Intelligent alarm data noise reduction for power systems based on singular value decomposition

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Abstract: The noise types of power system intelligent alarm data are complex. When reducing the intelligent alarm data, the profile noise statistics of the noise data are large, resulting in the actual noise reduction value is too small. To solve this problem, a power system intelligent alarm data noise reduction method based on singular value decomposition is designed. The selected normalized decomposition matrix iteratively processes the original matrix, the singular value decomposes the power system alarm data, sets an estimation quantity within the paradigm of the alarm data, controls the noise profile noise statistics, characterizes the noise alarm data structure, uses the SC algorithm to process the cluster basis vectors in the noise data structure, and constructs a repeated iterative convergence process to realize intelligent data noise reduction processing. The original alarm data within a known power system is used as test data, the power system alarm window is set, and the power system alarm data singular values are circled. The data mining-based alarm data noise reduction method, the regularized filter-based alarm data noise reduction method and the designed data noise reduction method are applied to the noise reduction process, and the results show that the designed data noise reduction method has the largest noise value and the best noise reduction effect.

1. Introduction
Singular value decomposition belongs to the category of linear algebra. In the existing matrix decomposition structure, the singular value obtained by decomposition is determined in the conjugate transpose formed by diagonalization similar processing method [1]. As a tool of power system security supervision, alarm data is an important index to judge the normal operation of power system. There are many operating environments in the power system in the substation [2]. In the process of monitoring the substation system, the analog quantity or switching value intelligent parameters representing the operating state will produce the influence of external noise. How to reduce the noise and deal with the intelligent alarm data of the power system has become a research hotspot at present. Therefore, the numerical optimization process in the singular value decomposition process is used as support [3], design the noise reduction method of intelligent alarm data.

Foreign research on alarm technology started early. According to the potential relationship between power systems, researchers mine the alarm data in the system by means of sequential processing, set a fixed alarm condition [4], and use post-processing to determine the transfer parameters of noise data to form a noise reduction process. The domestic research on alarm data started late. Combined with the site parameters of power system, set the alarm threshold of different numerical levels [5] according to the parameters, set the threshold priority, and use the Gaussian accounting method to convert the noise data binary into the alarm data with small noise value, forming a noise processing process. The noise reduction method in reference [6] extracts the trend item in the data by empirical mode decomposition,
and controls the superposition of the trend item with the data containing noise, so as to eliminate the noise in the data. In the data denoising method in reference [7], the S-transform is used to obtain the time-frequency matrix in the noise data, and a noise threshold is set in combination with the singular value difference spectrum theory, so as to eliminate the noise in the data. Through phased application exploration, it can be seen that the noise reduction value obtained by the existing data noise reduction processing methods is too small. Therefore, it is of research and development significance to design the power system intelligent alarm data noise reduction method based on singular value decomposition.

2. Noise reduction of power system intelligent alarm data based on singular value decomposition

2.1. Singular value decomposition power system alarm data

The actually obtained power system intelligent alarm data is processed into a data set that can be processed directly, and the data set is processed into an original matrix. The standardized decomposition matrix is selected to process the original matrix iteratively [8]. The iterative processing process can be expressed as:

\[
\begin{align*}
H_n &\rightarrow V^T \\
K_n &\rightarrow K_r^T \\
&\sum_{r\in I} H_r
\end{align*}
\]

(1)

Wherein, \(H_n\) and \(K_n\) respectively represent the iteration formed in the positive and negative directions, \(V^T\) represents the original matrix of alarm data, \(K_r^T\) represents the standardized matrix, and \(H_r\) represents the constructed decomposition matrix. Combined with the decomposition of intelligent alarm data [9], for the alarm matrix obtained by the above decomposition, decompose the singular value in the numerical relationship, and the singular value decomposition process can be expressed as follows:

\[
A = U \begin{bmatrix} 0 & V^T \\ 0 & 0 \end{bmatrix} H_r
\]

(2)

Where \(A\) represents singular value decomposition process, \(U\) represents left singular value vector, and the meaning of other parameters remains unchanged. According to the iteration period generated in the above positive and negative directions, the column vector [10] in the singular value is extracted, and the extraction process can be expressed as:

\[
\begin{align*}
Av^T &= \gamma^T u^T \\
Au^T &= \gamma^T v^T
\end{align*}
\]

(3)

Where \(v^T\) represents the column vector generated by the forward iteration process, \(u^T\) represents the column vector generated by the reverse iteration process, \(\gamma^T\) represents the singular value extraction disturbance parameters, and the meaning of other parameters remains unchanged. Take the column vector extracted above as the rotation direction [11], define the norm of singular value of alarm data, and the numerical relationship can be expressed as:

\[
\kappa = \frac{\|A\|}{\sqrt{A}}
\]

(4)
Where $\kappa$ represents the singular value norm of alarm data, $\|A\|$ represents the rotation direction of column vector, and the meaning of other parameters remains unchanged. Sort out the singular value norm in the alarm data, and characterize the noise alarm data structure according to the norm change in the time period.

### 2.2. Characterization of noise alarm data structure

Corresponding to the singular value norm calculated above, set an estimator in the norm according to the order of generating the norm corresponding to the rotation direction [12], and the value relationship of the estimator can be expressed as:

$$\tau^2 = \frac{\|\hat{A} - r(z)\|^2}{F}$$  \hspace{1cm} (5)

Where $\tau$ represents the calculated noise estimator, $\hat{A}$ represents the singular value estimation parameter, $r(z)$ represents the low order threshold, $F$ represents the rank value parameter, and $T$ represents the estimator period. Combined with the calculated estimator period value, the noise generated by the corresponding alarm data is obtained. The acquisition process is shown in Figure 1 below:

![Fig.1 noise generated by periodic alarm data of adjacent estimators](image)

When characterizing the alarm data structure, set a soft threshold operator into the estimator. At this time, the numerical relationship can be expressed as:

$$g^* = \sqrt{m \left(\frac{Y}{\tau}\right)}$$  \hspace{1cm} (6)

Where $g^*$ represents the characterization processing function, $m$ represents the set soft threshold operator, $Y$ represents the actually generated noise sequence, and the meaning of other parameters remains unchanged. Taking the noise alarm data structure of the above characterization processing as the processing object, when realizing the noise reduction of alarm data, the sparse coding processing process is adopted to sort out the fusion generated by vector basis [13], so as to realize the noise reduction of alarm data.

### 2.3. Noise reduction of alarm data

Under the alarm data structure after the above characterization processing, the SC algorithm is used to determine the cluster base vector in the data structure, and the numerical relationship can be expressed as:
\[ \|x\| = \min_x \left\| \frac{y}{D_x} \right\|^2 \]  

(7)

Where \( \|x\| \) represents the calculated cluster base vector, \( y \) represents the alarm data structure parameters, and \( D_x \) represents the over complete data node. The dimension value in the numerical tensor is defined, and the dimension value is treated as a cyclic matrix by using independent Gaussian distribution. The numerical relationship can be expressed as:

\[ p(y | x) = \prod_{k=1}^{K} (\Gamma_k) \]  

(8)

Where \( \Gamma_k \) represents the cyclization function, \( K \) represents a posteriori parameter, and the meaning of other parameters remains unchanged. The multiplier algorithm is set in the circularized matrix, and the structured values in the matrix are treated as equivalent numerical differences by variational method [14], and the numerical relationship can be expressed as:

\[ \ln P = \frac{S_j}{w_i} \]  

(9)

In the above numerical relationship, \( P \) represents the equivalent parameter, \( S_j \) represents the regularization function, and \( w_i \) represents the singular numerical parameter. Through the equivalent numerical difference obtained above and the defined tensor, the noise reduction update process is set, and the penalty coefficient is quoted to form an alternating convergence preset process. The numerical relationship can be expressed as:

\[ k_i = \frac{\ln P + \rho_k}{Z_k} \]  

(10)

Where \( k_i \) represents the constructed convergence preset function, \( \rho_k \) represents the augmented tensor, and \( Z_k \) represents the set update penalty coefficient. Control the above convergence preset process, continuously update the above set penalty coefficient, and correspond to the convergence conditions obtained by the penalty coefficient, so as to finally achieve the noise reduction processing of alarm data [15]. Based on the above processing process, the noise reduction of power system intelligent alarm data based on singular value decomposition is finally completed.

3. Noise reduction effect test

3.1. Setting power system alarm window

Randomly select the original alarm data of one month in the power system as the test data, set five alarm sequences with unit time in the operation and maintenance alarm scenario in the power system according to the time cycle of the original alarm data, and form rules between the given alarm time and alarm sequence according to the alarm time actually generated in the sequence alarm. Set the confidence actually generated in the capture rule, process the confidence parameter as a mining parameter, and the value relationship of confidence can be expressed as:

\[ c(X \rightarrow Y) = \frac{\sigma(X \cup Y)}{\sigma(X)} \]  

(11)

Among them, \( X \) represents the given alarm time, \( Y \) represents the set alarm sequence, \( \sigma(X) \) represents the numerical variance of the given alarm time, \( \sigma(X \cup Y) \) represents the variance value
between parallel data sets, the alarm sequence corresponds to a specific confidence value, which is taken as the threshold value of the alarm sequence, and sorted into five alarm monitoring rules with different capture contents. Therefore, the capture alarm sequence with time window is set in the actual capture process. The time window and corresponding alarm monitoring items are shown in the table below:

Table 1 set time window alarm sequence

| Grab sequence number | Time window | Alarm item | Capture rules |
|----------------------|-------------|------------|---------------|
| Z-01                 | (60,0,60)   |            | Rule4, Rule5  |
| Z-02                 | (60,120,180)| Rule2      |               |
| Z-03                 | (60,180,240)| Rule4, Rule5|               |
| Z-04                 | (60,240,120)| Rule1      |               |
| Z-05                 | (60,300,180)| Rule3, Rule1|               |
| Z-06                 | (60,360,240)| Rule4, Rule5|               |
| Z-07                 | (60,400,300)| Rule4      |               |
| Z-08                 | (60,120,360)| Rule3, Rule4|               |
| Z-09                 | (60,180,420)| Rule1      |               |
| Z-10                 | (60,60,120) | Rule1, Rule2, Rule3 |

According to the time window alarm sequence set in the above table, for the data with timing attribute, the numerical interval between the start time of the alarm sequence and the time window is agreed and defined as one time unit. Sort out the data obtained by the alarm item capture rules as the actual processing object, and delineate the singular value of the power system alarm data.

3.2. Delineate singular values of power system alarm data

Using the alarm data collected from the above window, the alarm data under different capture rules are weighted and fused. The processing process can be expressed as follows:

\[ w_{ij} = \exp \left( \frac{\| p_{ij} - p_{i-k} \|}{2T} \right) \]  

In the above numerical relationship, \( w_{ij} \) represents the weighted fusion function, \( p_{ij} \) represents the acquired data information block, \( p_{i-k} \) represents the alarm data information block acquired in the next time cycle, and \( T \) represents the time interval between alarm capture Windows. For the alarm data after data fusion, when delineating the singular value of power system alarm data, calculate the mean value of the data in the unified capture rule, take the value as the singular value, and calibrate the data noise in the alarm singular value. The noise value relationship can be expressed as:

\[ f(x, y, z) = \frac{w_{ij}}{\lambda(\phi_1 - \phi_2)} \]  

Where \( \lambda \) represents the introduced noise contrast parameter, \( \phi_1 \) represents the obtained noise ratio, \( \phi_2 \) represents the confidence measurement parameter, and the meaning of other parameters remains unchanged. Kriging difference method is used to convert the structure in the mean value of noise data. Sparse indicates that the alarm data is a three-dimensional structure, as shown in the following figure:
According to the three-dimensional structure of alarm data shown in the above figure, the data containing noise is highlighted in the acquisition diagram. Corresponding to the time window parameters, noise values and confidence values in the three-dimensional structure, a noise data contour processing process is constructed. The numerical processing process can be expressed as:

\[
\nabla n = \frac{\partial \phi(x, y, z)}{\partial l}
\]

(14)

Where \( \nabla n \) represents the contour gradient, \( \phi(x, y, z) \) represents the amplitude of noise value, and \( l \) represents the noise control point. Keep the axis of time window parameters and the axis of confidence parameters unchanged. The equal noise numerical structure of alarm data in the plane is shown in the following figure:

Corresponding to the equal noise numerical structure in the figure above, the alarm data noise reduction method based on data mining, the alarm data noise reduction method based on regularization filtering and the designed data noise reduction method are applied for noise reduction, and the noise reduction effects of the three data noise reduction methods are compared.
3.3. Noise reduction results and analysis

Based on the above processing process, sort out the noise value in the above figure as the noise change of alarm data. Corresponding to the above set capture window, sort out three alarm data noise reduction methods to reduce the size of noise value structure. The results are shown in the following figure:

(a) Noise reduction method of alarm data based on Data Mining

(b) Noise reduction method of alarm data based on regularization filtering
(c) The designed alarm data noise reduction method can deal with the noise structure

Fig.4 noise reduction structure results of three alarm data

According to the numerical noise reduction results shown in the above figure, according to the power system alarm data processed, the numerical range of noise is calculated according to the calculated numerical relationship, and the noise figure corresponding to the corresponding area is calibrated. The three alarm data denoising methods are used to identify the structure. According to the test results shown above, The alarm data denoising method based on data mining can successfully identify the area with noise between 10dB ~ 40dB, and the noise data area that can be denoised is large. The alarm data denoising method based on regularization filtering can successfully identify the alarm data structure with noise value between 10dB and 30dB. The designed alarm data noise reduction method can identify the noise value range of 10dB ~ 50dB. Compared with the two selected noise reduction methods, this alarm data noise reduction method can be applied to alarm data sets with a wider range of noise values.

Sort out the noise value in the equal noise numerical structure of the alarm data and take it as the standard noise value change in the alarm data. Apply the noise reduction algorithm of the three alarm data noise reduction methods to calculate the noise value of the actual noise reduction captured alarm data by the three noise reduction methods according to the data processing area covered by the noise structure. The numerical relationship can be expressed as:

$$R_{SSN} = S \times n - \frac{e_i}{W^T}$$  \hspace{1cm} (15)

Among them, $R_{SSN}$ represents the actual noise reduction value of the noise reduction method, $e_i$ represents the noise value generated by the alarm data in the structural area, $W^T$ represents the kernel function of the three noise reduction methods in the same time window, $S$ represents the area of noise generated by the window, and BB represents the noise number value corresponding to the area. Corresponding to different grab numbers, sort out the noise values of the noise reduction treatment of the three noise reduction methods. The noise reduction results are shown in the figure below:
According to the defined noise reduction numerical relationship, the alarm capture data sets processed by the three noise reduction processing methods are transformed, and the singular values of power system alarm data are delineated correspondingly to obtain the noise value change in the capture data set, and this value is used as the starting point of noise value processing. Sort out the noise reduction values obtained by the algorithms of the three noise reduction methods, and take the numerical difference between the value and the actually obtained noise value processing points as the comparison index. When the numerical difference is larger, it means that the noise treatment effect of the noise reduction method is better. According to the numerical difference results shown in the figure above, the noise reduction value of the alarm data noise reduction method based on regularization filtering is about 25dB, and the noise reduction effect is poor. The noise reduction value obtained by the noise reduction processing method based on data mining is about 40dB, which has poor noise reduction effect on alarm data. The noise reduction value obtained by the designed noise reduction method is about 52dB. Compared with the two applied noise reduction methods, the noise reduction value of the data of this noise reduction method is better.

**4. Conclusion**

Under extreme weather conditions, the alarm data of power system is an important medium to evaluate the operating conditions of the system. With singular value decomposition as the numerical processing support, the design of power system intelligent alarm data noise reduction method can improve the existing noise reduction process, which has the disadvantage of small noise processing value. In the future work, it is hoped that the designed alarm data noise reduction method can provide support for data noise reduction.

**Reference**

[1] Yang Zhiwei, Liu Hao, Bi Tianshu, et al. PMU data recovery method based on singular value decomposition [J]. Chinese Journal of electrical engineering, 2020,40 (03): 812-821

[2] Fan Xianguang, Wu Tengda, Zhi Yuliang, et al. Raman imaging data denoising method based on
singular value decomposition and median absolute deviation [J]. Spectroscopy and spectral analysis, 2020, 40 (02): 436-440

[3] Yang Juhua, Zhang Linjing, Chen Guangwu, et al. Error analysis and noise reduction of MEMS gyroscope based on SVD / wavelet [J]. Journal of Chongqing University of Posts and Telecommunications (NATURAL SCIENCE EDITION), 2020, 32 (02): 322-328

[4] Gu Tingyun, Gao Yumpeng, Wu Cong, et al. Power quality disturbance detection based on improved wavelet threshold function and singular value decomposition [J]. Electrical measurement and instrumentation, 2020, 57 (21): 111-118

[5] Wang Hongwei, Xie Lirong. Fuzzy model identification of non uniformly sampled nonlinear systems based on singular value decomposition [J]. Control and decision making, 2020, 35 (03): 757-762

[6] Liu Shuzhen, Chen Zhixing. Noise reduction method of nonlinear vibration signal based on singular value decomposition and EEMD [J]. Journal of detection and control, 2019, 41 (03): 37-42

[7] Niu Haiqing, song Tinghan, Luo Xin, et al. Partial discharge signal denoising method based on S-transform and singular value decomposition [J]. Journal of South China University of Technology (NATURAL SCIENCE EDITION), 2020, 48 (02): 9-15

[8] Shen Zhongting, Ding Renjie. Power system low frequency oscillation modal identification based on Improved EMD denoising and matrix beam [J]. Journal of Applied Science, 2019, 37 (06): 761-774

[9] Zhang Qi, Liu Ling, Wen Junhao. A singular value decomposition recommendation algorithm based on domain trust and distrust [J]. Computer science, 2019, 46 (10): 27-31

[10] Wei xiulei, Liu Shuyong. Signal denoising method of communication radar based on multilevel singular value decomposition and SG [J]. Journal of Wuhan University of Technology (traffic science and Engineering Edition), 2020, 44 (04): 658-662

[11] Hu Chaofan, Wang Yanxue. Research on multi-channel signal noise reduction method for composite fault of rolling bearing based on tensor decomposition [J]. Journal of mechanical engineering, 2019, 55 (12): 50-57

[12] Xing Tingting, Guan Yang, Liu Zihan, et al. Frequency close signal separation method based on variational modal decomposition and singular value decomposition [J]. Journal of metrology, 2020, 41 (11): 1404-1409

[13] Li Weijiang, Luo Panhu. Diversified recommendation algorithm integrating kernel density estimation and singular value decomposition [J]. Small microcomputer system, 2020, 41 (01): 56-60

[14] Yin Fang, song Yao, Li Ao. Collaborative filtering algorithm based on locally optimized singular value decomposition and K-means clustering [J]. Journal of Nanjing University of technology, 2019, 43 (06): 720-726

[15] Shao meiyang, Wu Junyong, Li Baoqin, et al. Power system transient stability assessment based on two-stage integrated deep confidence network [J]. Power grid technology, 2020, 44 (05): 1776-1787