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# Research on abnormal state detection of automation system based on adaptive filtering algorithm

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**Abstract** Fast detection of business data reduces the impact of automated systems by anomaly scheduling. In this paper, we address the limitations of traditional unsupervised anomaly detection methods, such as leakage detection, and design an anomaly detection method based on meta-learning hybrid selection integration (Meta-HESAD). Methods such as compact time series and isolated Senri are introduced to accomplish the base detector required for downscaling and anomaly detection of multimodal data. The adaptive filtering algorithm is optimized with improved Sigmoid function to improve the stability and convergence speed of the data anomaly detection process. The results show that the average value of the adaptive filtering algorithm is 0.9851, which is higher than that of the comparison algorithms, 0.8007, 0.8286, 0.8456. When the detection probability reaches 1.0, the false alarm rate of this paper's algorithm is smaller than that of the three comparison algorithms. In practice, the detection accuracy probability of this paper's algorithm exceeds 90% in all 10 iterations.

**Index Terms** compact time series; isolated Senri; adaptive filtering; Sigmoid function; anomaly detection

## I. Introduction

Automation systems play a crucial role in modern industrial production, medical care, intelligent transportation, and other fields [1]. However, these systems may experience various faults during long-term use, resulting in system performance degradation or even complete stoppage [2], [3]. Failures in automation systems can be categorized into two types: hardware failures and software failures [4]. Hardware faults include sensor faults, actuator faults, communication faults, etc., while software faults include algorithm errors, parameter setting errors, program crashes, etc [5]-[7]. Common types of faults include signal offset, signal noise, sensor or actuator failure, and communication anomaly [8]. These faults may lead to system performance degradation or system crash, which seriously affects productivity and product quality [9], [10]. Therefore, abnormal state detection of automation system is very important to ensure the stable operation of the system [11].

Common fault detection methods include model-based methods, statistical-based methods, and adaptive filtering-based algorithms are widely used because of both detection methods [12], [13]. Adaptive filtering algorithm is a filtering algorithm that estimates the features of the signal to be filtered and adjusts the filter parameters in order to achieve the best filtering effect [14]-[16]. The basic idea is to adjust the parameters of the filter by estimating the results of the signal in order to achieve the best filtering effect [17]. There are various types of adaptive filtering algorithms, among which the most common are the minimum mean square error adaptive filtering algorithm and the inverse filtering algorithm [18], [19]. The key point of abnormal state detection of automation systems based on adaptive filtering algorithms is based on dynamically adjusting the parameters of the filter to quickly react to the state changes of the automation system and to achieve accurate modeling, which provides important guidance for the safe operation of the automation system [20]-[23].

In this paper, we propose a meta-learning hybrid selective integration-based anomaly detection method (Meta-HESAD) to improve anomalous state detection for complex data. Compact time series are utilized to achieve dimensionality reduction of multidimensional time series data of automated systems. The anomaly detection is accomplished by eliminating the poor base detectors through the static selection method based on isolated forest and picking the good base detectors in combination with the unsupervised dynamic selection method based on meta-learning. Adaptive filtering algorithm is introduced to isolate anomalous observations and automatically adjust the observation noise matrix parameters to improve the stability of the algorithm. The adaptive filtering algorithm combines the single-channel variable step-size least mean square error (LMS) adaptive filtering algorithm with the improved Sigmoid function, which dynamically adjusts the variable step-size factor, taking into account the stability of the adaptive filtering data processing and the convergence speed.

## II. Analysis of anomaly detection techniques for automated systems

### *II. A. Business Anomaly Detection Methods Considering the Complexity and Variety of Data Distribution Patterns*

The power dispatch automation system collects resource utilization monitoring data of each business-related process in real time according to a fixed frequency, which makes the correlation between the data of adjacent sampling points exist. Since traditional unsupervised anomaly detection methods generally assume that the data are independent of each other, they are difficult to directly consider the time-dimensional correlations in the monitoring data, and are prone to miss or misreport business anomalies. In order to improve the performance of traditional methods on time-series data, a compact time-series representation technique is proposed, in which after dividing the time series into multiple fixed-length time windows, a multidimensional time series is converted into an ordinary multidimensional data by performing exponential smoothing in each window, and the time-series information can be compressed into the converted data, which enables the traditional methods to deal with multidimensional time series data more efficiently. This technique is used to transform a multidimensional time series composed of disk performance monitoring data and to determine whether a disk has failed by traditional binary classification methods. In this paper, we also use the compact time series representation technique to convert the time series composed of business monitoring data of power dispatch automation system, so as to convert the anomaly detection problem of multidimensional time series data into the traditional unsupervised anomaly detection problem and carry out research.

As the power dispatch automation system is characterized by the close coupling of business and hardware, a wide variety of business types, and complex hierarchical relationships, the business monitoring data often have complex and diverse distribution patterns. The data acquisition and surveillance and control (SCADA) application business monitoring data after dimensionality reduction is performed by compact time series representation techniques for conversion and using t-distribution stochastic nearest neighbor embedding (t-SNE). The normal data in the business monitoring data will appear multiple aggregated distribution patterns with different degrees of density, while the abnormal data will not only appear different distribution patterns such as dispersed and aggregated, but will also exist multiple complex situations such as far away from the normal data, close to the normal data, and wrapped by the normal data.

Existing traditional unsupervised anomaly detection methods often have large performance differences in different data distribution patterns, and the lack of category information in unsupervision also makes it difficult to select methods and hyperparameters through techniques such as cross-validation. Integration learning can improve the performance stability of the methods when dealing with multiple complex data distribution patterns by combining different base detectors, while dynamic selection integration can further improve the performance of the integrated methods by individually selecting the appropriate base detector for each data to be detected to be combined. Existing anomaly detection methods based on dynamic selection integration require the use of a false-truth value as a benchmark to evaluate the performance of the base detectors, however, the false-truth value is susceptible to bias by some of the poorly performing base detectors, which can negatively affect the selection process. In addition, most of the existing methods rely on a specific metric to evaluate the performance of the base detector, however, these metrics are unavoidably inapplicable, resulting in that the existing methods that only use a single base detector performance evaluation metric tend to have limited performance in the face of a variety of complex data distribution patterns.

To address the above problems, this paper proposes a meta-learning hybrid selection integrated anomaly detection method (Meta-HESAD), which firstly uses a compact time series representation technique to convert the anomaly detection problem of multidimensional time-series data into a traditional unsupervised anomaly detection problem, and then pre-culls out some of the poorly performing base detectors through a static selection method based on isolated forests, so as to improve the performance of subsequent dynamic selection methods. Then the static selection method based on isolated forest is used to preclude some of the poorly performing base detectors to improve the accuracy of the false truth values in the subsequent dynamic selection process; finally, an unsupervised dynamic selection method based on meta-learning is designed on the basis of the existing supervised dynamic selection framework to select the better base detectors for anomaly detection, and to improve the performance of the method on multiple data distribution patterns through the complementary performance evaluation indexes of the multiple base detectors.

### *II. B. Adaptive Filtering Algorithm*

If the observed signal does not detect anomalies, the setting of its observation noise variance parameter also needs to be considered. This paper proposes an adaptive filtering algorithm based on anomaly detection. The traditional Kalman filter cannot adaptively adjust the observation information matrix. The key algorithm in this paper is to isolate

the abnormal observations by combining the anomaly detection technique, and for the observations that cannot be determined to be abnormal, the anomaly detection of the observation is performed according to the observation new information sequence, the abnormal observations are isolated, and the adjustment of the observation noise matrix parameter is performed automatically. For the problem of poor GNSS signals, the detection of abnormal GNSS signals is based on the anomaly detection technique and the new hibernation sequence, and if there are anomalies, the strategy of isolating the abnormal observations or automatically amplifying the GNSS variance is adopted to avoid the impact of abnormal GNSS signals on the overall system. The conclusions can also be applied to odometry, geomagnetism, NHC and other observation information. To address the problem of weakening adaptive ability when the new interest sequence is too long, the equal-weighted formula is changed to an exponential asymptotic memory-weighted average. At the same time, the adaptive factor is added so that the adaptive observation variance can better reflect the uncertainty of the current calendar element.

In the adaptive filtering algorithm, the new interest is the difference between observation and prediction, i.e., (1):

$$V_k = Z_k - H_k X_k \tag{1}$$

$Z_k$ is the observation and $X_k$ is the system prediction; in the error state adaptive filtering algorithm, $Z_k$ is the difference between the observation and the system prediction (inertial guidance), $X_k$ is the error in the system prediction, and $H_k$ is the observation matrix, and $V_k$ is the new interest.

When the observations $Z$ obey a Gaussian distribution, $V$ also obeys a Gaussian distribution to obtain the new interest variance $D(V)$ Equation (2):

$$D(V) = E(V^2) - (E(V))^2 = E(V^2) = D(Z - HX) \tag{2}$$

Since the observation $Z$ is independent of $HX$, the above equation can be written as (3):

$$E(V^2) = D(Z) + D(HX) \tag{3}$$

In the adaptive filtering algorithm is denoted as (4):

$$R = D(Z) = E(V^2) - HPH^T \tag{4}$$

The new interest squared mean $E\left(V^2\right)$ can be obtained statistically on the time series, so that at the $k$ th moment there is (5):

$$\begin{aligned} R_k &= \frac{1}{k}\left[\sum_{i=1}^{k}\left(V_i^2 - H_i P_i H_i^T\right)\right] \\ &= \frac{1}{k}\left[\sum_{i=1}^{k-1}\left(V_{i-1}^2 - H_{i-1} P_{i-1} H_{i-1}^T\right) + \left(V_k^2 - H_k P_k H_k^T\right)\right] \\ &= \frac{1}{k}\left[(k-1) R_{k-1} + \left(V_k^2 - H_k P_k H_k^T\right)\right] \\ &= \left(1 - \frac{1}{k}\right) R_{k-1} + \frac{1}{k}\left(V_k^2 - H_k P_k H_k^T\right) \end{aligned} \tag{5}$$

As the system solution time is too long, i.e., when $k$ tends to infinity, the adaptive ability of filtering will be weakened, so it can be changed to exponential asymptotic weighted average.

It should be noted that the above $R$ parameter adaptive algorithm is based on the observation of $Z$ error is Gaussian distribution, when the observation state is smooth, the use of the new interest time series of the method can be a better estimate of the variance of the observation noise, but if the observation of the sudden jumps and is not detected, then it is difficult to make a timely reflection. Therefore, an adaptive factor $\alpha$ is added to the above. The adaptive factor $\alpha$ can be judged based on the new interest and systematic variance (6):

$$\alpha = \frac{V_k}{\sqrt{P_k}} \tag{6}$$

When $\alpha$ is less than 1, the current observation calendar element is within the anomaly control range and no further adjustment is made. When $\alpha$ is greater than 1, the pair is adjusted for the observation noise variance at the current moment only (7):

$$R_{k'} = \alpha R_k \tag{7}$$

At this point, when the observation is smoother, the observation noise variance can be calculated adaptively based on the new interest series. When the observation is anomalous, the adaptive factor can adjust the observation noise value of the current calendar element to avoid the impact of individual outliers on the system.

### *II. C.Single-channel variable-step LMS adaptive filtering*

#### II. C. 1) Single-channel LMS adaptive filtering algorithm

The standard LMS adaptive filter has two signal input channels. Figure 1 shows the adaptive filter structure. Where the main channel is the detected signal and the secondary channel is the reference noise, but in this paper there is only one detected signal involved and there is no reference noise signal to utilize, so it is not possible to use the standard two-channel LMS algorithm directly.

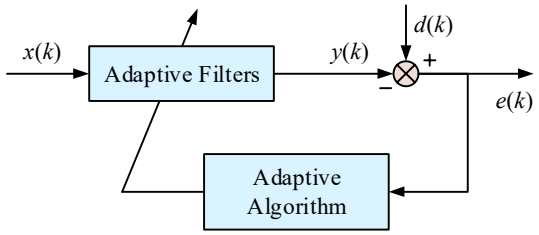



Figure 1: Structure diagram of adaptive filter

In Figure 1, $x$ is the input signal, $d$ is the desired signal, $y$ is the filter output signal, and $e$ is the difference between the desired signal $d$ and the output signal $y$. The adaptive filter adjusts the filter weight coefficients by $e$ and the filter step factor $\mu$ together to make the output signal closer to the desired signal value at the next moment, and $k$ denotes the current time.

To address the difficulty of not being able to obtain the reference noise, this paper, based on the study of the standard dual-channel LMS algorithm, utilizes the correlation of the detected signal and the non-correlation of its noise, to construct a single-channel LMS adaptive filter, whose reference input is the time-domain delay of the detected signal, and the structure of the single-channel LMS adaptive filter is shown in Fig. 2.

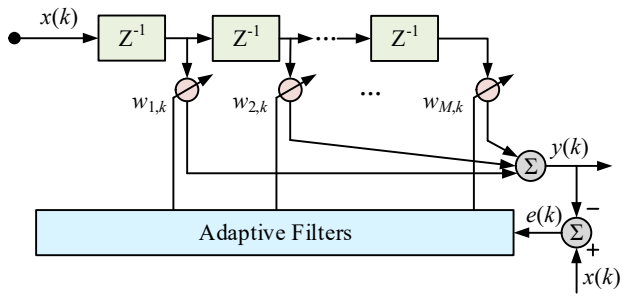



Figure 2: Structure of single-channel LMS adaptive filter

Fig. 2 Removing the correlation of noise using delay and preserving the correlation of the detected signal. The desired input $x$ is the detected noise-containing signal, and the reference input is the $x$ delayed signal. The principle of single-channel LMS implementation is to predict the current data using the short-time correlation of the detected signal and adaptively adjust the weight coefficients of the prediction filter according to the prediction error $e$.

#### II. C. 2) Improved variable step size LMS adaptive filtering algorithm

The traditional fixed-step-length LMS adaptive filter cannot simultaneously take into account the two performance indexes of steady state error and convergence speed, i.e., the smaller the step size, the smaller the steady state error, but the convergence speed is relatively slow. Qin Jingfan et al. propose a variable step-size LMS adaptive filtering algorithm based on the Sigmoid function, where the step-size factor $\mu$ in the filtering process is the Sigmoid function of the prediction error $e$, i.e.

$$\mu(k)=\beta\left[\frac{1}{1+\exp\left(-\alpha\left|e(k)\right|\right)}-0.55\right] \tag{8}$$

where $\alpha$ controls the shape of the Sigmoid function, the value of which determines the rate of rise of the function curve, and $\beta$ controls the range of values of the Sigmoid function. Since $\mu(k)$ decreases with the decrease of $e(k)$, when $e(k)$ is 0, $\mu(k)$ also decreases to 0. It can be seen that the algorithm meets the demand of adaptive change of step size, but in the process of convergence of the curve, the change of the step size is large when the error is close to 0, which makes the algorithm poorly stabilized, and it has an effect on the performance of filtering. For this reason, this paper improves the Sigmoid function so that it adopts a larger step size when the error is larger in order to accelerate the convergence speed; when the error is smaller, it adopts a smaller step size in order to improve the performance of the whole algorithm. The improved Sigmoid function is shown in equation (9).

$$\mu(k)=\beta\left[\frac{1}{1+\exp\left(-\alpha\left|e(k)\right|^{3}\right)}-0.55\right] \tag{9}$$

When the error is 2.5, both the Sigmoid function and the improved Sigmoid function curve have reached or are close to the maximum value of the step factor, which indicates that the convergence of the filtering algorithm is faster at this time, which is conducive to the rapid change of the filtering output results in the direction of error reduction; when the system is close to the convergence, the step factor of the improved Sigmoid function is changing more slowly, which causes smaller oscillations, and therefore the system stability is better. Therefore, the system stability is better.

## III. Practice of abnormal state detection of automation system based on adaptive filtering algorithm

### *III. A. Data set pre-processing*

The experimental data used in this paper are real spacecraft pitch motor current telemetry data. The pitch motor is a key component in the spacecraft attitude control system, and if the power dispatch of the pitch motor is abnormal, it may cause the spacecraft attitude to be out of control, thus jeopardizing the safety of the spacecraft.

The data used are time series data, and 50,000 data points are selected for the experiment. It is first preprocessed to eliminate erroneous data points. Figure 3 shows the comparison between the original data and the preprocessed data. The comparison shows that there are some wrong data points in the original data of 50000 data points, and the current of this part of the data points will increase to more than 1.05A in the continuous time, and the highest even reaches 1.12 A. After the preprocessing of the data, the part of the wrong data points are eliminated, so that the research data remain below 1.05A in the time series, which meets the requirements of the subsequent processing.

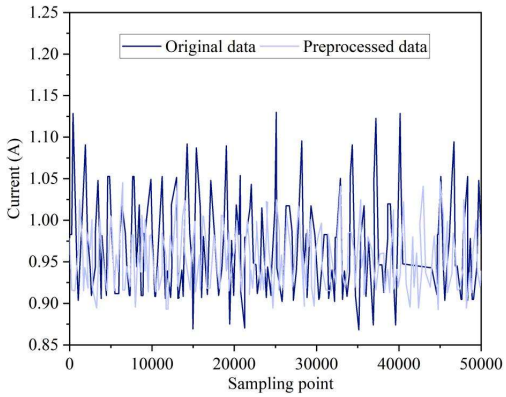



Figure 3: Comparison of the original data with the preprocessed data

### *III. B. Objective performance comparison*

#### III. B. 1) Comparison of AUC values

The performance level of the adaptive filtering algorithm in this paper is judged by the comparison of AUC value and ROC curve. The 50,000 time series data points from the previous paper are divided into 4 parts to construct 4

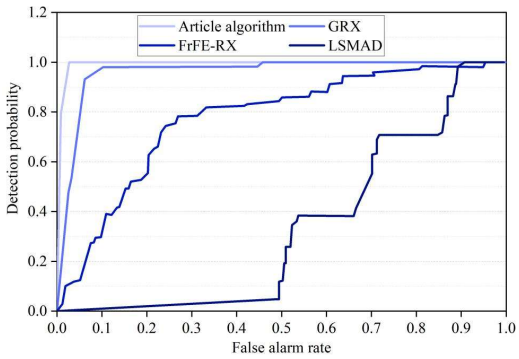
data sets. Three popular algorithms are selected as the comparison algorithms, which are global anomaly detection algorithm (GRX), fractional order Fourier transform anomaly detection algorithm (FrFE-RX), and low-rank and sparse matrix decomposition algorithm (LSMAD). Table 1 shows the AUC values of the four algorithms on the four datasets. The AUC values of this paper's adaptive filtering algorithm on the four datasets are more than 0.95, reaching 0.9873, 0.9798, 0.9868, 0.9875, respectively, with an average value of 0.9851, which is higher than the average values of the compared algorithms, 0.8007, 0.8286, and 0.8456. Therefore, this paper's algorithm is more robust than the other algorithms and performs the best in general.

Table 1: Comparison results of AUC values

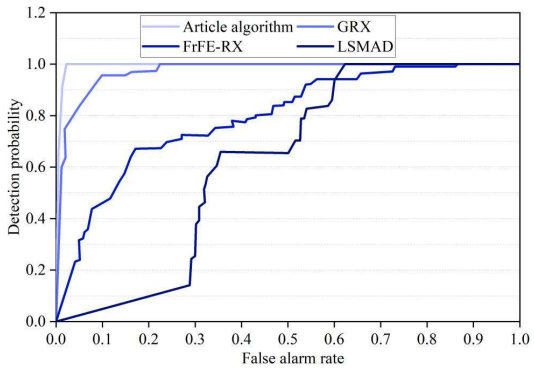
| Algorithm | Data set | | | | |
|---|---|---|---|---|---|
| | A | B | C | D | Average |
| GRX | 0.7864 | 0.7951 | 0.7903 | 0.8311 | 0.8007 |
| FrFE-RX | 0.8130 | 0.8246 | 0.8241 | 0.8425 | 0.8286 |
| LSMAD | 0.8356 | 0.8475 | 0.8436 | 0.8562 | 0.8456 |
| Article algorithm | 0.9873 | 0.9798 | 0.9868 | 0.9875 | 0.9851 |

### III. B. 2) Comparison of ROC curves

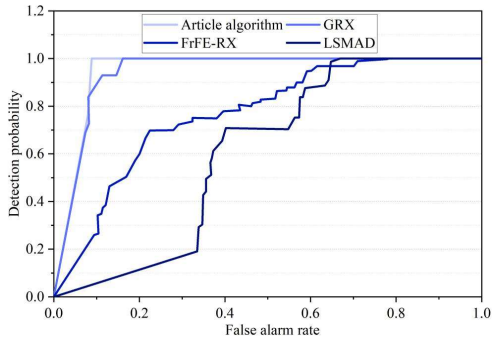
Fig. 4 shows the results of the ROC curves of the four algorithms in the four datasets.In the four datasets, when the detection probability reaches 1.0, the false alarm rate of this paper's algorithm is the smallest, which is 0.027, 0.022, 0.089, and 0.020, respectively, i.e., the area of the ROC curve is the largest. Therefore, as far as the ROC curve is concerned, this paper's algorithm outperforms the other three comparison algorithms in the four datasets. It can be judged that this paper's algorithm has better abnormal state detection effect.



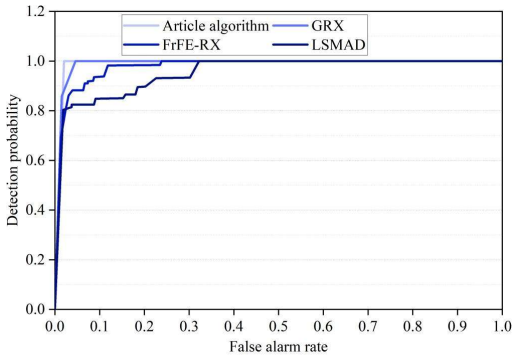

(a) Data set A




(b) Data set B




(c) Data set C




(d) Data set D

Figure 4: ROC curve result

### *III. C. Example validation*

The adaptive filtering algorithm and anomaly detection method of this paper are applied in the business data anomaly detection of a photovoltaic power generation system automated scheduling to study the practical effect of

the anomaly detection method based on adaptive filtering algorithm of this paper. Under the condition that the installed capacity is 10MW and the standard voltage is 8kV, the data anomaly detection of the PV power generation system automated dispatching is carried out, and the time-domain waveform of the input data is obtained. Figure 5 shows the time-domain waveform of the scheduling data. From the test results, it can be seen that there are abnormal voltage fluctuations during the PV power system scheduling process, and the voltage fluctuation amplitude is between 0-35kV, which is far beyond the range of 5%.

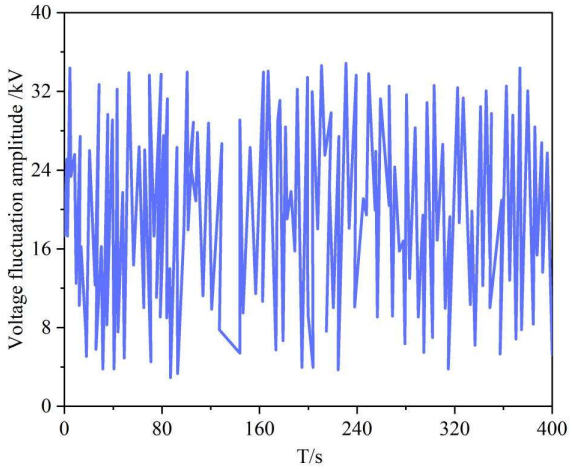



Figure 5: Time domain waveform of scheduling data

The scheduling data is divided into three components: user load, static load and decomposed PV, and according to the results of the scheduling data decomposition, the method of this paper is used to detect anomalies in the scheduling data of the PV power generation system, and to obtain the results of the detection of the anomalous feature points. Figure 6 shows the anomaly detection results of the PV automated power generation system. After the detection, it is found that the automated power generation system has abnormal fluctuations in 298s, 543s, and 677s, and the voltage fluctuation amplitude correspondingly reaches 94.29 kV, 94.04 kV, and 93.53 kV.The use of this paper's method for the abnormal detection of the PV power generation system's automated scheduling data is able to accurately locate the abnormal characteristic points.

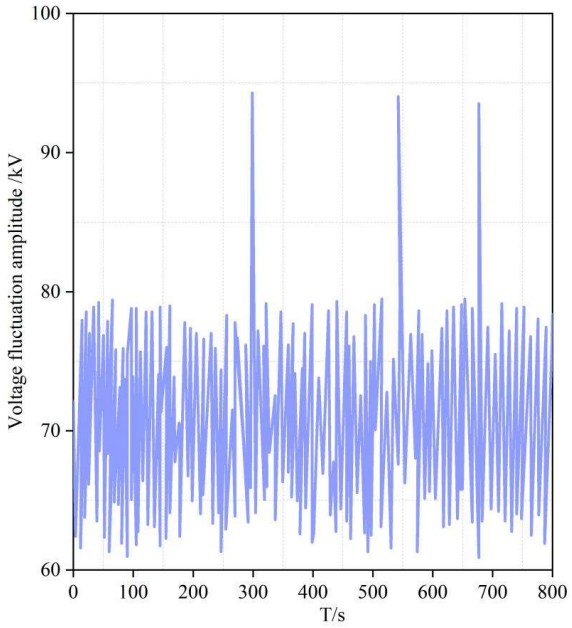



Figure 6: Abnormal detection result

The three comparative methods of the previous paper and the method of this paper are used to test the accuracy probability of the automated dispatch detection of the PV power system. Figure 7 shows the obtained detection performance comparison results. In 10 iterations, the detection accuracy probability of this paper's anomaly state detection method based on adaptive filtering exceeds 90%, with the highest reaching 99.75% and the lowest reaching 93.58%. While the detection accuracy of the other three methods hovered around 60%, 70% and 80%. The detection accuracy of the method in this paper is much higher, and it can fulfill the anomaly detection task of the automated system well.

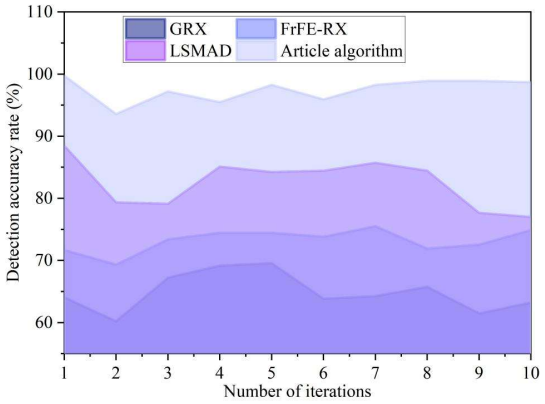



Figure 7: Test performance comparison results

## IV. Conclusion

In this paper, an improved adaptive filtering algorithm is introduced for stable and efficient anomaly detection of business data in automated systems. The algorithm achieves AUC values of 0.9873, 0.9798, 0.9868, and 0.9875 in the four datasets, which are higher than the comparison algorithm. Meanwhile, when the detection probability reaches 1.0, the algorithm has the smallest false alarm rate: 0.027, 0.022, 0.089, 0.020, i.e., the ROC curve area is the largest. In the example validation, the method in this paper accurately detects abnormal fluctuations in the automated power generation system at 298 s, 543 s, and 677 s. The detection accuracy probability of 10 iterations ranges from 93.58% to 99.75%, which is much higher than that of the comparison method. In the future, the anomaly detection method based on adaptive filtering algorithm can be applied to different types of automated systems to improve the generalization performance of the algorithm.

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