Adaptive Kalman filter for Voltage Sag detection in Power System

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Abstract—this paper proposed an adaptive kalman filter to detect the voltage sag problem in power system, the state covariance matrix is changed through the simulation to enhance the kalman filter in order to detect the amplitude changing of the fundamental component. In the proposed method, there is no need to estimate the noise covariance matrices, which is usually needs a lot of calculation and assumptions, it will depend only on updating the state covariance matrix, where there is no need for extra calculations. The proposed algorithm was tested in several severe circumstances such as high order harmonics and frequency changing.

Keywords—kalman filter; voltage sag; power system; adaptive filter.

I. INTRODUCTION

Kalman filter was widely used in power system harmonics detection, frequency and voltage measurement of a noisy measurement signal, since it is essential to have an accurate measurement of the fundamental component of voltage amplitude, where using the measured value immediately from the sensors this may cause a wrong decision of the control devices since it is usually has noise and harmonics.

the optimality of the kalman filter depends on the knowledge of the noise covariance matrices, based on that many adaptive algorithms were proposed to estimate the noise covariance matrices Q and R to improve the kalman filter performance, some researches calculate and update either Q or R or update both of them, Jiang et al. [1] proposed an adaptive algorithm for online updating of the covariance matrices, in order to improve the robustness of the UKF, they update the covariance matrices by minimizing the difference between the calculated and the measurement innovation covariance matrix. Loebis et al. [2]proposed intelligent algorithm for navigation system, they improved the performance of the extended kalman filter by updating the covariance noise matrices. Charkhgard and Farrokhi [3]proposed a method to estimate the charge state of lithium-ion batteries using neural network and extended kalman filter, the covariance matrices of the process noise are estimated adaptively, Maybeck's formula was used for updating Q matrix, they mentioned of a possibility of having negative values of the eigenvalues using this formula, so to avoid this problem they reset them, the covariance matrix R was kept constant and equal to the mean of square of the noise rms value. Based on their results the proposed algorithm showed a good accuracy and fast convergence to the actual values. Choi et al. [4] mention the importance of having a good prior knowledge of the process covariance matrices in the kalman filter convergence, R matrix is updated every iteration based on the innovation weights. Routray et al [5]proposed Kalman filter reset the covariance matrices based on the error and the convergence, where, they mentioned that the covariance matrices should be reset when some of the parameters are changed.

In many applications, the noise covariance matrices can’t be determined or need a lot of calculations, Sangsuk-lam and Bullock [6] analyzed the divergence and convergence of the kalman filter with incorrect noise covariance matrices, they concluded, even though the noise covariance matrices in some cases are incorrect, the Kalman filter was asymptotically stable, and if the system is modeled accurately then the incorrect of the error covariance matrices will never cause the divergence of the Kalman filter.

The aim of the proposed algorithm is to improve the performance of kalman filter by updating the state covariance matrix without extra calculations, to let the kalman filter to react again with the measured data, based on the simulation results, the algorithm shows good and fast response in many worse circumstances such as frequency changing, where in such cases the system becomes nonlinear and usually, either extended or unscented kalman filter are used.

II. KALMAN FILTER

Kalman filter is optimal linear recursive filter, where it is used to extract the signal from noisy measurement environment, the kalman filter first must be modeled accurately to represent the real system in order to be able to predict the signal in the predict stage, then the predicted value interact with the measured value to have better signal estimation through the updating stage. To ensure the optimality of the kalman filter, the noise should be white additive Gaussian noise, actually there are two sources of noise; the process noise $W(t)$ and the observation noise $V(t)$. The kalman filter equations as follows:

$$X_{k|k-1} = A_kX_{k-1|k-1} + B_kU_{k-1} + W_k$$  \hspace{1cm} (1)

$$P_{k|k-1} = A_kP_{k-1|k-1}A_k^T + Q_k$$ \hspace{1cm} (2)

$$y_k = z_k - C_kX_{k|k-1}$$ \hspace{1cm} (3)
\[ S_k = C_k X_{k-1} C_k^T + R_k \]  
(4) 

\[ K_k = P_{k-1} C_k^T S_k^{-1} \]  
(5) 

\[ X_{k+1} = X_k + K_k y_k \]  
(6) 

\[ P_k = (I - K_k C_k) P_{k-1} \]  
(7) 

Where, \( X_k \) : is the state vector, 
\( A_k \) : is the transition matrix 
\( B_k \) : is the input control vector. 
\( W_k \) : is the process noise, and it is assumed to be white Gaussian noise with zero mean and covariance matrix \( Q_k \), i.e \( N(0,Q_k) \). 
\( Z_k \) : is observation of the state \( X_k \). 
\( C_k \) : is the observation matrix. 
\( V_k \) : is the observation noise, and it is also assumed to be Gaussian white noise with zero mean and \( R_k \) covariance matrix, i.e \( N(0,R_k) \). 
\( P_k \) : is state covariance matrix. 
\( K_k \) : is optimal kalman gain. 
\( y_k \) : is innovation residual. 
\( S_k \) : is innovation covariance. 

III. PROPOSED ALGORITHM

The kalman filter is modeled in this paper to include only the fundamental component for simplicity, the kalman filter model will be as follows:

\[ A_k = \begin{bmatrix} \cos(wT) & -\sin(wT) \\ \sin(wT) & \cos(wT) \end{bmatrix} \]  
(8) 

\[ B_k = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \quad C_k = \begin{bmatrix} 1 & 0 \end{bmatrix} \]  
(9) 

Where; \( T \) is the sampling time and \( w \) is the fundamental angular frequency.

After calculating the state vector, the amplitude of the fundamental component can be calculated as follows:

\[ \text{Amp}_k = \sqrt{x_{1,k}^2 + x_{2,k}^2} \]

Based on the previous works[7] , it is necessary to update the noise covariance matrices for dynamic change in the system variables to improve the kalman filter performance, the performance of the kalman filter could also be improved by updating the state covariance matrix, the state covariance matrix \( P \) decreases and approach zero as soon as the kalman filter reaches the steady state value in the normal operation, when dynamic change occurs in the system variables such as the amplitude, the response of the kalman filter will be very slow and this is due to the \( P \) matrix. if the \( P \) is increased as soon the system variable is changed, this will yield to better performance. The state covariance matrix could be updated into two ways; the first one is to update periodically after specific time and the other one is to update the covariance state matrix based on certain convergence criteria. An example of converge criteria that could be used is the maximum value of the state covariance matrix is less than \( \epsilon_1 \), and the difference between two successive iteration is less than certain tolerance \( \epsilon_2 \).

IV. SIMULATION RESULTS

For the electrical signal \( y_i(t) \)

\[ y_i(t) = 1.41\cos(100\pi t + \frac{\pi}{6}) + 0.3\cos(300\pi t + \frac{\pi}{5}) + 0.1\cos(500\pi t + \frac{\pi}{8}) \]  
(1)

\( y_i(t) \) has a fundamental component, first and third order harmonic components, signal plot with and without the harmonics is shown in Fig.1. The noise is white additive Gaussian noise with \( R_n=0.2 \). The amplitude of the fundamental signal using kalman filter is shown in Fig.2. as it is shown in Fig. 2 the kalman filter is capable to estimate the amplitude of the fundamental component for different values of \( R \), while \( Q \) is kept constant, the value of \( R \) actually affect the speed of kalman filter. In [7] we discussed the effect of \( Q \) and \( R \) in kalman filter performance, where it was concluded that it is not necessary to estimate them accurately to have good kalman model. 

For a dynamic change in the amplitude of the fundamental signal, the kalman filter response shows a weak response in Fig.3. The kalman filter parameters are kept constant when drop in voltage occurs, even though these parameters shows a good response at the beginning of the kalman filter operation, many of previous researches were suggested to adapt the covariance matrices in the transient period to get better performance and they showed a good result based on this technique. The question arises here, why the kalman filter performance is changed even though that the noise covariance matrices are not changed and they showed a good response before the dynamic change occurs, after investigation carefully the kalman matrices, it is noticed that the state covariance matrix is very small when the sudden change occurs since the kalman filter converges, and this prevents the kalman filter to react well with the amplitude changing. Fig.4 shows the amplitude of the fundamental signal estimated using kalman filter when the state covariance matrix \( P \) is increased as soon as the sudden change occurs. Based on the results shown in Fig.4, it is necessary to update the state covariance matrix to ensure a good performance of kalman filter when a dynamic change occurs. So the proposed method will be depend on updating the \( P \) matrix for dynamic change, there are two important factors; the first one is the required increment to the state matrix, and the second one is the instant time to update the state covariance matrix.

Fig. 5 shows the amplitude of the fundamental signal estimated by kalman filter for different values of updating state
covariance matrices, when the value of state covariance matrix is small the response of the kalman filter is slow, as the value of $P$ is increased the response becomes faster but it caused overshoot at the updating instant, if the estimated value of the kalman filter at the updating instant is ignored, then any large value of state covariance matrix will be sufficient for kalman filter improvement.

The second important factor is to determine the transient time $t_r$ to update the $P$ matrix, if the exact time of the dynamic change is known, it will be the suitable time for updating the state covariance matrix, but it will require extra calculation and extra techniques to determine $t_r$. To keep the proposed method simple, it will be unnecessary to determine $t_r$, the state covariance matrix could be updated in two ways; one of them is to be updated periodically, Fig. 6 shows the amplitude of the fundamental signal estimated by kalman filter when the state covariance matrix is updated periodically, in order to reduce the transient in amplitude at $t_r$, it could be ignored as it is shown in Fig.7 or calculate the mean value of the amplitude as it is shown in Fig.8.

Fig.9 and Fig. 10 show the estimated amplitude for a dynamic change in the amplitude for different value of $t_r$, as the value of $t_r$ is increased this will cause a delay in the proposed algorithm, Fig.11 shows the estimated amplitude by kalman filter after the estimated amplitude at $t_r$ is removed and Fig. 12 shows the mean value of the estimated amplitude by kalman filter.

![Fig. 1. $z(t)$ plot with and without noise.](image)

![Fig. 2. Amplitude of the fundamental component estimated using kalman filter for different values of R.](image)

![Fig. 3. Amplitude of the fundamental signal estimated by kalman filter for dynamic change in the amplitude.](image)

![Fig. 4. Amplitude of the fundamental signal estimated by kalman filter when the $P$ is increased.](image)

![Fig. 5. Amplitude of the fundamental component estimated by kalman filter for different updating state covariance matrices.](image)
Fig. 6. The estimated amplitude by kalman filter for different values of \( t_r \) time.

Fig. 7. Estimated amplitude by kalman filter after ignoring the estimated values at the updating time for different \( t_r \) time.

Fig. 8. The average of the estimated amplitude by kalman filter for different updating \( t_r \) time.

Fig. 9. The estimated amplitude by kalman filter for different values of \( t_r \) time.

Fig. 10. Estimated amplitude by kalman filter after ignoring the estimated values at the updating time for different \( t_r \) time.
The fundamental frequency usually changed due to load change, and in normal condition it could be vary up to 49.5Hz, the fundamental frequency is assumed to be constant in the kalman filter matrix, which may cause wrong prediction values. To investigate the capability of kalman filter to estimate the amplitude under such circumstance, the fundamental frequency is changed at \( t = 0.4 \)sec, the estimated amplitude using kalman filter and the proposed algorithm are shown in Fig. 13, the proposed algorithm shows better response, usually, when the frequency is changed, the system become nonlinear and extended kalman filter could be used, while in the proposed algorithm, even though kalman filter is used, it still has the capability to estimate the amplitude under frequency changing. Fig. 14 shows the estimated amplitude using kalman filter and the proposed algorithm for dynamic change in the amplitude and the fundamental frequency, the proposed algorithm shows a very good performance for amplitude detecting.

The last experiment for investigating the proposed algorithm performance is to increased the harmonics order, then change the fundamental frequency, Fig. 15 shows a square signal, that contains the fundamental signal in additive with all odd harmonics with and without the measurement noise, while Fig. 16 shows the estimated amplitude of the fundamental signal of the square wave by kalman filter and the proposed algorithm for two frequencies 50Hz and 49.5 Hz, kalman filter estimated the amplitude of the fundamental component regardless of the order of harmonics when the frequency is the constant and equal to the frequency set in its matrices, while it couldn't estimate it as soon as the frequency is changed. The proposed algorithm has a good response in spite of the harmonics order and the frequency variation.
Fig. 14. Estimated amplitude by kalman filter and the proposed algorithm when the amplitude and frequency are changed.

Fig. 15. Square wave signal with and without noise.

Fig. 16. Estimated amplitude using kalman filter and the proposed algorithm for two fundamental frequencies 50Hz and 49.5 Hz.

V. CONCLUSIONS AND FUTURE WORKS

A new adaptive kalman filter was proposed in this paper, the proposed algorithm depends on updating the state covariance matrix to let the kalman filter to react again with the measurement data, the proposed method was examined under several circumstances to prove its capability for voltage amplitude detecting, and it is improved the kalman filter in cases where an extended kalman filter is needed.

In the proposed method is designed to be simple, so the kalman filter matrices are including only the fundamental component, and the state covariance matrix is updated periodically, in future, different criteria will be examined for updating the state matrix, and will include the harmonic components in the kalman filter matrices to investigate if they could increase the capability of proposed algorithm in harmonics detection, even though the proposed method in this paper shows a good performance.

REFERENCES


