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Fundamental Frequency Tracking of Distorted Power Signal Based on the Improved EKF Algorithm

Zhang Xiaobing, Yang Mengchen, Yan Yixin and Fang Guozhi

College of Measure-control Technology & Communication Engineering
Harbin University of Science and Technology, Harbin, China
Zhxiaobing@163.com

Abstract

To reduce the impacts of harmonics and noises on frequency measurements, a novel method of frequency tracking is presented based on improved EKF algorithm and wavelet transform. Firstly, the power signal was preprocessed to extract the fundamental wave by wavelet filtering. Then, an improved Extended Kalman Filter was introduced to achieve fast and accurate frequency tracking. By adding a robust factor and modifying the covariance matrix in real time, it enhanced the stability for detecting distorted signals. The proposed tracking algorithm can effectively solve the problems of traditional Extended Kalman Filter such as lack of adaptability, instability and divergence. And it improved the tracking speed and accuracy. Finally, Detailed simulations on several typical models of power signals have been carried out and the Simulation results shown that the new algorithm increases the speed, convergence and accuracy. It effectively suppresses the impacts of harmonics and noises on the frequency tracking results.

Keywords: *EKF algorithm; frequency tracking; fundamental component extraction; wavelet transform*

1. Introduction

In power system, the frequency of the dynamic behavior directly affects the power quality and system security and stability of [1]. Fundamental wave frequency as the main physical parameters of power system is to measure the power quality and power of the important indices for accurate measurement. Through the real-time accurate tracking of fundamental wave frequency, can be measured as distortion signal under the condition of electricity to lay a solid foundation, at the same time the evaluation and control of the system running state is of great significance [2].

In the field of power grid frequency measurement, the traditional frequency tracking algorithms are fast Fourier transform [3], minimum mean square error method [4-5], the adaptive notch filter, *etc.* These algorithms in tracking speed, accuracy and computation, the ease of implementation, the harmonic inhibition and antinomies ability each have advantages and disadvantages, but generally to the needs of the two aspects of both real time and accuracy. Therefore, some scholars proposed algorithm is simple in structure and has a certain frequency tracking accuracy of the kalman filtering algorithm is applied in the signal frequency tracking and achieved some results. But when the system initial state error or by nonlinear model, the fixed parameter Settings cannot be made to the frequency of mutations response [6], seriously affected the filtering accuracy and even lead to filter divergence. Some scholars also use Sigma point kalman filter algorithm, improve the accuracy of the frequency tracking. But the Sigma point kalman filtering accuracy easily affected by noise, the lack of adaptive ability, easy to produce the nonlocal effect of sampling, and to a certain extent, increased the complexity of the algorithm [7]. According to the above problem, this paper puts forward a kind of based on improved extended kalman filter (EKF) and the wavelet transform of fundamental wave

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power system frequency tracking algorithm. The algorithm to a certain extent, reduce the effects of the original signal to frequency tracking process, ensure the accuracy of the algorithm, improves the traditional EKF algorithm accuracy is not high, poor anti-interference ability, unstable, or even divergence.

2. The Fundamental Frequency Tracking Algorithm

The harmonic wave and noise signal components affect the stability of frequency tracking algorithm, is not conducive to the base wave frequency of accurate tracking. Therefore, before the base wave frequency tracking, first of all should be carried out on the original signal preprocessing, filter the signal harmonic and noise interference of ingredients, accurately extract the fundamental wave signal, and then using the improved EFK algorithm to fundamental wave frequency tracking, so that we can improve the tracking accuracy of the algorithm.

2.1. Based on the Wavelet Transform Principle of Fundamental Wave Extraction

Fundamental component extraction method of analog filter is often used to [8], the method is simple in circuit structure, low cost, can filter out some of the natural frequency of the harmonic, but filter center frequency is influenced by external factors, when the grid frequency changes slightly, the accuracy of fundamental wave extraction decreased, and the real-time performance is poor. Some scholars also apply Fourier transform to extract fundamental wave, but accuracy is not high, the reason is Fourier transform is only applicable to stable periodic signal [9], the power grid in actual operation, the signal change, frequency drift, and so on and so forth.

Has the characteristics of multi-resolution analysis of wavelet transform, the singularity, instantaneity, especially the ability to have the analysis of the transient signal is accurate and reliable, so the wavelet transform is to analyze the unsteady signal or with the most effective way to signal singularity mutations. According to the laws of the wavelet filter, power grid can be high harmonic signal and noise filtering, finally only keep the fundamental component of the signal.

Discrete form of power voltage signals can be represented as:

$$u_a(t) = u_I(t) + u_s(t) \tag{1}$$

Among them, the $u_I(t)$ stands for fundamental component; the $u_s(t)$ stands for distortion component. And $u_s(t)$ contains every harmonic component, dc, voltage harmonics, the superposition of Gaussian white noise, and other forms of distortion component.

By multi-resolution analysis theory, $u(t)$ can be decomposed into different frequency components:

$$\begin{aligned} u(t) = & \sum_k c_0(k)\varphi(t-k) \\ & + \sum_k \sum_{j=0}^{J-1} d(k) 2^{j/2} \psi(2^j t - k) \end{aligned} \tag{2}$$

Among them, the J stands for decomposition of the number of layers; $c_j(k)$ stands for scale factor; $d_j(k)$ stands for wavelet coefficients, scale function is a set of orthogonal basis:

$$c_j(k) = \langle u(t), \varphi_{j,k}(t) \rangle \tag{3}$$

$$d_j(k) = \langle u(t), \psi_{j,k}(t) \rangle \tag{4}$$

The double scale equation shows that:

$$c_{j-1}(k)=\sum_n h(n-2k)c_j(n) \tag{5}$$

$$d_{j-1}(k)=\sum_n g(n-2k)c_j(n) \tag{6}$$

The $h(k)$ called low-pass filter, the $g(k)$ called high-pass filter coefficient, which satisfied:

$$g(k)=(-1)^k h(1-k) \tag{7}$$

The initial scale coefficient $c_j(k)$ is obtained by direct sampling signal $u(t)$. Analysis of wavelet transform is applied to power system transient, the correct selection of transformation scale is very important. If the signal of the sampling frequency is greater than the Nyquist frequency, then $c_j(k)$ close to $u(t)$.

By initial scale coefficient can decompose step by step the voltage signal is decomposed into different frequency bands.

Voltage of the wavelet coefficients of each frequency component can be expressed as a matrix form:

$$\mathbf{C_{signal}}=[c_{0.k},d_{0,k},...,d_{J-1,k}] \tag{8}$$

The fundamental wave signal $u_I(t)$ wavelet coefficient matrix $\mathbf{C_{basis}}$ can be expressed as follows:

$$\mathbf{C_{basis}}=[c_{0.b},d_{0,b},d_{1,b},...,d_{J-1,b}] \tag{9}$$

According to the actual situation of power grid, the unwanted wavelet coefficients are set to zero (such as noise in wavelet coefficient, *etc.*) [10], then get reconstruction wavelet coefficient matrix of fundamental wave signal:

$$\mathbf{C^u}_{\mathbf{basis}}=\left[c^u{}_{0,b},d^u{}_{0.b},d^u{}_{1,b},...,d^u{}_{J-1,b}\right] \tag{10}$$

Will get the fundamental voltage on type into the reconstruction equation:

$$\begin{aligned} u'_I(t)&=\sum_k c_0{}^u\varphi(t-k)\\ &+\sum_k\sum_{j=0}^{J-1} d_j{}^u(k)2^{j/2}\psi(2^j t-k) \end{aligned} \tag{11}$$

2.2. The Frequency Tracking Algorithm Based on Improved Extended Kalman Filter

The grid signal after wavelet transform preprocessing s_k can be represented as [11]:

$$\begin{cases} s_k=z_k+v_k\\ z_k=\alpha_1\sin(k\omega_1 T_s+\theta) \end{cases} \tag{12}$$

Among them, v_k stands for the noise of the signal s_k after filtering residual volume; z_k stands for the power frequency signal; α_1 stands for the signal amplitude; $\omega_1=2\pi f$ stands for angular frequency signal; θ stands for the beginning of the signal phase Angle.

In this paper, according to the amplitude, phase and frequency of the signal z_k information to establish a model of state vector is shown below:

$$\mathbf{x_k}=\left[x_1(k)\quad x_2(k)\quad x_3(k)\right]^T \tag{13}$$

Among them, $x_1(k)$ stands for amplitude condition; $x_2(k)$ stands for the amount of phase state; $x_3(k)$ stands for the frequency condition.

By adjacent dynamic change characteristics before and after the sine signal sampling times known state transition equation is:

$$\mathbf{x_{k+1}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 2\pi T_s \\ 0 & 0 & 1 \end{bmatrix} \mathbf{x_k} = \mathbf{F_k x_k} \tag{14}$$

And,

$$s_k = z_k + v_k = g(x_k) + v_k \tag{15}$$

$$g(x_k) = x_1(k)\sin(x_2(k)) \tag{16}$$

Among them, $g(x_k)$ stands for measurement function; $\mathbf{F_k}$ stands for state transition matrix.

The above equation linearization and first-order EKF algorithm:

$$\begin{cases} \tilde{\mathbf{x}}_\mathbf{k} = f(\hat{\mathbf{x}}_\mathbf{k-1}) \\ \mathbf{P_{k,k-1}} = \mathbf{F_k P_{k-1.k-1} F_k}^\mathbf{T} \\ \mathbf{G_k} = \mathbf{P_{k,k-1} H_k}^\mathbf{T} (\mathbf{H_k P_{k,k-1} H_k}^\mathbf{T} + \mathbf{R})^{-1} \\ \hat{\mathbf{x}}_\mathbf{k} = \tilde{\mathbf{x}}_\mathbf{k} + \mathbf{G_k}(s_k - \mathbf{g}(\tilde{\mathbf{x}}_\mathbf{k})) \\ \mathbf{P_{k,k}} = (\mathbf{I} - \mathbf{G_k H_k})\mathbf{P_{k,k-1}} \end{cases} \tag{17}$$

Among them,

$$\begin{cases} \mathbf{F_k} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 2\pi T_s \\ 0 & 0 & 1 \end{bmatrix} \\ \mathbf{H_k} = \dfrac{\partial g(\tilde{x}_k)}{\partial \tilde{x}_k} = \begin{bmatrix} \sin(x_2(\tilde{k}) \\ x_1(\tilde{k})\cos(x_2(\tilde{k}) \\ 2\pi T_s x_1(\tilde{k})\cos(x_2(\tilde{k})) \end{bmatrix}^T \end{cases} \tag{18}$$

Among them, $\hat{\mathbf{x}}_\mathbf{k}$ stands for the status update values; $\tilde{\mathbf{x}}_\mathbf{k}$ stands for the state prediction ; $\mathbf{R}$ stands for the measurement error covariance ; $\mathbf{G_k}$ stands for the kalman gain ; $\mathbf{P_{k,k-1}}$ stands for the estimation error covariance ; $\mathbf{P_{k,k}}$ stands for the filtering error covariance ; T_s stands for the sampling interval; $\mathbf{H_k}$, $\mathbf{F_k}$ stands for the parameter matrix ; $(s_k - g(\tilde{x}_k))$ Stands for the new rates.

Traditional EKF measurement error covariance as A fixed value, for the actual power system, measurement data, abnormal signal mutation happens often, this case once the new rates by abnormal signal pollution, contaminated the new rates will be introduced in to the state estimation of $\hat{x}_k$. Make the EKF algorithm tracking accuracy is greatly reduced, serious when even will cause filtering divergence.

In order to improve the stability of the algorithm, the introduction of the robust factor [12], using the prediction residual error covariance of filtering algorithm **R** the real-time correction, and thus enhanced the robustness of algorithms for the system error. According to the experimental results, the design robust factors are as follows:

$$\begin{cases} \mathbf{R_k} = \mathbf{R_0} / \sigma(k) \\ \sigma(k) = e^{-|v_k|} \end{cases} \tag{19}$$

Among them, $\sigma(k)$ stands for weight index function; R_0 is the initial value of measurement error covariance.

In iteration, use $\mathbf{R_k}$ update **R**, can effectively inhibit the abnormal signal interference. For example, when the input signal s_k is abnormal, $\sigma(k)$ will be in accordance with the law of index weights, $\mathbf{R_k}$ will increase, $\mathbf{G_k}$ type (17) to reduce. In state estimation, the product of $\mathbf{G_k}$ and the new rate decreases, thus reducing the influence of abnormal data, enhance the convergence of the system.

Based on the system equation and experimental results, to set the initial value is as follows:

$$\begin{cases} \mathbf{x_0} = [x_0(1) \quad x_0(2) \quad x_0(3)] \\ \mathbf{P_{0,0}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ \mathbf{R_0} = E\left(v_0 v_0^{\ T}\right) \end{cases} \tag{20}$$

Among them, $\mathbf{x_0}$ stands for filter initial state vector; $\mathbf{P_{0,0}}$ stands for the filtering error covariance initial value.

Through the estimation formula [14] and [15] define the state vector of $\mathbf{x_k}$ dynamic tracking, extract of variables $x_3(k)$ in $\mathbf{x_k}$ can get the information signal of base wave frequency information.

3. The Numerical Simulation Experiments and Error Analysis

This paper validated the above algorithm in the Matlab environment. The grid characteristics shows that in addition to the fundamental wave, 3, 5, and 7 odd harmonic minor influence weight is bigger, so set the test signal is:

$$\begin{aligned} u = 220 \times \sin(2\pi f_1 kT_s) + 220 \times \frac{1}{6} \\ \sin(2\pi f_3 kT_s + \frac{\pi}{6}) + 220 \times \frac{1}{12} \sin(2\pi f_5 kT_s) \\ + 220 \times \frac{1}{18} \sin(2\pi f_7 kT_s) + v_k \end{aligned}$$

Among them, the white noise v_k meet the normal distribution, the sampling period T_s is 0.3125ms.

3.1. Fundamental Wave Extraction Experiments

This article take sampling frequency f_s = 3200 Hz, sampling points n = 256, adopting Db40 wavelet decomposed voltage on the output voltage u 4 layer of wavelet coefficient, according to the wavelet coefficients of low frequency refactoring fundamental component of 0-100 Hz; The simulation results are shown in Figure 1.

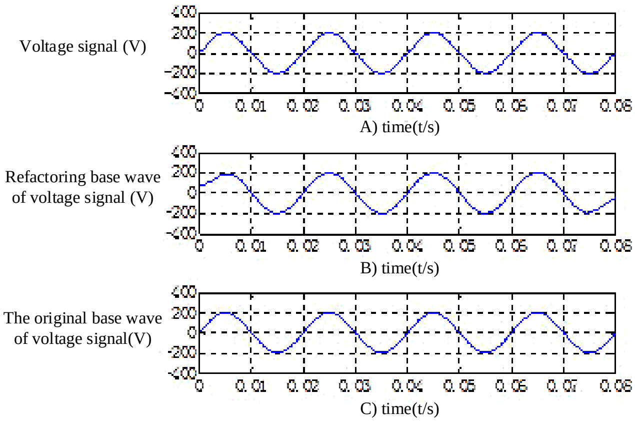

Figure 1. Power Grid Voltage Signal and Decomposition

From Figure 1, you can see that the proposed algorithm can effectively separate the base of the signal wave and the total harmonic. The simulation data shows that refactoring fundamental voltage signal and the original fundamental voltage signal amplitude is 199.5989 V and 198.0000 V respectively, relative error is 0.79% between amplitude, filtering effect is remarkable, meet the requirements of the extraction accuracy.

3.2. Fundamental Wave Frequency Tracking Experiments

Aiming at three typical grid signal, the application of Matlab simulation experiments. In this paper, the fundamental frequency tracking algorithm is compared with other frequency tracking algorithms, to verify the performance of the algorithm.

3.2.1. Frequency Constant: Set s_k test signal keep in ideal state in the whole simulation period frequency 50 Hz, accompanied by white noise v_k interference. In this model for the transient frequency tracking, get the frequency of the waveform is shown in Figure 2.

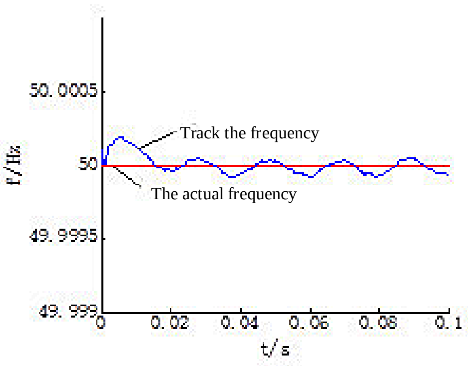

Figure 2. Instantaneous Frequency Tracking Results of Signal

By the simulation result shows that although the tracking frequency exists slight fluctuations, but the frequency tracking maximum absolute error is less than 0.0005 Hz, and the literature [13-14] the research results show that the tracking error is 0.0008 Hz, respectively 0.01 Hz, by contrast, the frequency of the algorithm in this paper the tracking error is small.

3.2.2. The Frequency, Amplitude, Phase Change at the Same Time: Starting from 0 time reduced to 70% of the original amplitude, phase jumped from 0° to 45°. At the same time a given frequency changes model:

$$f = \begin{cases} 50\,\text{Hz} & t = 0 \\ 54\,\text{Hz} & 0 < t \leq 0.04 \\ 52\,\text{Hz} & 0.04 < t \leq 0.1 \end{cases}$$

Based on the signal model of the dynamic change, tracking results as shown in Figure 3.

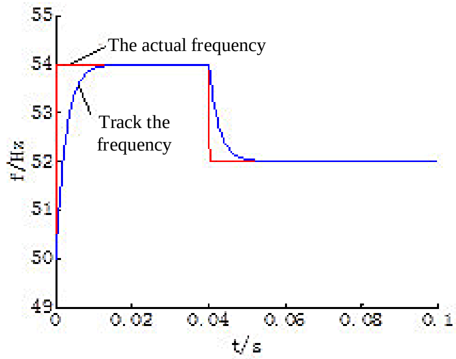

Figure 3. Estimation of Sudden Changes in Frequency Amplitude and Phase

The frequency tracking result shows that the mutated in about 28ms delay, in the entire process of tracking frequency tracking error is less than 0.005 Hz. In mutation and [13] about 50ms lag, frequency tracking error is less than 0. 005 Hz. [15] delay for 50ms, frequency tracking error is 0. 5 Hz. CSPKF in ref. [7] algorithm for frequency tracking delay of 45ms, the tracking error is 0. 018 Hz.

3.2.3. Frequency of Graded: Power grid in normal work, frequency variation is small, to test and verify the features of algorithm in frequency graded, hypothesis test signal s_k frequency within 0.1 s from 50 Hz linear growth to 52 Hz, frequency tracking waveform as shown in Figure 4.

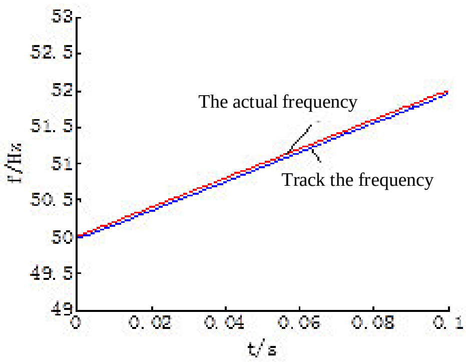

Figure 4. Estimation of Linear Variations in Frequency

The simulation results shows that the algorithm can track the frequency of slow change and the frequency tracking error is less than 0.005 Hz in the whole process of tracking, there are 20ms delay at the same time, and the frequency of literature [7] the tracking error is 0.018 Hz, tracking delay of 20ms.

Thus, this paper adopts improved EKF algorithm has excellent dynamic tracking performance, and in a rapidly track frequency while maintaining the low tracking error.

3.3. Factors that affect the Tracking Error

From the above simulation results can be seen, fundamental mean there is an error signal extraction and tracking algorithm, through the analysis of the principal causes of error are:

(1) Wavelet transform can extract the fundamental wave component is power grid, but reconstructing wave signal and a little error between original fundamental wave signal. Error is mainly from the adjacent frequency band of signal spectrum aliasing. Spectrum

aliasing will lead to all levels of the wavelet frequency limits is unclear, the error of fundamental wave extraction. , on the other hand, although most of the high frequency noise and random noise can be fixed by filter out, but still there are some same band noise, the noise is mixed with the band in the reconstruction of fundamental wave signal.

(2) With the improved EKF tracking fundamental wave frequency error is mainly affected by the residual noise in power grid power frequency signal. In the dynamic frequency tracking at the same time there is **R** delay effect, this is because when the system parameters, the algorithm need to reset the error covariance matrix, recalculate the gain matrix $\mathbf{G}_k$, but this process takes up **R** very short time, will not affect the effect of real-time algorithm for frequency tracking.

4. Conclusion

In this paper, wavelet transform was adopted to realize fundamental wave signal accurate extraction and application of improved EKF algorithm for power system of fundamental wave frequency accurate tracking and get the following conclusion:

(1) The application of wavelet transform filtering characteristics effectively harmonic with white noise attenuation, significantly better reduce the harmonic and noise interference with improved kalman filtering algorithm, improves the accuracy of the algorithm.

(2) Build a grid of the three elements of sine signal model, the improved EKF algorithm to the system state variables tracking more quickly. By introducing the robust factors, which greatly improves the convergence speed and stability of the algorithm.

(3) The result of simulation shows that the proposed improved EKF algorithm with adaptive ability, on the fast track frequency at the same time also has low tracking error.

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