Phasor Estimation Considering DC Component Using UKF

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Abstract: Electric power quality is ability of the system to deliver electric power service in high quality so that the end use equipment will operate within its design specifications. Introducing power generation using renewable energy can increase regulations and need for reserves due to its natural intermittency. The impact of variables in distributed generation may range from negligible to significant depending on the level of penetration. Therefore, monitoring power quality accurately can reduce challenges occur in modern grid integration. This means, more reliable and accurate methods are needed to estimate phasors in the presence of signal distortion. This paper introduces a new phasor estimation method based on unscented Kalman filter (UKF). Several computer simulated test results are presented. The initial parameters for the method were chosen carefully using an establish parameter estimation method, least square. And it is concluded that the proposed algorithm has low computational demand and can track amplitude, frequency and dc component of distorted signals which makes it a promising method in the next generation of phasor estimation technique.

Keywords: unscented transformation, Kalman filter, phasor estimation, dc component.

1 Introduction

Modern digital relaying techniques for protection of power system devices are mostly based on phasor estimators. During a system event (e.g. fault), the power system signals are distorted and contain some or all of the following components: fundamental frequency, harmonic distortion and decaying dc components [1]. Several techniques have been proposed including least-error squares [2], fast Fourier transform [3], Kalman filter [4] and Newton type algorithm [5]-[6].

One of the most famous methods is extended Kalman filter (EKF) [11]-[13]. In EKF, Kalman filter method can be used by linearizing nonlinear model so that Kalman filter method can be applied[11]. The drawbacks of EKF fall on its linearization procedures [11]: when the assumptions of local linearity are violated, linearization can produce an unstable filter. Moreover, the linearization procedure uses jacobian matrices which often leads to significant implementation difficulties and requiring longer execution times, which the algorithm unsuitable for real-time applications.

This paper proposed a new digital signal processing algorithm for the phasor estimation (fundamental amplitude, frequency) including the dc component using Unscented Kalman Filter (UKF). This method is based on Unscented Transformation (UT) theory [12]. UKF does not linearize the nonlinear model equations. This method uses a statistical distribution of the state and propagates it through nonlinear equations.

In this paper, several computer simulations are carried out to analyze performance of the proposed method for amplitude, frequency and dc components estimation.

2 Methodology

A. Unscented transformation

The *Unscented Transformation* (UT) is a method developed with an idea that it is easier to approximate Gaussian distribution than nonlinear function [11]. In UT, a set of sigma points with mean $\bar{x}$ and covariance $\mathbf{P}_{xx}$ are deterministically selected and propagated through a nonlinear transformation to obtain new mean $\bar{y}$ and covariance $\mathbf{P}_{yy}$ [11]-[12]. The sigma points can be obtained using the following formula.

$$\chi_0 = \bar{x} \tag{1}$$

$$\chi_i = \bar{x} + \left(\sqrt{(n+\lambda)\mathbf{P}_{xx}}\right)_i \tag{2}$$

$$\chi_{i+n} = \bar{x} - \left(\sqrt{(n+\lambda)\mathbf{P}_{xx}}\right)_i \tag{3}$$

where $\left(\sqrt{(n+\lambda)\mathbf{P}_{xx}}\right)_i$ is the *ith* column of matrix $\sqrt{(n+\lambda)\mathbf{P}_{xx}}$ and $\lambda = \alpha^2(n+\kappa) - n$. Parameter α is suggested to be between 10^{-4} and 1.0 [15] and value of parameter κ is $3-n$ or 0.

The sigma points are then propagated through the function below.

$$\gamma_i = f(\chi_i)\text{, where } i = 0,1,...,2n \tag{4}$$

The next step is calculating mean and covariance of the propagated points given by:

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$$\bar{y} = \sum_{i=0}^{2n} W_i^m \gamma_i \tag{5}$$

$$P_{yy} = \sum_{i=0}^{2n} W_i^c [(\gamma_i - \bar{y})(\gamma_i - \bar{y})^T] \tag{6}$$

The weights W_i^m and W_i^c are defined below:

$$W_0^m = \frac{\lambda}{n+\lambda} \tag{7}$$

$$W_0^c = \frac{\lambda}{(n+\lambda)} + (1-\alpha^2+\beta) \tag{8}$$

$$W_i^m = W_i^c = \frac{1}{2(n+\lambda)} \tag{9}$$

B. Unscented Kalman filter

UKF is an algorithm which can solve nonlinear systems in the following form:

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k) + \mathbf{q}_k \tag{10}$$

$$\mathbf{y}_{k+1} = h(\mathbf{x}_{k+1}) + \mathbf{r}_{k+1} \tag{11}$$

where **x** is a discrete state vector, **y** is discrete measurement vector, **q** and **r** are the system and measurement Gaussian noises with zero mean and covariance matrices **Q** and **R**, respectively.

There are three stages in the UKF method [14][15]:

1. Sigma points calculation

In the beginning, an initial state vector $\mathbf{x}_0$, initial covariance $\mathbf{P}_0$, process noise covariance **Q** and measurement-noise covariance **R**, are defined. These values can be defined in advance based on *a priori* knowledge of the system.

In this stage, sets of 2*n*+1 sigma points are created based on previous state with following formula:

$$\mathbf{X}_{k-1} = [\mathbf{x}_{k-1} \quad \cdots \quad \mathbf{x}_{k-1}] + \sqrt{(n+\lambda)}[\mathbf{0} \quad \sqrt{\mathbf{P}_{k-1}} \quad -\sqrt{\mathbf{P}_{k-1}}] \tag{12}$$

2. Kalman filter state prediction

Next, sigma points in the first stage are propagated through function below:

$$\boldsymbol{\chi}^*_{k|k-1} = f(\boldsymbol{\chi}_{k-1}) \tag{13}$$

The following step is computing the predicted state mean vector $\bar{\mathbf{x}}_{k|k-1}$, and predicted covariance matrix $\mathbf{P}_{k|k-1}$:

$$\bar{\mathbf{x}}_{k|k-1} = \sum_{i=0}^{2n} W_i^m \boldsymbol{\chi}^*_{i,k|k-1} \tag{14}$$

$$\mathbf{P}_{k|k-1} = \sum_{i=0}^{2n} W_i^c [(\boldsymbol{\chi}^*_{i,k|k-1} - \bar{\mathbf{x}}_{k|k-1})(\boldsymbol{\chi}^*_{i,k|k-1} - \bar{\mathbf{x}}_{k|k-1})^T] + \mathbf{Q} \tag{15}$$

3. Kalman Filter state correction

In the last stage, the sigma points related to the predicted state mean vector and covariance matrix are calculated with the following formula:

$$\boldsymbol{\chi}_{k|k-1} = [\bar{\mathbf{x}}_{k|k-1}, \bar{\mathbf{x}}_{k|k-1} \pm \sqrt{(n+\lambda)\mathbf{P}_{k|k-1}}] \tag{16}$$

Then, the sigma points are propagated through measurement-update function:

$$\boldsymbol{\gamma}_{k|k-1} = h(\boldsymbol{\chi}_{k|k-1}) \tag{17}$$

The following step is calculating propagated points:

$$\bar{\mathbf{y}}_{k|k-1} = \sum_{i=0}^{2n} W_i^m \boldsymbol{\gamma}_{i,k|k-1} \tag{18}$$

Then, we can obtain the measurement covariance matrix $\mathbf{P}_{yy}$ and cross-covariance of the state and measurement $\mathbf{P}_{xy}$:

$$\mathbf{P}_{yy} = \sum_{i=0}^{2n} W_i^c [(\boldsymbol{\gamma}_{i,k|k-1} - \bar{\mathbf{y}}_{k|k-1})(\boldsymbol{\gamma}_{i,k|k-1} - \bar{\mathbf{y}}_{k|k-1})^T] + \mathbf{R} \tag{19}$$

$$\mathbf{P}_{xy} = \sum_{i=0}^{2n} W_i^c [(\boldsymbol{\chi}_{i,k|k-1} - \bar{\mathbf{x}}_{k|k-1})(\boldsymbol{\gamma}_{i,k|k-1} - \bar{\mathbf{y}}_{k|k-1})^T] \tag{20}$$

Finally, we can compute Kalman gain, the state mean and covariance below:

$$\mathbf{K}_k = \mathbf{P}_{xy}\mathbf{P}_{yy}^{-1} \tag{21}$$

$$\bar{\mathbf{x}}_k = \bar{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\mathbf{y}_k - \bar{\mathbf{y}}_{k|k-1}) \tag{22}$$

$$\mathbf{P}_k = \mathbf{P}_{k|k-1} - \mathbf{K}_k\mathbf{P}_{yy}\mathbf{K}_k^T \tag{23}$$

3 Algorithm testing

The UKF algorithm is tested using computer-simulated data records. The signal used during the test is defined as:

$$u(t) = U_{DC} + \sum_{h=1}^{k} U_h \sin(h\omega t + \varphi_h) + \xi(t) \tag{23}$$

where $u(t)$ is an instantaneous value (voltage or current) at time t, U_{DC} is the magnitude of dc voltage, k is the highest order of the harmonic presented in the signal, U_h is the magnitude of hth harmonic, $\omega = 2\pi f$ is the fundamental angular velocity where f is fundamental frequency, φ_h the phase angle of hth harmonic and $\xi(t)$ is a zero mean random noise.

A. *Static Test*

The following signal model was used during static test:

$$u(t) = 0.5 + \cos(\omega t + 30) + \ldots$$

$$.. + 0.3\cos(3\omega t + 90) + 0.2\cos(5\omega t + 150) \tag{24}$$

where the fundamental frequency used during the test was 50 Hz.

At $t=0.3s$, U_{DC} disturbance was introduced to the signal. Its value is changed from 0.5 to 0.8 p.u. and the other values were maintained the same. The input signal is presented in Fig. 1.

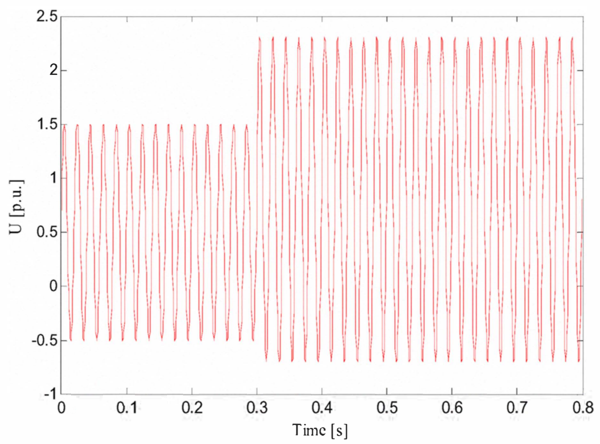

Figure 1 Input signal for static test.

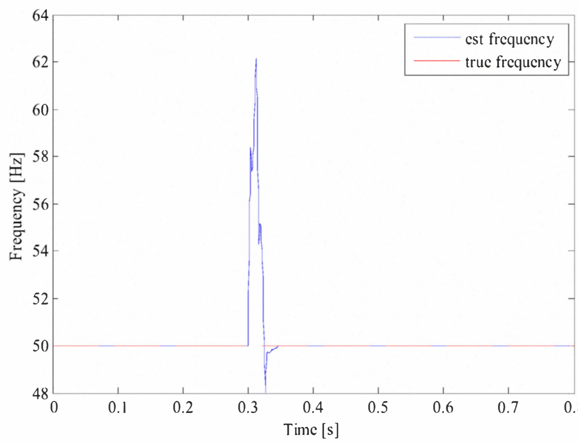

Figure 3 Estimated frequency.

Fig. 2 shows the amplitude of voltage signal and the dc voltage. It is shown that the UKF can track and separate voltage signal to dc component with very short convergence time. The estimated frequency is illustrated in the Fig. 3. It is revealed that this method also can track frequency precisely.

B. *Decaying dc test*

The following signal model was used during dynamic test:

$$u(t) = 0.5 + \cos(\omega t + 30) + ..$$

$$..+ 0.3\cos(3\omega t + 90) + 0.2\cos(5\omega t + 150) \qquad (25)$$

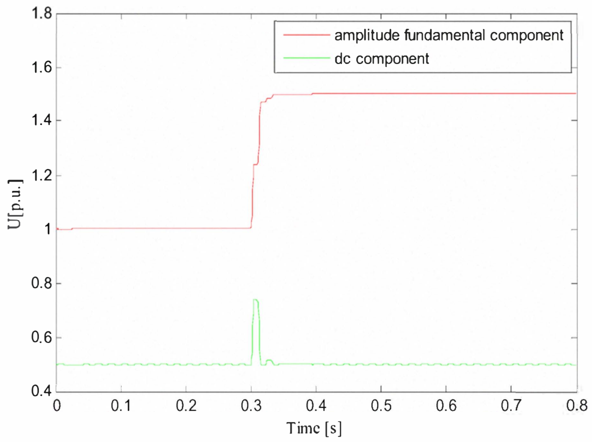

Figure 2 Estimated amplitude of fundamental component and dc component.

During the test, signal parameters are dynamically changed. Several disturbances were introduced to the signal at $t = 0.3s$. The frequency of the signal was changed from 50Hz to $f = 50 + 2\sin(4\pi t - 0.8\pi) + 2(t - 0.2)$Hz. Amplitude of the signal was changed from 1.0 p.u. to 1.5 p.u. and the dc component of the signal was changed from 0.5 p.u. to $U_{DC} = 0.8e^{-0.5t}$. Input signal is illustrated in Fig. 4.

The estimated amplitude and dc component are presented in Fig. 5. It is shown that UKF method can successfully tracked amplitude and dc component of the signal with highest error less than 10^{-2}% excluding the convergence period.

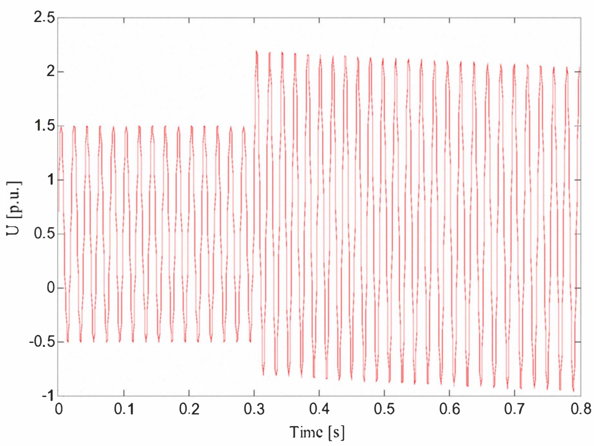

Figure 4 Input signal for decaying dc test.

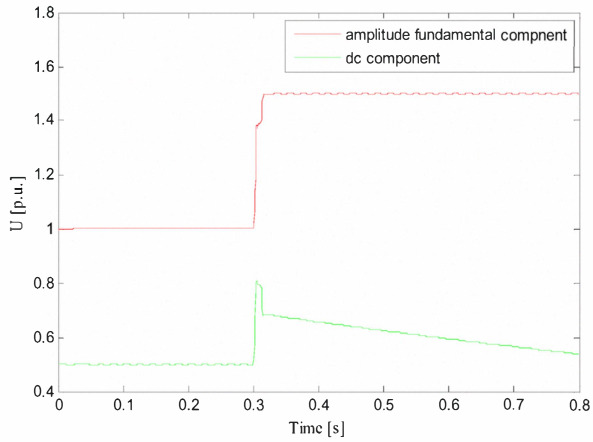

Figure 5 Estimated amplitude of fundamental component and dc component.

The estimated frequency using UKF is presented in Fig. 6. The algorithm convergence properties are determined by initial covariance. Faster convergence period can be obtained by reducing measurement noise covariance and vice versa. As recognized, Fig. 6 shows that UKF method can track frequency precisely.

4 Conclusion

In this paper, a new phasor estimation method based on Unscented Kalman Filter is presented. Various static and dynamic simulations have been carried out to analyze its performance for frequency, amplitude and dc component tracking. The results of simulations show that UKF obtained high estimation accuracy under normal and noisy conditions.

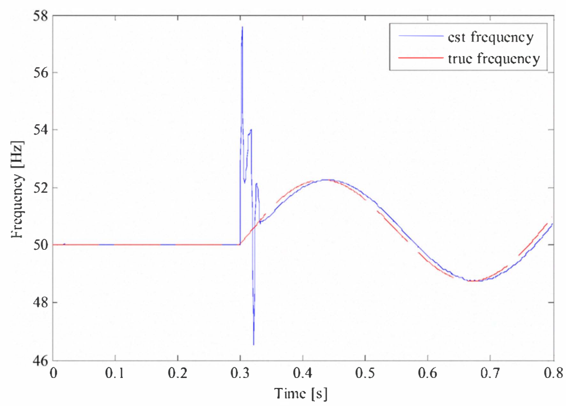

Figure 6 Estimated frequency.

Through the extensive algorithm testing, it is shown that this method can be effectively applied as a reliable tool for phasor estimator devices. This method is originally developed for a single phase systems. However, multiphase approach can also be applied. The authors are now extensively using this method for processing real data recorded from several wind farms in the UK and other European countries.

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