



A Fault Signal Processing Method Based on An Improved Prony Algorithm

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The fault of power systems introduces a severe challenge in terms of fault recording analysis, and the traditional Prony method cannot perform satisfactorily in the process of signal recordings fitting caused by faults. Therefore, an improved adaptive Prony algorithm is proposed in this article to study the characteristics of fault recordings. Specifically, the search step size is taken as an adaptive variable, and the mean square relative fitting error (MSRFE) is set as the criterion. Then, a large step is employed to rapidly determine an approximate segmentation point in the initial stage of the searching process, and its horizon is gradually reduced to establish an accurate subsegment point. Finally, the Prony algorithm is deployed to analyze the subsegment fitting original signal. The proposed approach has been simulated on an assumed fault signal, and the results validate the accuracy and efficiency of the method.

Keywords: power systems, fault recording, Prony algorithm, improved adaptive, signal fitting

INTRODUCTION

An accurate assessment plays an indispensable role in the safety active control systems (Shen et al., 2021a; Shen and Raksincharoensak, 2021a; Shen and Raksincharoensak, 2021b). Similarly, it is significant to study an effective fault signal analysis method for safe and stable operation in power systems (WangJin et al., 2019; Yang et al., 2019; Yang et al., 2021a; Zhang et al., 2021). Although the technology of fault analysis has already been developed in the existing literature, there are still obstacles to fault identification using the electrical parameters of recording signals. In practice, the state of power systems is monitored using intelligent monitoring terminals in real time. In this way, the fault recording accuracy of the system can be guaranteed, but producing redundant data increases the difficulty of data storage. On the other hand, if only targeted data sampling is carried out for the power grid in case of fault, despite data redundancy can be cut down, it may lead to a lack of recording data and a decrease in recording accuracy. Therefore, the research on fault recording algorithms of power systems has theoretical and practical significance.

For research of signal recordings, it can be analyzed based on steady state and transient (Sajadi et al., 2019). However, the steady-state efficiency of fault identification is bounded. The main reason is that renewable energy to access power systems is becoming increasingly complicated in recent years, and fault analysis has to accord with the requirements of sensitivity, fast, and accurate at the same time (Liao et al., 2018; Zhu et al., 2019; Liu et al., 2020a; Zhu et al., 2020; Wang et al., 2021). These problems have been solved based on transient analysis, showing practical application (Saleh

et al., 2015; Yu et al., 2020). In addition, the demand for data is urgent with the rapid development of deep learning technology in power systems (Yang et al., 2018; Yang et al., 2021b). In this context, one of the most critical points is how to extract the characteristic information of transient electrical signals such as voltage, current, and frequency in the research of fault recording. For one thing, the random noise can lightly bury the transient with low energy and small amplitude due to the hybrid of transient and steady state. For another, although the extracted transient characteristics are directly applied in the fault research because the extracted data are massive and irregular (Xu et al., 2017; Shen et al., 2020a; Desai and Makwana, 2021), they still fail to achieve the goal of identifying specific faults. Therefore, the effective extraction of its feature information is crucial to the fault identification problem, which is directly related to the effectiveness and accuracy of fault identification and location.

Numerous works have studied methods to ensure the safety of power grids (Shen et al., 2017; Liu et al., 2020b; Shen et al., 2020b; Li et al., 2021a; Shen et al., 2021b; Hosseini et al., 2021). In the study of Li et al. (2021a), a combined high voltage direct current measurement method is present to improve the extraction accuracy of the measured signal. Besides, some traditional methods such as Hilbert–Huang transform, wavelet transform, and Fourier transform are used in signal processing (Borghetti et al., 2008; Satpathi et al., 2018; Li et al., 2021b). However, the previous methods only separate fault recordings and cannot realize the direct extraction of fault feature information. Its characteristics are obtained directly through the Prony algorithm. In Tawfik and Morcos. (2005), a fault location method integrating the Prony method and artificial neural networks is presented, and the modified scheme provided good accuracy. Yet, when the amplitude of the high-frequency component of the signal is small, the estimation is prone to errors in practice. In Ando. (2020), the difference algorithm is introduced to improve the characteristics of high-frequency components of signals, but its inherent defect has not been tackled. Later, a segmented Prony method is proposed (Jansen and Garoosi, 2000), which divides the signal into different subsegments to ensure good continuity and minor variation in each subsegment, improving the impact on signal characteristics. Nevertheless, the segmented method rarely focused on how to segment to obtain the best analysis results. Based on this, an adaptive Prony method is presented, taking MSRFE as the criterion to realize the adaptive segmentation of the fault signal (Bracale et al., 2007). However, the algorithm searches the subsegment boundary point by enumeration search with a fixed step, resulting in low efficiency. These methods also have the inadequacies of fault signal recognition accuracy for certain signals overall.

In this article, when a power system fault materializes, an improved adaptive Prony method is proposed to describe the accurate variation of electrical parameters. The point of the subsegment is searched by variable step-size strategy, and MSRFE is considered the criterion. The proposed approach has been simulated on an assumed fault signal, and results show that the improved Prony algorithm has higher accuracy and efficiency than the traditional method.

PRONY METHOD MODEL

The Prony method is formulated as a linear combination of exponential functions to describe the mathematical model of equal distance sampling data and linearized approximate solution. The amplitude, phase, frequency, and attenuation factor of the corresponding signal can be obtained directly by this method. The general solution procedure of the Prony algorithm is as follows.

The continuous signal $x(t)$ is equidistantly sampled according to the sampling frequency. There are N sampling data obtained and stated as $x(0), x(1), \dots, x(N-1)$, and x_n can be stated in Eqs 1, 2.

$$x_n = \sum_{i=1}^p b_i z_i^n, n = 0, 1, \dots, N-1 \quad (1)$$

$$\begin{cases} b_i = A_i e^{j\theta_i} \\ z_i = e^{(\alpha_i + j2\pi f_i)T_s}, i = 1, 2, \dots, p, \end{cases} \quad (2)$$

where A_i , θ_i , α_i , and f_i denote the amplitude, initial phase angle, attenuation factor, and frequency of the i th complex exponential function, respectively; N and p are the number of sampling points and the order, respectively; and T_s is the sampling period.

Then, obtain α_i and z_i by constructing the difference equation and its characteristic equation. The singular value decomposition and the least square method should be used to solve α_i , thereby improving the calculation accuracy (Liu et al., 2008).

Finally, the required parameter can be obtained from previous equations, respectively, as shown in Eq.3.

$$\begin{cases} A_i = |b_i|, \\ \theta_i = \arctan(\text{Im}(b_i)/\text{Re}(b_i)), \\ \alpha_i = \ln(z_i)/T_s, \\ f_i = \arctan(\text{Im}(z_i)/\text{Re}(z_i))/2\pi T_s, \end{cases} \quad (3)$$

IMPROVED PRONY ALGORITHM STRATEGY

The traditional Prony method has some practical limitations, which may lead to inaccurate fitting results of some specific signals under certain conditions, such as mutation signals when a fault occurs in power systems. Specifically, on the one hand, the search step size of the traditional Prony algorithm is performed with a fixed step. On the other hand, the accuracy of the fitting depends on the selected order. The order is selected artificially by using the traditional method. Although there will be an order to make the fitting accurate, it will take more time for an operation. At the same time, it will also bring extra components. Thus, the method proposed in this article is an improvement in these aspects. The steps involving the parameters of the analysis algorithm are explained as follows.

Step 1: Initialize the original data and parameters, including the signal information, search step k , minimum length of subsegment L_{\min} , sampling frequency, a maximum value of MSRFE E_m , and some remaining parameters.

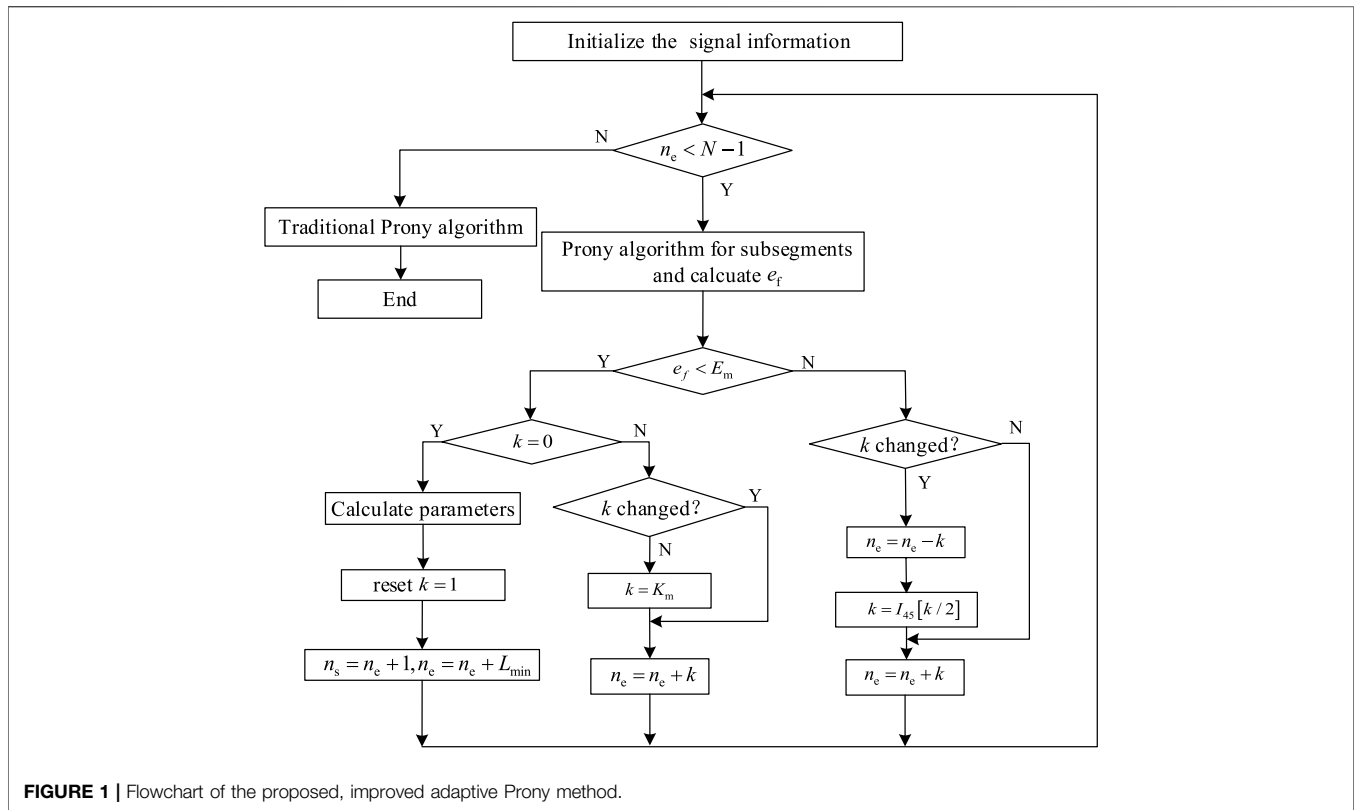


FIGURE 1 | Flowchart of the proposed, improved adaptive Prony method.

Step 2: Compare the number of sampling points and the sequence number at the end of the subsegment. When the number of sampling points is greater than the end sequence of the subsegment, the Prony algorithm is directly applied in the subsegment. Otherwise, proceed to step 3.

Step 3: Using the Prony algorithm for subsegments and calculating MSRFE e_f . According to MSRFE obtained from the subsegment, whether its value is lower than the maximum value assumed. If MSRFE is lower than its maximum value, proceed to step 4. Otherwise, proceed to step 5.

Step 4: Judge whether the step is equal to 0. If its value is 0, reset the step to 1. Otherwise, judge whether the step was changed, if not changed, then make it set the maximum search step K_m .

Step 5: Check the step was changed, and update the corresponding parameters, where I_{45} means rounding.

Step 6: Until the condition of step 2 is met, output the characteristic parameter of signal information.

The detailed procedure is shown in Figure 1, and the expression of MSRFE is shown in Eq. 4.

$$MSREF = \frac{1}{n_0} \sum_{n=n_s, x_n \neq 0}^{n_e} \frac{[x_1(n) - x(n)]^2}{x(n)^2}, \quad (4)$$

where $x(n)$ is the real value, $x_1(n)$ is the estimated value, n_0 is the total number of non-zero values in the subsegment, and n_s and n_e are the start sequence number and end sequence number, respectively.

To better evaluate the accuracy of fitting and real value, the root-mean-square error (RMSE) is introduced in this article, which is defined as Eq. 5.

$$RMSE = \sqrt{\frac{1}{L} \sum_{n=1}^N [x_1(n) - x(n)]^2}, \quad (5)$$

where L is the length of the signal.

CASE STUDY

Instance and Setup

In this article, two types of original voltage signals mimic recordings. The signals under the normal operation and fault are simulated by a smooth and a signal of mutational processes, respectively. The mathematical expression of the smooth voltage signal is shown in Eq. 6, and its parameters are shown in Table 1.

$$\begin{aligned} x(t) &= x_1(t) + x_2(t) + x_3(t) + x_4(t) \\ &= 110e^{-2.0t} \cos(2\pi \times 50t + \pi/3) \\ &\quad + 220e^{-2.0t} \cos(2\pi \times 50t + \pi/6) \\ &\quad + 220e^{-1.0t} \cos(2\pi \times 80t + \pi/6) \\ &\quad + 330e^{-0.5t} \cos(2\pi \times 60t + \pi/6), \end{aligned} \quad (6)$$

Process Simulation Verification

The total number of sampling points, the sampling period, and the sampling frequency are set 1,000, 0.025 s, and 4 kHz in the

TABLE 1 | Specific parameters of the smooth signal.

Component	Frequency (Hz)	Amplitude (V)	Initial phase angle	Attenuation factor
1	50	110	60	-2.0
2	50	220	30	-2.0
3	80	220	30	-1.0
4	60	330	30	-0.5

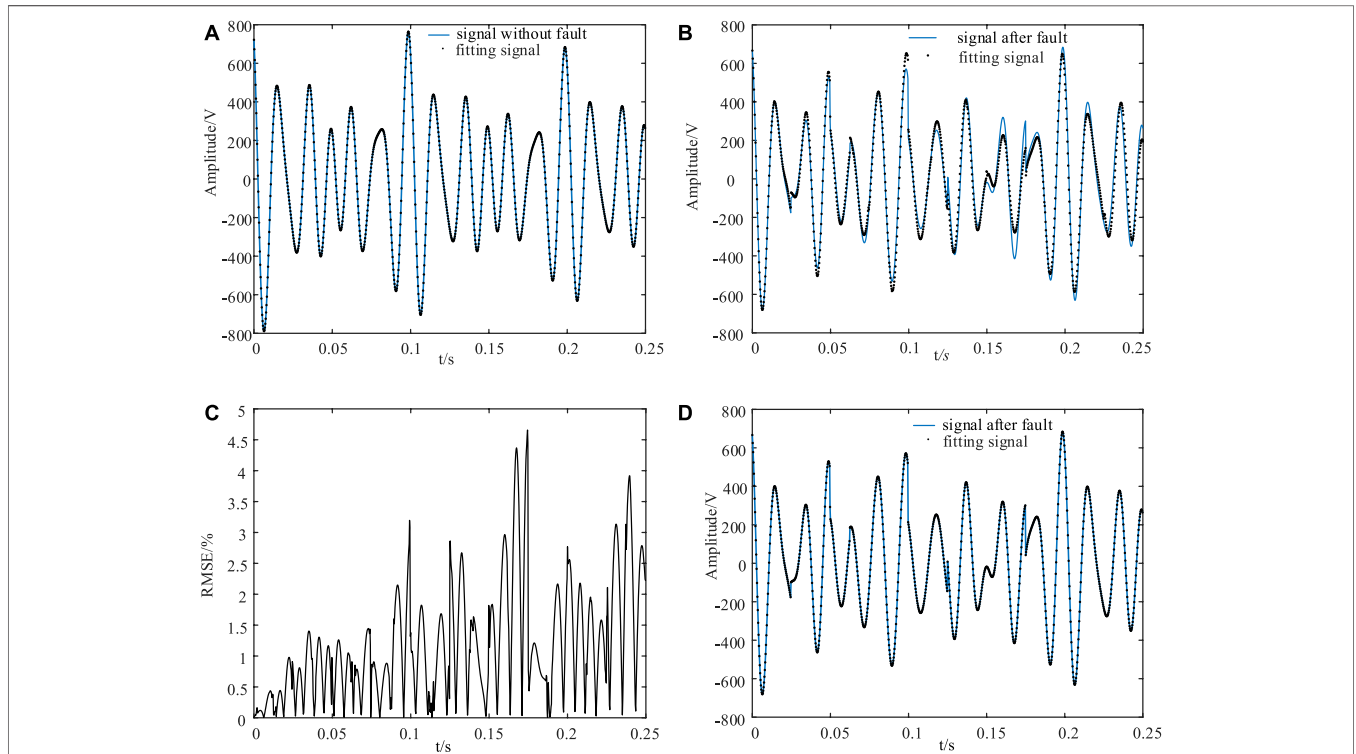


FIGURE 2 | Simulation results: **(A)** Smooth signal simulation based on the traditional Prony method. **(B)** Mutation signal simulation based on the traditional Prony method. **(C)** RMSE of the original and fitting signals based on the traditional Prony method. **(D)** Mutation signal simulation based on the proposed method in this article.

simulation, and the start sequence point and the end sequence point are defined as 1 and 20, respectively. The minimum length of the subsegment is 20, and the maximum search step is 20. **Figure 2A** is plotted to depict the fitting under the normal condition provided by known parameters. We can observe that the simulation results show an excellent agreement is consistent, the order is 230, and the RMSE is so tiny that it can be ignored.

Comparative Simulation Verification

In this case, based on the assumption of the smooth signal, $x_1(1: 200) = 0$, $x_2(100: 500) = 0$, $x_3(200: 500) = 0$, and $x_4(400: 700) = 0$ is set in the program to simulate the signal with sudden operation change, and the meaning of x_1 from 0 to 0.05 s, x_2 from 0.025 to 0.125 s, x_3 from 0.05 to 0.125 s, and x_4 from 0.1 to 0.175 s all failing to react. The traditional Prony method is used for the fault recording, and the comparison between fitting and the original signal is given in **Figure 2B**. We can see that the trend of the two signals is deviated.

Furthermore, **Figure 2C** shows the maximum RMSE of both is around 4.5%, and the traditional method is intractable for fitting the signal. The reason for such a difference may be that the traditional method makes decisions by considering the original signal is always continuous and smooth without mutation, and it results in mutagenicity when a fault occurs. It is bound to skip some vital parts while fitting by this method, resulting in some information being ignored. Moreover, the order is often set in advance in the fitting process, and it takes a longer time to manually and continuously adjust the order to fit the original signal.

The previously assumed fault recording signal is analyzed by using the proposed method in this article, and the corresponding result is shown in **Figure 2D**. We can see that the performance of the proposed method is satisfying, overlapping with the original signal. The reason is that the search step, as a variable, will be segmented when encountering sudden change points in the search stage, avoiding some information being ignored at the critical moment of analysis. On the other hand, the time of fitting

TABLE 2 | Component parameters of subsegment based on simulation.

Subsegment	Frequency (Hz)	Amplitude (V)	Initial phase angle	Attenuation factor
1	50	220	30	-2.0
	80	220	30	-1.0
	60	330	30	-0.5
2	60	325.94	-150.4	-0.5
	80	214.62	29.8	-1.0

is decreased shorter than the traditional Prony method because the order of this method does not need to rule in advance. Meanwhile, to further illustrate the effectiveness of the proposed method, fitting dates are further analyzed. The signal is divided into eight subsegments in total, taking the first two segments of the total date as an example for analysis, as given in **Table 2**.

Table 2 indicates that the signal with a component frequency of 50 Hz and an amplitude of 110 V is not present in subsegment 1, so the corresponding data are missing, and the information of other components is accurately extracted. Similarly, the subsegment signal is not affected by components 1 and 2, so there is only relevant information of components 3 and 4 in the subsegment. More specifically, some data obtained through an attenuation process, such as amplitude and initial phase angle, do not get in line with **Table 1**. By taking the first line of subsegment 2 as an example, the sequence point of subsegment 2 ranges from 100 to 199. After 0.025 s, the accuracy of amplitude becomes $330 \times e^{-0.5 \times 0.025} = 325.91$, and the initial phase angle transforms from 30 to $\arg[30 + (2 \times \pi \times 60 \times 0.025 \times 180) / \pi] = -150.0$.

CONCLUSION

The traditional Prony algorithm is improved in this article. First, the basic model of the Prony algorithm is constructed. On this basis, the mean square relative fitting error is set as the criterion, and the variable step method is used to search the subsegment boundary points. Finally, a fault recording signal processing with an improved adaptive Prony algorithm is proposed. The conclusions based on simulation analysis are as follows.

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The improved adaptive Prony algorithm proposed in this article can not only fit the signal under normal conditions but also obtain higher accuracy after the signal characteristics change under abnormal conditions.

In the fault recording signal fitting, the proposed method does not need to set the order in advance. Compared with the traditional Prony algorithm, it can greatly reduce the fitting time and improve the calculation efficiency.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

NY put forward the main research points; YL, JZ, and ZZ contributed to manuscript writing and revision; LD, CY, and ZD performed simulation research; SL, WX, and BZ collected relevant background information; LZ, YH, and XZ revised for grammar and expression. All authors contributed to manuscript revision and read and approved the submitted version.

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