = \frac{1}{J+1} \]  

(21)

Specifically, the MASFKH-FCM algorithm steps are as follows:

Step 1. Set the number of krill N, moving Step, fuzzy index m, number of trials TryNumber, \( \delta \), number of cluster division c, search range Visual and other parameter values;

Step 2. According to the location of the krill, compare the current results with the records on the bulletin board, select the better value and update the information on the bulletin board;

Step 3. Calculate the initial values of the sample cluster center and the objective function according to equations (6) and (3), and evaluate the fitness;

Step 4. Perform MASFKH induction, foraging, and diffusion behavior;

Step 5. Update the status of the krill and adjust the Visual value adaptively according to equation (15);

Step 6. Compared with the end condition, if the end condition is met, the result is taken as the initial value of the FCM cluster. Go to Step 7 to continue the FCM cluster analysis process; If not, go to Step 2 and continue the MASFKH process.

Step 7. Use the FCM algorithm to perform continuous iterative calculations until the constraints are met and the final result is obtained.
3.3 Anomaly Detection Algorithm Based On MASFKH-FCM

Introducing MASFKH to optimize the FCM algorithm can make it better for anomaly detection. Therefore, the MASFKH-FCM based anomaly detection algorithm is designed. The algorithm flow is as follows:

Step 1. Put the training data into the matrix $X_{n \times l}$;

Step 2. Assign initial values to the krill herd according to the coding rules;

Step 3. Calculated according to MASFKH until the termination condition is met;

Step 4. Take the optimal result from Step 3 as the initial value of FCM;

Step 5. Standard evolutionary processing of test data set $X_{n \times l}$:

$$x_i' = \frac{x_i-\min(i)}{\max(i)-\min(i)}.$$  

$\max(i)$ and $\min(i)$ represent the maximum and minimum values of the attribute, respectively;

Step 6. Iterative calculation based on FCM algorithm. An abnormal sample set is obtained when the termination condition of the algorithm is satisfied.

Wherein, when the FCM algorithm detects the data set, it sets the data to be $X_{n \times l}$ matrix every time a certain amount of data is captured. Warn if there is an exception.

From the time cost analysis of each part above, the time of MASFKH-FCM anomaly detection is $O(PN^2) + O(nlcf) + O(nl) = O(PN^2) + O(nlcf)$. This time cost is acceptable.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 MASFKH-FCM Anomaly Detection Experiment

The experiment uses the well-known KDD CUP 1999 dataset in the field. First, data preprocessing is needed to convert the discrete attributes into continuous attributes, such as the protocol attributes. The experimentally set transformation rules are: $TCP \rightarrow 1$, $UDP \rightarrow 1$, $ICMP \rightarrow 1$ etc. Then, randomly select 6 herds of samples for experiment. Set one of them to be the training data set, containing 30,000 records, of which 363 are abnormal records. The remaining 5 herds are used as test data sets, each herd contains 10000 records, of which 120 are abnormal records.

Evaluating the performance of an anomaly detection generally requires calculating the detection rate and false-positive rate, its definition is as follows:

$$DR = \frac{\text{Number of intrusions detected}}{\text{Total intrusion in the data set}}$$

$$FR = \frac{\text{False positive data for intrusion}}{\text{Normal data in the data set}}$$

The algorithm related parameter setting process is the same as the previous experiment, and the parameters are set as follows according to the literature [17]: $N$ is 50, $P$ is 200, TryNumber is 50, Step is 0.8, Visual is $4, \delta, \lambda, \gamma$ are both 0.5, $m$ is 2 in FCM, and $c$ is 5.

1) In order to verify the effect of the algorithm on different test data sets, and verify the feasibility of each method of capturing a certain amount of data for a centralized processing, we randomly select 6 sets of data from the test data set, each herd contains 1000 data. Make up the $X_{n \times l}$ matrix and conduct experiments. The results are summarized as shown in Figure 3. As can be seen from the figure, each time the test data is selected differently, the algorithm shows different detection performance, but the fluctuation is within the acceptable range. The main reason for the fluctuation is that the algorithm has different cognitive abilities for different anomalies.
2) In order to test the detection stability of the algorithm in different test data sets, we repeat 5 experiments for each data set. The results are summarized in Table 1. The MASFKH-FCM has the same parameters, the mean values of DR and FR of different test sets are different, but the results are satisfactory, and the standard deviation is within the reasonable range of variation. This is because the training set and test set selected in this experiment are randomly sampled, the number is limited, and the characteristics of the included abnormal samples are not the same. Overall, FSF anomaly detection based on MASFKH optimization has better detection performance, especially in terms of stability.

Table 1 MASFKH-FCM’s Detection Results with Different Test Set

| Data Set | DR          | FR          | DR          | FR          |
|----------|-------------|-------------|-------------|-------------|
|          | Mean (DR)   | Standard Deviation (DR) | Mean (FR)   | Standard Deviation (FR) |
| 1        | 0.90983     | 0.00172     | 0.03477     | 0.00263     |
| 2        | 0.91885     | 0.00081     | 0.01963     | 0.00067     |
| 3        | 0.93952     | 0.00077     | 0.02768     | 0.00046     |
| 4        | 0.92953     | 0.00063     | 0.02173     | 0.00143     |
| 5        | 0.91988     | 0.00073     | 0.04057     | 0.00167     |

To verify the performance of FCM anomaly detection after adding MASFKH, the above five sets of test sets were tested using basic FCM, KH-FCM, MASFKH-FCM anomaly detection, and the parameters used were the same. The results are summarized in Table 2 and Figure 8–10.

Table 2 FCM, KH-FCM and MASFKH-FCM’s Detection Results

| Data Set | FCM DR | FCM FR | KH-FCM DR | KH-FCM FR | MASFKH-FCM DR | MASFKH-FCM FR |
|----------|--------|--------|-----------|-----------|---------------|---------------|
| 1        | 0.7971 | 0.0532 | 0.8673    | 0.0327    | 0.9073        | 0.0312        |
| 2        | 0.8125 | 0.0417 | 0.8853    | 0.0238    | 0.9187        | 0.0185        |
| 3        | 0.8491 | 0.0572 | 0.9132    | 0.0316    | 0.9381        | 0.0268        |
Figure 6 shows the comparison of detection rates of three algorithms in one of the test sets in different iteration cycles. The MASFKH-FCM anomaly detection can achieve the optimal value when the number of iterations is 85. The other two algorithms require 100–110 iterations to achieve better results, but the results are worse than MASFKH-FCM anomaly detection.
This is because MASFKH optimizes KH, adaptively adjusts the value of Visual, improves the local and global optimization ability of KH, reduces the number of iterations of the algorithm, and makes it difficult to fall into local extremum, thus obtaining the global optimal solution. And this improvement significantly improves the efficiency of the algorithm. Then, combining MASFKH with FCM can solve the problem that FCM algorithm is too dependent on the initial value and is easy to fall into local optimum. Finally, taking full advantage of the advantages of both MASFKH and FCM, the anomaly detection algorithm based on this design can obtain better detection results.

5. CONCLUSIONS

In this paper, the artificial fish swarm algorithm is easy to fall into the local optimal problem when the optimal solution is impending, and the adaptive mechanism is introduced. The value of Visual is adaptively changed with the increase of the number of iterations of the algorithm, thus improving the local and global search ability of MASFKH. Then, using its characteristics of intelligent optimization and better robustness, it is applied to FCM anomaly detection, which solves the drawback that FCM is too dependent on the initial value and is easy to fall into local optimum without getting the optimal solution. Experiments show that the proposed MASFKH-FCM anomaly detection algorithm can obtain better detection performance.

MASFKH-FCM anomaly detection can be adjusted to apply to multiple application areas, such as intrusion detection technology in network security. FCM-based intrusion detection system is one of the important technical branches of intrusion detection. The MASFKH-FCM-based IDS can cluster the network attack sample set to improve the performance of the system to detect various attacks. In actual operation, compared with the traditional FCM algorithm, while the detection performance of the system is effectively improved, the convergence speed and operating efficiency of the algorithm are relatively high, which can better meet the real-time requirements of IDS. How to further balance the accuracy and real-time performance of IDS detection is the focus of future research.

REFERENCES

[1] Mao Jiali, Jin Cheqing, Zhang Zhigang, et al. Anomaly detection for trajectory big data: Advancements and framework [J]. Journal of Software, 2017, 28(1):17-34 (in Chinese)
[2] Qian Yanyan, Li Yongzhong, Yu Xiya. Intrusion detection method based on multi-label and semi-supervised learning [J]. Computer Science, 2015, 42(2):134-136 (in Chinese)
[3] Han Jiawei, Kamber M. Data mining: Concepts and techniques [M]. Data Mining Concepts Models Methods & Algorithms Second Edition, 2011, 5(4): 1-18
[4] Qian Sen, Weng Guirong. Medical image segmentation based on FCM and level set algorithm[C]// Proc of 7th IEEE Int Conf on Software Engineering and Service Science. Piscataway, NJ: IEEE, 2017: 225-228
[5] Tang Chenghua, Liu pengcheng, Tang Shensheng, et al. Anomaly intrusion behavior detection based on fuzzy clustering and features selection [J]. Journal of Computer Research and Development, 2015, 52(3): 718-728 (in Chinese)
[6] Xue Xiao, Liu Yian, Kan Yuan, et al. A research of intrusion detection system based on FCM-GRNN clustering [J]. Computer Simulation, 2010, 27(6):151-154 (in Chinese)
[7] Zhang Min, Yu Jian. Fuzzy partitional clustering algorithms [J]. Journal of Software, 2004, 15(6):858-868 (in Chinese)
[8] Jansi S, Subashini P. Modified FCM using genetic algorithm for segmentation of MRI brain images[C]// Proc of 1st IEEE Int Conf on Computational Intelligence and Computing Research. Piscataway, NJ: IEEE, 2015: 150-158
[9] Xiao Mansheng, Xiao Zhe, Wen Zhicheng, et al. Improved FCM clustering algorithm based on spatial correlation and membership smoothing[J]. Journal of Electronics & Information Technology, 2017, 39(5):1123-1129 (in Chinese)
[10] Chen Haipeng, Shen Xuanjing, Long Jianwu, et al. Fuzzy clustering algorithm for automatic identification of clusters [J]. Acta Electronica Sinica, 2017, 45(3):687-694 (in Chinese)
[10] Nalluri M S R, Saisujana T, Reddy K H, et al. An efficient feature selection using artificial fish swarm optimization and SVM classifier [C]// Proc of 1st Int Conf on Networks & Advances in Computational Technologies. Piscataway, NJ: IEEE, 2017: 407-411

[11] Manikandan R P S, Kalpana A M. Feature selection using fish swarm optimization in big data[J]. Cluster Computing, 2017, Article in Press

[12] Alobaidi A T S, Hussein S A. An improved artificial fish swarm algorithm to solve flexible job shop[C]// Proc of 2017 Annual Conf on New Trends in Information and Communications Technology Applications, Baghdad, Iraq, 2017: 7-12.

[13] Sengottuvelan P, Prasath N. BAFSA: Breeding artificial fish swarm algorithm for optimal cluster head selection in wireless sensor networks [J]. Wireless Personal Communications, 2017, 94(4): 1979-1991

[14] Kumar K P, Saravanan B, Swarup K S. Day ahead scheduling of generation and storage sources in a microgrid using artificial fish swarm algorithm[C]// Proc of the 21st International Conference on Century Energy Needs-Materials, Systems and Applications. Piscataway, NJ: IEEE, 2016, Article number: 8052753

[15] Liu Rujuan, Jia Bin, Xin Yang. Network anomaly detection model based on information gain feature selection [J]. Journal of Computer Applications, 2016, 36(s02): 49-53 (in Chinese)

[16] Kumari V V, Varma P R K. A semi-supervised intrusion detection system using active learning SVM and fuzzy c-means clustering[C]// Proc of the 1st Int Conf on IoT in Social, Mobile, Analytics and Cloud. Piscataway, NJ: IEEE, 2017: 481-485.