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Hybrid Particle Swarm Optimization and Unscented Filtering Technique for Estimation of Non-stationary Signal Parameters

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ABSTRACT

This paper proposes an adaptive unscented Kalman filter for parameter estimation of non-stationary signals, like amplitude and frequency, in the presence of significant noise and harmonics. This paper proposes an iterative update equation for model and measurement error covariances Q and R to improve tracking of the filter in the presence of high noise. The initial choice of the model and measurement error covariances Q and R, along with the UKF parameters, are crucial in noise rejection. This paper utilizes a modified particle swarm optimization (MPSO) algorithm for the initial choice of the error covariances and UKF parameters. Various simulation results for time varying signals reveal significant improvement in noise rejection and accuracy in obtaining the frequency and amplitude of the signal.

Keywords:
Extended Kalman filter, Modified particle swarm optimization, Unscented Kalman filter.

1. INTRODUCTION

Various estimation techniques have been extensively studied, taking into account the signal model. Classical methods of frequency estimation include both parametric and nonparametric methods. Many of these methods had their origin in Prony's work and include weighted least squares methods. Fast algorithms based on singular value decomposition (SVD) and reduced rank approximations have been developed by Kumarson and Tufts [1]. Pisarenko's method [2], and the MUSIC [3] algorithm exploit the orthogonal property of the signal and noise subspaces but result in large computational overhead. Other methods like ESPIRIT [4], higher order statistics, and wavelet transform etc. are used to estimate signal frequency varying with time accurately with high signal to noise ratio (SNR), but with low SNR, the performance degrades considerably. This is also true for most of the parametric methods.

Amongst the several other methods for frequency, amplitude and phase estimation of non-stationary signals, ANN-based methods offer an efficient and robust estimation while they suffer from inaccuracies in the presence of low SNR. Newton-type methods, adaptive notch filters, Adalines, and leas squares techniques are some of the signal processing methods that have been suggested for signal with time varying frequency. However, the classical nonlinear filter is extended Kalman filter (EKF) [5]; its filter equation is the same as linear Kalman filter equation by linearizing the nonlinear equation based on 1-order Taylor expansion at the predicted points. So the filter maybe diverge when observability of the system is low, instable due to linearization, erroneous parameters or costly for calculation of derivatives and when the biased nature of estimates and sometimes Jacobian matrix does not exist; in this case, the EKF cannot be used to address the deficiencies of EKF, Julier [6] proposed a new unscented transform, which can be efficient and unbiased for the mean and variance, based on this transform - unscented Kalman filter. It is shown that this filter has 2-order approximate convergence for Taylor expansion.

The unscented transformation used in UKF uses nonlinear transfer function, instead of linearization, to compute the state and error covariance matrices. This results in a more accurate estimation of the parameters of a non-stationary signal. However, its accuracy decreases significantly if SNR is low and the noise co variances and some of the parameters used in unscented transformation are not chosen correctly. Thus for best signal tracking performance, this paper proposes a modified particle swarm optimization technique (MPSO), for the optimal choice of UKF parameters and error covariances Q and R.

The particle swarm optimization technique is a population based, self-adaptive optimization technique developed by Eberhert and Kennedy which stimulates the social behavior of birds or fish. In this paper, particle swarm optimization (PSO) technique [7-9] is used to optimize noise covariance matrices to achieve the best UKF performance. The PSO technique can generate very high quality, shorter calculation time and stable convergence characteristics when compared to other population based methods like genetic algorithm and evolutionary programming. Generally, PSO has global searching ability at the beginning of the run and a local search near the end of the run. Therefore, while solving problems with more local optima, there are more possibilities for the PSO to explore local optima at the end of the run. Although PSO is easy to implement and has few parameters to adjust, it suffers from premature convergence, velocity explosion, and immediate good solutions. We use the MPSO technique. The paper uses adaptive unscented Kalman filter to track signal parameters under high noise condition based on an optimal choice of Q and R. The simulation results of tracking sinusoids corrupted in noise with low SNR and harmonics reveal significant accuracy and noise rejection property.

2. SIGNAL MODEL

Consider a signal consisting of I sinusoids, the discrete time equation is given by

$$z_k = \sum_{i=1}^{I} A_{ik} \cos(k\omega_{ik} T_s + \phi_{ik}) + \varsigma_k,\ k = 1, 2, ...L \tag{1}$$

Where z_k is the measured signal, A_{ik}, ω_{ik} and φ_{ik} are amplitude, frequency and phase of the i^{th} sinusoid respectively, where T_s is the sampling period. The measurement noise is represented as ζ_k, which is a zero mean Gaussian white noise. For easy analysis only the fundamental component of the signal is considered, as described below

$$z_k = A\cos(k\omega T_s + \varphi) + \zeta_k, \tag{2}$$

where $\zeta_k \sim N(0,R_k)$, and the measurement error covariance is given by $R_k = E[\varsigma_k \varsigma_k^T]$ (3)

The discrete time signal can be modeled in state space form as

$$x_{k+1} = F_k x_k + w_k \tag{4}$$

where $wk \sim N(0,Q_k)$,and the model error covariance is given by $Q_k = E[w_k w_k^T] = qI$ (5)

The state variables are expressed as

$$\begin{bmatrix} x_{1k} \\ x_{2k} \\ x_{3k} \end{bmatrix} = \begin{bmatrix} A\sin(x_{3k}.kT_s + \phi) \\ A\cos(x_{3k}.kT_s + \phi) \\ \omega \end{bmatrix} \tag{6}$$

And the state-transition matrix in this case becomes

$$F_k = \begin{bmatrix} \cos(x_{3k}T_s) & \sin(x_{3k}T_s) & 0 \\ -\sin(x_{3k}T_s) & \cos(x_{3k}T_s) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{7}$$

The measurement model for the signal represented by equation (2) is obtained as

$$z_k = h(x_k) + \zeta_k \tag{8}$$

here $h(x_k) = [1\ 00]\ x_k$, and the measurement transition matrix H is given by

$$H = [1\ 0\ 0], \text{ and } x_k = [x_{1k}\ x_{2k}\ x_{3k}\ ]^T \tag{9}$$

3. ADAPTIVE UNSCENTED KALMAN FILTER

EKF is the most widely used filter but suffers from instability due to first order linearization of nonlinear models, costly calculation of Jacobean matrices and the biased nature of its estimates. The unscented Kalman filter known as UKF is considered in this paper is an improvement to EKF. The main advantage of UKF is that it does not use linearization to calculate the state predictions and covariance matrices and provides accurate Kalman gain estimates. It utilizes a deterministic sampling approach in choosing $2 \times N + 1$, sigma points (N is the state dimension) based on a square-root decomposition of the prior covariance. These sigma points are propagated through the nonlinearity, without approximation, and a weighted mean and covariance is found. The UKF thus involves the recursive application of the sampling approach to the state space equations of the signal. The UKF algorithm is summarized in the following steps: For the N –dimensional random variable x, initialize with mean $\bar{x}_0$ and covariance P_0 as

$$\bar{x}_0 = E[x_0], P_0 = E[(x_0 - \bar{x}_0)(x_0 - \bar{x}_0)^T], \tag{10}$$

Given a state vector at time step k−1, sigma points are computed and stored in the columns of $N \times (2N + 1)$ sigma point matrix χ_{k-1}. For the present problem of estimating fundamental component, $N = 3$ so χ_{k-1} is a 3×7 matrix. The sigma points are computed as,

$$\chi_{i,k-1} = [\bar{x}_{k-1}, \bar{x}_{k-1} + \left(\sqrt{(N+\lambda)P_{k-1}}\right)_i, \\ \bar{x}_{k-1} - \left(\sqrt{(N+\lambda)P_{k-1}}\right)_i],\ i = 0, 1, 2, ..., N \tag{11}$$

where $\left(\sqrt{(N+\lambda)P_{k-1}}\right)_i$ is the i^{th} column of the matrix square root of $(N + \lambda)P_{k-1}$).

The parameter λ is used to control the covariance matrix, and is given by $\lambda = \alpha^2(N + \kappa) - N$ (12)

Both λ and κ are scaling parameters. The constant α determines the spread of the sigma points and its value is between $0.0001 \le \alpha \le 1$. After computing the sigma points the time update of state estimates are given by

$$\chi_{i,k/k-1} = \mathrm{F}_{k-1}(\chi_{i,k-1}) \tag{13}$$

$$\bar{\mathrm{x}}_{k/k-1} = \sum_{i=0}^{2N} W_i^m \chi_{i,k|k-1} \tag{14}$$

Where the weights W_i^m are defined by

$$W_0^m = \frac{\lambda}{N+\lambda}, W_i^m = \frac{1}{2(N+\lambda)}, i = 1,...,2N \tag{15}$$

The a priori error covariance is given by

$$\mathrm{P}_{k/k-1} = \sum_{i=0}^{2L} W_i^c \left[\chi_{i,k|k-1} - \bar{\mathrm{x}}_{k/k-1}\right]\left[\chi_{i,k|k-1} - \bar{\mathrm{x}}_{k/k-1}\right]^T + \mathrm{Q}_k \tag{16}$$

Where the weights W_i^c are defined by

$$W_0^c = \frac{\lambda}{(N+\lambda)} + (N - \alpha^2 + \beta), W_i^c = \frac{1}{2(N+\lambda)}, i = 1,..,2N \tag{17}$$

The estimated output is

$$\mathrm{z}_{i,k|k-1} = \mathrm{H}(\chi_{i,k|k-1}) \tag{18}$$

$$\bar{z}_{k/k-1} = \sum_{i=0}^{2L} W_i^m \mathrm{z}_{i,k|k-1} \tag{19}$$

The a posterior state estimate is computed as

$$\bar{\mathrm{x}}_k = \bar{\mathrm{x}}_{k/k-1} + \mathrm{K}_k(z_k - \bar{z}_{k/k-1}) \tag{20}$$

Where K_k is the Kalman gain given by

$$\mathrm{K}_k = \mathrm{P}_{\bar{\mathrm{x}}_k \bar{z}_k} \mathrm{P}_{\bar{z}_k \bar{z}_k}^{-1} \tag{21}$$

$$\mathrm{P}_{\bar{\mathrm{x}}_k \bar{z}_k} = \sum_{i=0}^{2N} W_i^c \left[\chi_{i,k|k-1} - \bar{\mathrm{x}}_{k/k-1}\right]\left[\mathrm{z}_{i,k|k-1} - \bar{z}_{k/k-1}\right]^T \tag{22}$$

$$\mathrm{P}_{\bar{z}_k \bar{z}_k} = \sum_{i=0}^{2N} W_i^c \left[\mathrm{z}_{i,k|k-1} - \bar{z}_{k/k-1}\right]\left[\mathrm{z}_{i,k|k-1} - \bar{z}_{k/k-1}\right]^T + R_k \tag{23}$$

R_k is measurement error covariance matrix. The a posterior estimate of the error covariance matrix is given by

$$\mathrm{P}_k = [\mathrm{P}_{k/k-1}]^{-1} - \mathrm{K}_k \mathrm{P}_{\bar{z}_k \bar{z}_k} \mathrm{K}_k^T \tag{24}$$

Proper selection of UKF parameters like Q_k, R_k, α,β,κ are crucial. In most of the case it is to be chosen by trial and error. The measurement and model error covariances R_k and Q_k are chosen to be constant and determined a priori. This paper presents a self-tuning procedure for covariance setting is presented to improve the performance of the filter. The innovation covariance at instant k is given as

$$\rho_k = (z_k - \bar{z}_{k/k-1}), \tag{25}$$

The innovation covariance is used to update the measurement and the model error covariances as

$$R_k = \eta R_{k-1} + e^{-(\rho_k \rho_{k-1})} \tag{26}$$

and $q_k = \eta q_{k-1} + e^{-(\rho_k \rho_{k-1})}$, where $\mathrm{Q}_k = q_k \mathrm{I}$ (27)

where η is forgetting factor and $0 \le \eta \le 1$

Model and measurement error covariances are updated in every iteration in this way. This new value of covariances Q_k and R_k are used to improve the estimate of the state through the iterative procedure. The AUKF algorithm provides better performance over UKF, with a proper choice of the parameters α , λ , β and the initial values of the covariances Q_k and R_k. Thus to improve the performance of UKF, a stochastic optimization technique like the PSO and its variants are used to obtain the parameters α, λ , β , Q_k, and R_k instead of trial and error approach. The fitness function chosen is to minimize the mean square of the innovation v_k, and is given for the i^{th} particle by

$$J_i = \frac{1}{1 + (1/M)\sum_{k=1}^{M}(z_k - \bar{z}_{k/k-1})(z_k - \bar{z}_{k/k-1})} \tag{28}$$

where M is the number of samples chosen for determining the mean.

4. PARTICLE SWARM OPTIMIZATION OF AUKF ALGORITHM

The particle swarm optimization technique, as discussed in the introduction, is an optimized solution to obtain a better performance with low SNR. The basic PSO algorithm is started by scattering a number of particles called swarms in the function search space. Each particle moves in the search space looking for the global minimum or maximum. During its flight each particle adjusts its trajectory by dynamically altering its velocity according to its own flying experience and the flying experience of other particles in the search space. For particles moving in a multidimensional search space, let S_i and V_i denote the position and velocity of i^{th} particle in a d-dimensional search space and can be represented as

$\mathrm{S}_i = (s_{i1}, s_{i2}, s_{i3}......s_{id})$, and $\mathrm{V}_i = (v_{i1}, v_{i2}, v_{i3}.v_{id})$. The velocity and position of each particle is updated as

$$v_{id}(k+1) = K.(wv_{id}(k) + c_1.rand().(pbest_{id} - s_{id}(k)) + c_2.rand().(gbest_{id} - s_{id}(k))) \tag{29}$$

$$s_{id}(k+1) = s_{id}(k) + v_{id}(k+1) \tag{30}$$

where K is the constriction factor and given by

$$K = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \text{ where } \varphi = c_1 + c_2; \varphi > 4 \quad (31)$$

and w is the inertia weight factor, c_1 and c_2 are acceleration constant, rand ( ) is a random number in the range [0,1], $pbest_{id}$ is the local best of each particle, and $gbest_{id}$ is the global best position.

A suitable selection of inertial weight w and acceleration coefficients c_1 and c_2 is crucial in providing a balance between the global and local search in the flying space. The particle velocity at any instant limited to a chosen $V_{max,}$ which if too high will result in allowing the particles to fly past good solutions. On the other hand, if V_{max} is too small, particles end up in local solutions only. Although the conventional PSO can produce optimal solutions of AUKF parameters, it still suffers from premature convergence and gets stuck in local minima. Besides, it suffers from an ineffective exploration strategy around local minima and therefore a change in particle motion methodology may speed up the search by improving exploration. This paper uses inertia weight updated iteratively by the fitness function of the algorithm.

4.1 Modified Particle Swarm Optimization Algorithm

The inertia weight w is updated by finding the variance of the population fitness as

$$\sigma^2 = \sum_{i=1}^{I}\left(\frac{J_i - J_{avg}}{J}\right)^2 \quad (32)$$

where J_{avg} is the average fitness of the population of particles in a given generation. J_i is the fitness of the ith particle in the population. I is the total number of particles.

$$J = \{\max(|J_i\text{-}J_{avg}|)\}, \text{ i} = 1,2,3.....\text{I} \quad (33)$$

In the equation given above J is normalizing factor which is used to limit σ. If σ is large, the population will be in a random searching mode, while for small σ or σ = 0, the solution tends towards a premature convergence and will give the local best position of the particles. To circumvent this phenomenon and obtain the best solution, the inertia weight factor is updated

$$w(k) = \mu w(k-1) + (1-\mu)\sigma^2 \quad (34)$$

The forgetting factor μ is chosen as 0.9 for faster convergence. Another alternative form will be

$$w(k) = \mu_1 w(k-1) + rand\,(\,)/2 \quad (35)$$

where rand ( ) is a random number in the range [0,1]. The influence of the past velocity of a particle on the current velocity is chosen, to be random, and the inertia weight is adapted randomly depending on the variance of the fitness value of a population. This result is an optimal coordination of local and global searching abilities of the particle. The complete flow chart for modified particle swarm optimization is given in Figure 1.

5. NUMERICAL RESULTS AND DISCUSSION

The performance of the proposed method is evaluated through test signals embedded in high noise condition. The test signal considered for the estimation of signal parameters is given as

$$z_k = A\cos(k\omega\,(k)T_s + \phi) + \zeta_k, \quad (36)$$

where A and φ are the amplitude and phase of the signal, ω is angular frequency, k = sampling instant. UKF parameters are chosen as: Q_k, R_k, α, β and κ need to be initialized, Here β and κ are chosen as $\beta = 2$, and $k = 0$, and α, Q_k, R_k are initially chosen as $\alpha = 0.5$, $Q_k = qI_{3\times3}$, and $R_k = 0.05$, where I is a 3rd order unit matrix. Since the signal is modeled for three parameters, the value of N is set equal to 3, and thus the number of sigma points for this estimation is $2N + 1$, i.e. 7. For optimizing the UKF performance, the PSO parameters are initialized with a population of 100

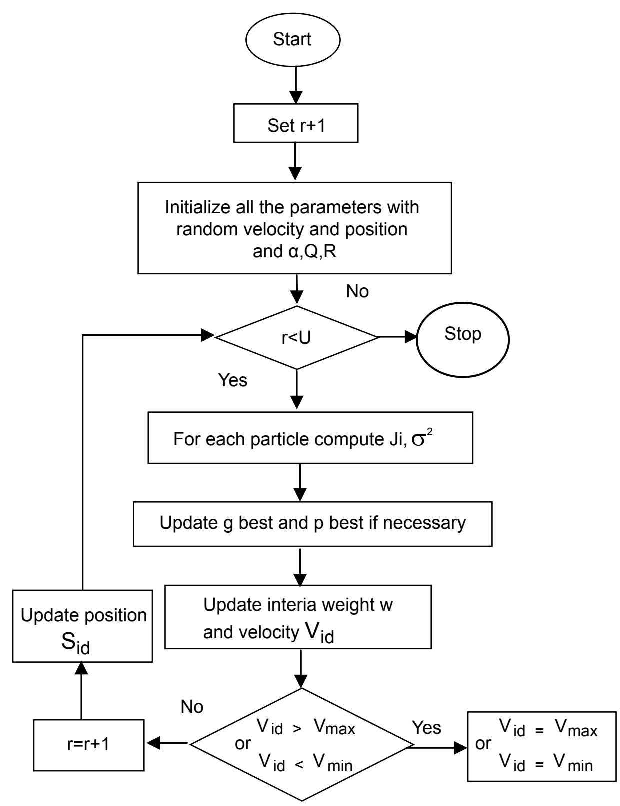

Figure 1: Flow chart for modified particle swarm optimization implementation.

particles. The parameters of UKF to be optimized are α q and R_k. For the conventional PSO algorithm, the initial values of parameters c_1, c_2, w_{max}, w_{min} are chosen as $c_1 = 2.1$, $c_2 = 2.1$, $w_{\max} = 0.9$, $w_{\min} = 0.4$, lower and upper band of α, q and R_k are chosen as $\alpha_{lower} = 0.001$, $q_{lower} = 0.0001$, $R_{lower} = 0.001$, $\alpha_{upper} = 0.7$, $q_{upper} = 0.8$, $R_{upper} = 0.5$. The chosen fitness function is given in equation (28). The following case studies on frequency, amplitude and phase of the non-stationary signals in noise are presented to highlight the adaptive EKF, adaptive UKF and MPSO performance.

5.1 Case 1: Linear Frequency Variation

The frequency of the test signal in (36) is varied as- for first 300 samples $f(k) = f_0 = 50$Hz, it increases linearly for next 400 samples at a rate of $\Delta f(k) = 0.012(k - 300)$ and then remains constant. The sampling frequency is chosen as 1 kHz, time varying frequency, amplitude, and phase of the signal are obtained for different SNR varying from 60 dB to 10 dB. Figures 2 and 3 show estimated frequencies and comparison of parameter estimation errors for noise levels of 30 dB and 10 dB respectively. From Figure 2 it is observed that the adaptive EKF shows better tracking of all the parameters compared to standard EKF with constant Q and R at 30 dB SNR. As the SNR is decreased to 10 dB, the performance of the EKF tracker is found to deteriorate as shown in Figure 3. The same signal is analyzed using UKF, AUKF and AUKF with MPSO. Figure 4 shows the improvement of AUKF which uses tuning of measurement and model error covariances. Then the parameters of AUKF are chosen through modified PSO (MPSO) and further improvement is found in presence of 30dB SNR. As the SNR is

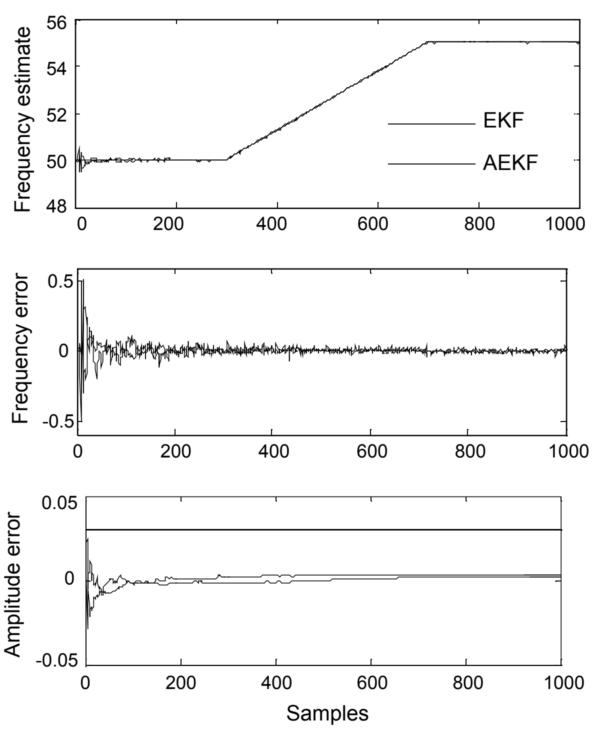

Figure 2: Comparison of extended Kalman filter and AEKF for linear frequency variation with 30dB noise.

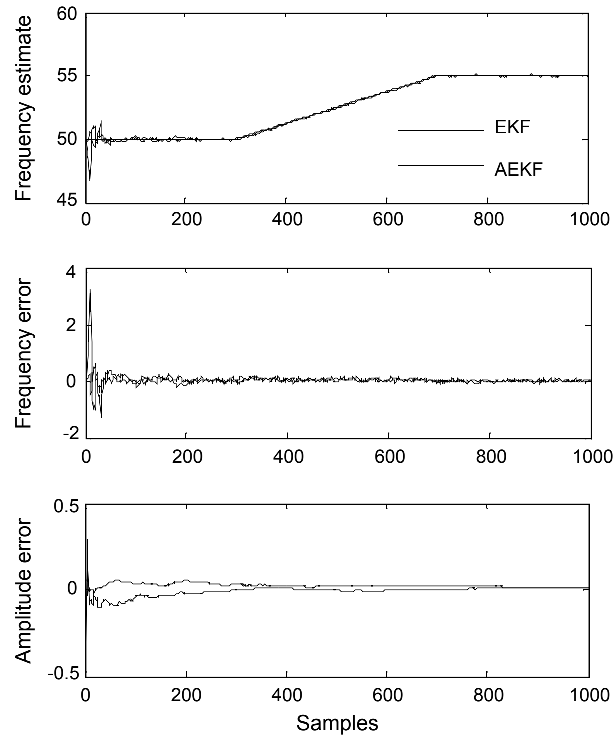

Figure 3: Comparison of extended Kalman filter and AEKF for linear frequency variation with 10 dB noise.

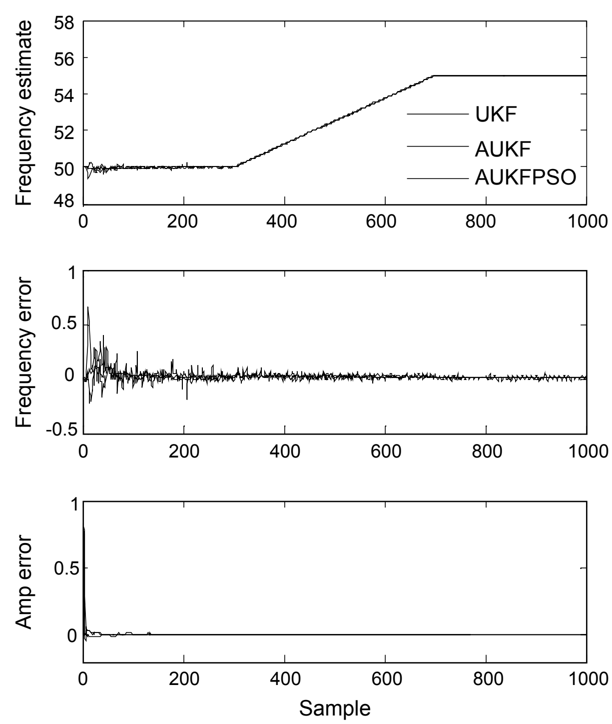

Figure 4: Comparison of UKF, AUKF and AUKFPSO for linear frequency variation with 30 dB noise.

Table 1: Mean of MSE over 100 independent runs

Algorithm	60 dB	30 dB	20 dB	10 dB
EKF	0.0051	0.0062	0.3105	0.497
AEKF	0.0047	0.0057	0.3019	0.479
UKF	0.0041	0.0054	0.2897	0.437
AUKF	0.0028	0.0032	0.0205	0.0574
AUKFPSO	0.0020	0.0029	0.0107	0.037

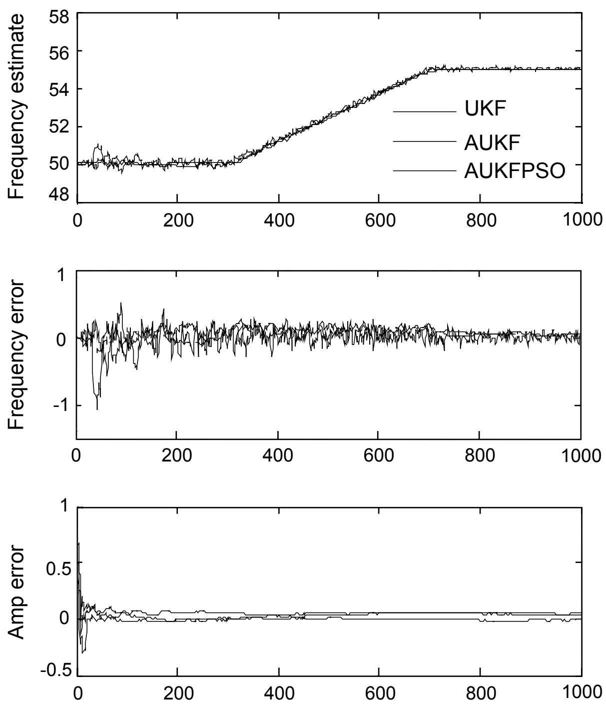

Figure 5: Comparison of UKF, AUKF and AUKFPSO for linear frequency variation with 10 dB noise.

decreased to10 dB, the performance of the UKF tracker deteriorates compared to AUKF and MPSO algorithms as shown in Figure 5, but comparatively better than EKF and AEKF. To have a meaningful comparison of the performance of various filters like EKF, AEKF, UKF, AUKF and AUKF optimized by the MPSO, the mean values of MSE over 100 iterations are given in Table 1 at different noise levels.

5.2 Case 2: Time-varying Frequency

In this test, frequency of the sinusoid is modulated by two small sinusoidal components and the resultant frequency is tracked with various filters as mentioned in case 1. The test signal used in this case is as in equation (36) and the time varying frequency is given by,

$$\omega(k) = 2\pi[50 + \sin(2\pi.1.kT_s) + 0.5\sin(2\pi.6.kT_s)] \quad (37)$$

Figure 6 shows the results of tracking of frequency, frequency error and amplitude error of the signal with 30 db noise. At 30 dB noise both EKF and AEKF performs well in tracking accurately the frequency and amplitude

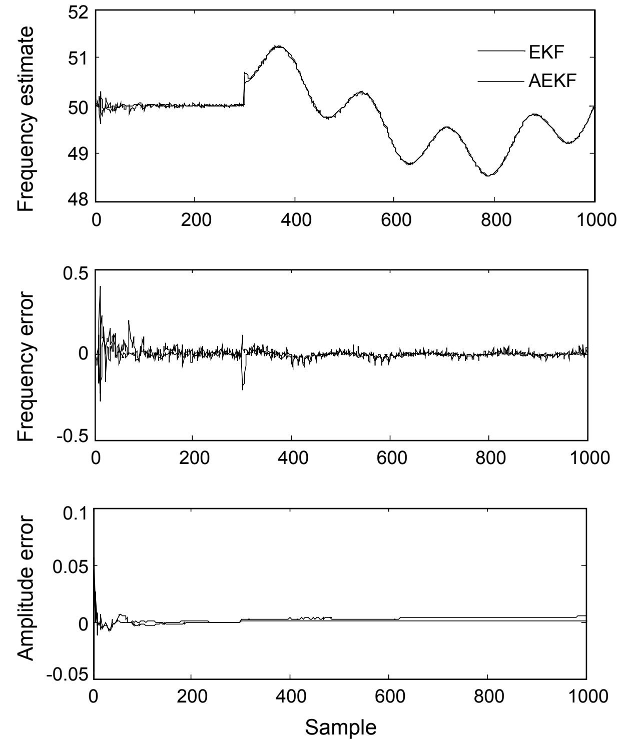

Figure 6: Comparison of extended Kalman filter and AEKF for time-varying frequency with 30 dB noise.

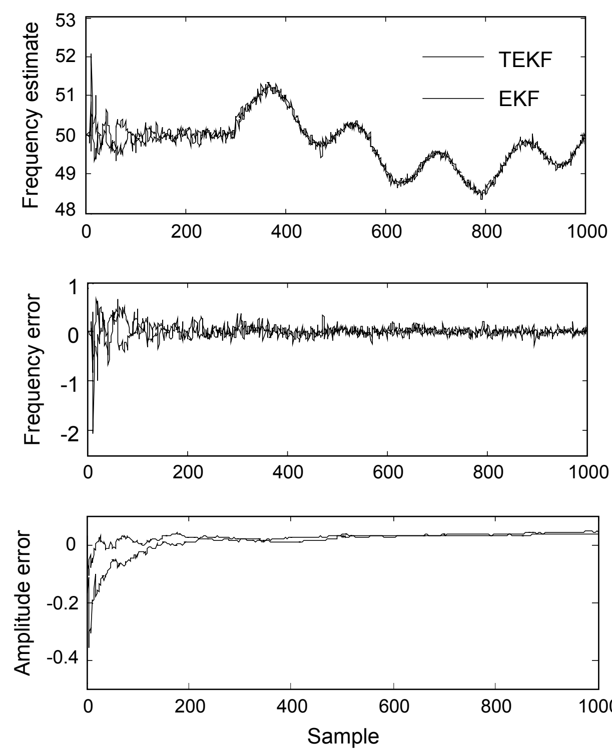

Figure 7: Comparison of extended Kalman filter and AEKF for time-varying frequency with 10 dB noise.

of the time varying signal. However, when the SNR is lowered to 10 dB, the frequency tracking performance of the Kalman filters deteriorate and significant errors creep

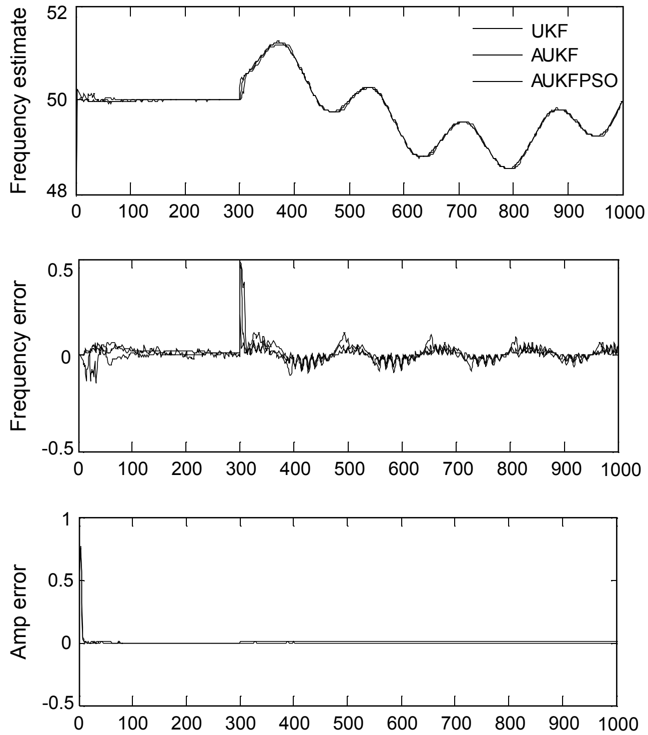

Figure 8: Comparison of UKF, AUKF and AUKF - PSO for time-varying frequency with 30 dB.

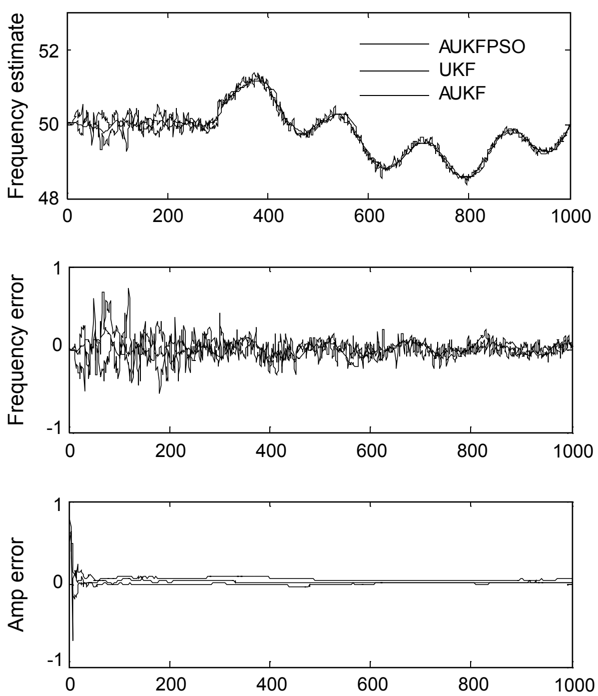

Figure 9: Comparison of UKF, AUKF and AUKFPSO for time-varying frequency with 10 dB noise.

in as shown in Figure 7. As in case 1, the above signal is analyzed using UKF, AUKF and AUKF with MPSO. Figure 8 shows the improvement of AUKF and MPSO

Table 2: Mean of MSE over 100 independent runs

Algorithm	60 dB	30 dB	20 dB	10 dB
EKF	0.0049	0.0794	0.237	0.243
AEKF	0.0045	0.0721	0.201	0.219
UKF	0.0037	0.0692	0.197	0.207
AUKF	0.0021	0.0375	0.057	0.1551
AUKFPSO	0.0017	0.0223	0.039	0.0214

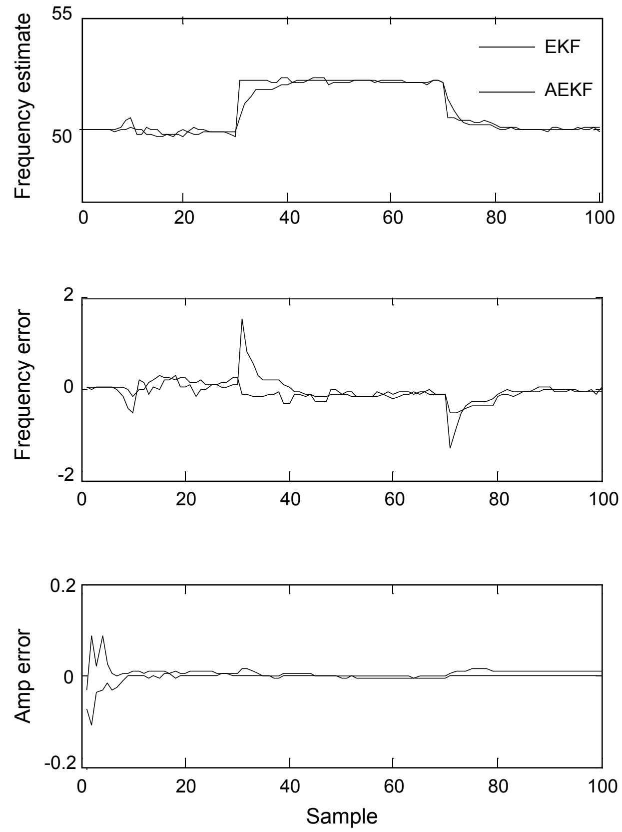

Figure 10: Comparison of extended Kalman filter and AEKF for step frequency variation with 30 dB noise.

over UKF at 30 dB SNR. As the SNR is decreased to10 dB, the performance of the UKF tracker deteriorates but comparatively better than EKF and AEKF as shown in Figure 9. The performance of various filters and mean values of MSE over a100 iterations are given in Table 2 for different noise levels.

5.3 Case 3: Step Frequency Variation

In this case the test signal taken is as in equation (36) with a frequency jump of f_0 = 50 Hz to f_1 = 52 Hz. Figure 10 shows the signal parameter tracking results of EKF and AEKF at SNR = 30 dB and Figure 11 shows the tracking performance of UKF, AUKF and MPSO at 30dB SNR. From Figures 11 and 12 it is clear that the performances of AUKF and MPSO are better than UKF, EKF and AEKF. Similar to case.1, the above signal is

Table 3: Mean of MSE over 100 independent runs

Algorithm	60 dB	30 dB	20 dB	10 dB
EKF	0.1021	0.0623	0.189	0.421
AEKF	0.0953	0.0501	0.190	0.401
UKF	0.0917	0.0327	0.178	0.398
AUKF	0.0501	0.016	0.123	0.288
AUKFPSO	0.0102	0.0091	0.096	0.126

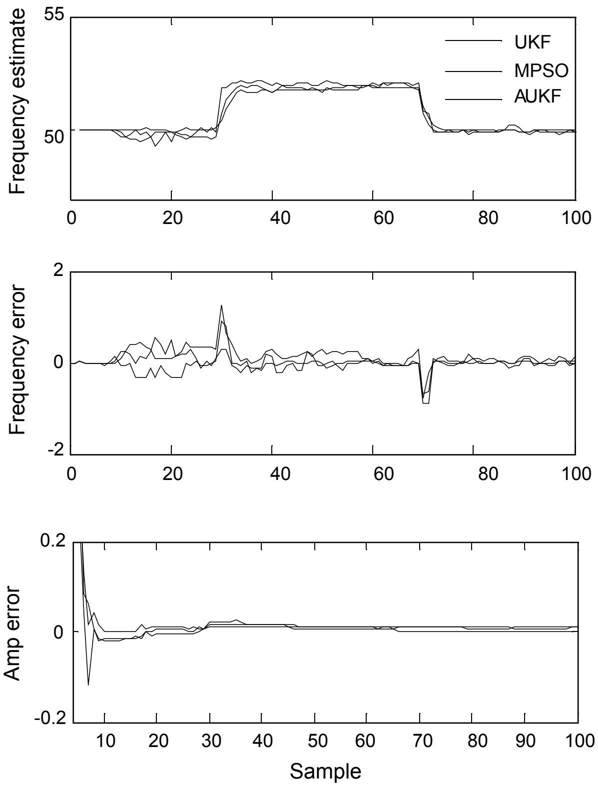

Figure 11: Comparison of UKF, AUKF and AUKFPSO for step frequency variation with 30 dB noise.

analyzed for different noise levels and the mean values of MSE over 100 iterations are presented in Table 3. Figure 12 shows the effect of harmonics present in the signal as noise. Here the signal is corrupted with 30 dB noise, third and fifth harmonic components. Figure 12 illustrates the negligible effect of third and fifth harmonic components on parameter estimation of the fundamental component. Thus, UKF and its variants are able to track non-stationary signal frequency and amplitude efficiently in presence of noise and harmonics.

6. CONCLUSION

In this paper, we have proposed an adaptive unscented Kalman filter technique with optimized error covariances, and a modified PSO optimization technique to estimate the amplitude and frequency of the signal with frequency varied either linearly, time-varying or in a step-wise

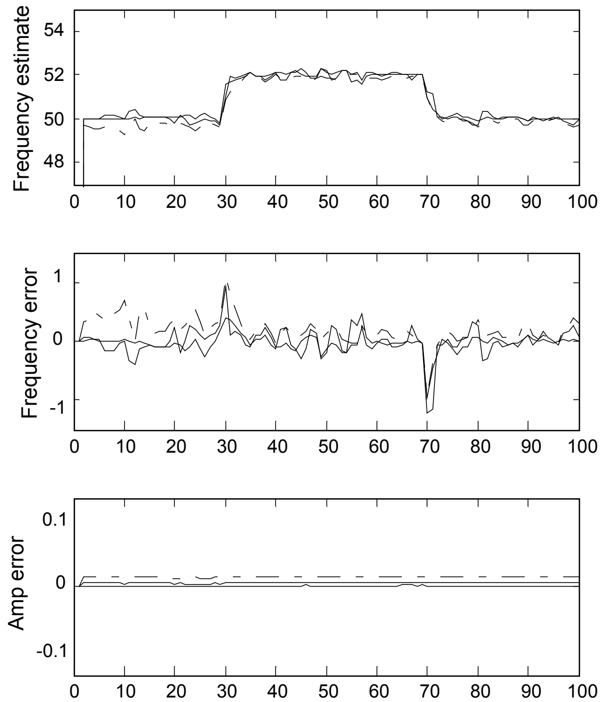

Figure 12: Comparison of UKF and its variants with harmonic and 30 dB noise.

manner. Both large and small frequency variations along with different noise level are considered for performance evaluation of the proposed algorithm in comparison with other algorithms. It is observed that the error in frequency estimation decreases significantly in UKF with iterative Q and R and UKF parameters optimization using MPSO. The paper also presents the effects of an adaptive measurement error covariance R and model error covariance Q on the overall performance of the UKF in tracking accurately the signal parameters along with frequency.

REFERENCES

1. R Kumaresan, and D W Tufts, Estimating the parameters of exponentially damped sinusoids and pole-zero modeling in noise, *IEEE Trans. on Acoust., Speech, Signal Processing*, Vol. ASSP-30, pp. 833-40, 1982.
2. V F Pisarenko, The retrieval of harmonics from a covariance function, *Geophysics, J. Royal Astron. Soc. No. 33*, pp. 511-31, 1973.
3. R O Schmidt, A signal subspace approach to multiple emitter location and spectral estimation, Ph.D. dissertation, Stanford University, Stanford, 1981.
4. R H Roy, and T Kailath, ESPIRIT-A subspace rotation approach to estimation of parameters of cisoids in noise, *IEEE Trans., Acoust., Speech, Signal Processing*, Vol. 34, Oct. 1984.
5. P K Dash, R K Jena, G Panda, and A Routray, An extended complex Kalman filter for frequency measurement of distorted signals, *IEEE Trans. on Instrument and Measurement*, Vol.49, pp.746-53, 2000.
6. S J Julier, and J K Uhlmann, Unscented filtering and nonlinear estimation, in *Proceedings of the IEEE*, Vol. 92. No.3, Mar. 2004.
7. J Kennedy, and R C Eberhart, Swarm Intelligence, Morgan Kaufmann Publishers; 2001.

8. Z la, T Y Ji, W H Tang, and Q H Wu, Optimal harmonic estimation using a particle swarm optimizer, *IEEE Trans. on Power Delivery*, Vol.23, No.2, pp.1166-74, Apr. 2008.

9. M A Abido, Optimal design of power system stabilizers using particle swarm optimization, *IEEE Trans. on Energy Conversion*, Vol.17, pp. 406-13.

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