Adaptive Filtering of Non Stationary Signals for Frequency Estimation Using hybrid KDE

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Summary
The paper highlights a novel hybrid EKF (Extended Kalman Filter) and Differential evolution (DE) called KDE (Kalman differential evolution) approach for tracking Parameters of a signal corrupted with noise and harmonics. The modeling and measurement of error covariance matrices Q and R are optimized using differential evolution. A new adaptive filtering technique is employed for self adaption of mutation scale factor in DE. To improve the convergence speed of optimization process K-DE, a variant of standard DE is considered for the optimization of Q and R matrices. Simulation results for time varying frequency of the power signal reveal significant improvement in noise rejection and accuracy in obtaining the frequency of the signal.

Key words:
Differential evolution, Extended Kalman filters, covariance, Kalman Differential Evolution

1. Introduction

Signal parameter estimation is a widely studied subject by various researchers in electrical and electronics engineering. Estimating the frequency and other parameters of sinusoids in white noise in radar, nuclear magnetic resonance, power networks etc., have been main focus of research. The various estimation techniques available in literature are based on the signal models of each filed. Several parametric and nonparametric techniques are developed to estimate parameters. Weighted least square method is a very primitive and well established method. Fast algorithms based on singular value decomposition (SVD) and reduced rank approximation has been developed by Kumarson and Tufts [1]. Pisarenko's method [2], and the Schmidt, [3] algorithm exploit the orthogonality 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. perform better with high signal to noise ratio (SNR), however, they tend to degrade for low SNR. This is found to be true for most of the parametric methods.
In this paper, an Extended Kalman Filtering (EKF) technique [5, 6, 7, 15] is used to estimate the frequency, amplitude and phase of a non stationary signal mixed with random noise. We have used the Differential evolution technique to optimize the noise covariance matrices in order to achieve the best EKF performance. The DE generates very high quality shorter calculation times and provides stable convergence characteristics than other stochastic methods like Particle swarm optimization algorithm [8, 9], (PSO) and evolutionary programming. The hybridization of DE and EKF is able to solve problems with more local optima due to the effective filtering capabilities of EKF. Thus with a hybrid EKF and DE based algorithm, it is possible to track signal frequency and amplitude variation with SNR as low as 10 dB quite accurately. In earlier reported results with EKF amplitude and frequency tracker, a SNR <30 dB will produce erroneous results. In this paper we have suggested a new adaptive approach for selection of amplification factor (F). In this approach the F is self adapted [10, 11] taking into account the variance of population fitness in a given generation. A comparison with the pso algorithm and variable noise covariance parameter is also presented in the paper to highlight the robustness in time varying frequency and amplitude of a non stationary signal embedded in noise.

2. Signal Model and EKF Algorithm

The model of a discrete signal is represented as $Z_k = A\sin(kwT_s + \phi) + v_k$ (1)
Where A, T_s w ϕ, represents Signal amplitude, sampling Time, Frequency and Phase angle with v_k is a measurement noise assumed to be white sequence with covariance R.
The state space representation of discrete signal can be represented

$$x_{k+1} = F_k x_k + w_k \quad (2)$$

Where

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$$x_k(1) = A\cos\phi,\ x_k(2) = A\sin\phi,\ x_k(3) = w \qquad (3)$$

For such case the state transition matrix $F_k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

The observation matrix can be represented by

$G_k = \left[\sin\left(kx_k(3)T_s\right)\cos\left(x_k(3)kT_s\right)\ 1\right]$ (4) If the above system is made linear, the EKF algorithm is obtained as follows:

$$\hat{x}_{k/k} = \hat{x}_{k/k} + K_k(Z_k - H_k x_{k/k-1})$$

$$Z_k = H_k x_k + w_k \qquad (5)$$

The Kalman filter gain K_k is obtained as

$$K_k = \hat{P}_{k/k-1} H_k^T (H_k \hat{P}_{k/k-1} H^T + R)^{-1} \qquad (6)$$

$$\hat{P}_{k/k} = P_{k/k-1} - K_k H_k \hat{P}_{k/k-1}$$

(7) $\hat{P}_{k+1/k} = \hat{P}_{k/k} + Q,\ Q = \begin{bmatrix} q_1 & 0 & 0 \\ 0 & q_2 & 0 \\ 0 & 0 & q_3 \end{bmatrix}$ (8) Where noise Q is a covariance matrix and R is the measurement noise covariance.

Another alternative EKF model for estimating amplitude, phase and frequency of a time varying signal is obtained choosing the signal states as

$$x_k(1) = A\sin(x_k(3).k\Delta T_s + \phi) \qquad (9)$$

$$x_k(2) = A\cos(x_k(3).k\Delta T_s + \phi)$$

(10) $x_k(3) = w$ (11)

The state-transition matrix in this case becomes equal to

$$F_k = \begin{bmatrix} \cos(x_k(3)\Delta T_s & \sin(x_k(3)\Delta T_s & 0 \\ -\sin(x_k(3)\Delta T_s & \cos(x_k(3)\Delta T_s & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

And the covariance matrix $\hat{P}_{k+1/k}$ is obtained as

$$\hat{P}_{k+1/k} = F_k \hat{P}_{k/k} F_k^T + Q \qquad (12)$$

The observation matrix H is obtained here as, H= [1 0 0].The performance of the extended Kalman filter in tracking signal frequency, amplitude, and phase is highly dependent on the correct of choice of noise of covariance Q and R, or simply q and R, if Q = qI, and I is 3×3 unit matrix. The performance of EKF in estimating signal parameters can improve by updating the error covariance R in the following manner is computed from the error between the observed and estimated values of x_k as

$$R = (Z_k - H_k \hat{x}_k)^T (Z_k - H_k \hat{x}_k) \qquad (13)$$

The covariance R can be recursively updated as

$$R_k = \lambda_k R_{k-1} + e_k^2 \qquad (14)$$

Where the error e_k is given by

$$e_k = Z_k - H_k x_k \qquad (15)$$

And λ_k is a forgetting factor which is varied as

$$\lambda_k = \frac{1}{1 + \left|R(k)/R_0\right|} \qquad (16)$$

Where R_0= initial value. Although this variation of R might improve the performance of the filter somewhat, but the degradation with low SNR is found difficult to remove.

3. Differential Evolution of EKF algorithm

To obtain optimal solution with low SNR we have implemented DE for optimization purpose. Differential Evolution (DE) is a parallel direct search method developed by Storn and Price in 1997 which is a population-based global optimization algorithm. It uses a real-coded representation [5]. This approach for numerical optimization is simple to implement and requires little or no parameter tuning, but gives a remarkable performance. Like all other evolutionary algorithms, the initial population is chosen randomly.

Like all other evolutionary algorithms, DE method also consists of three basic steps:

(i) Generation of population with N individuals in the d-dimensional space, randomly distributed over the entire search domain

$\vec{X_i}(t) = \left[x_{i,1}(t), x_{i,2}(t), x_{i,3}(t) \ldots x_{iD}(t)\right]$, where t=0, 1, 2….t, t+1 (17)

(ii) Replacement of this current population by a better fit new population, and

(iii) Repetition of this replacement until satisfactory results are obtained or certain criteria of termination is met. The basic scheme of evolutionary algorithms is given below:

a) Mutation

After the random generation of population, in each generation, a Donor vector $\vec{V_i}(t)$ is created for each $\vec{X_i}(t)$.This donor vector can be created in different ways (see DE mutation schemes).

b) Recombination

Now a trial offspring vector is created by combining components from the Donor vector $\vec{V_i}(t)$ and the target vector $\vec{X_i}(t)$. This can be done in the following way

$$U_{i,j}(t) = V_{i,j}(t) \quad \text{If } rand_{i,j}(0,1) <= Cr$$
$$= X_{i,j}(t) \quad \text{Otherwise} \qquad (17)$$

Where C_r is the probability of recombination

c) Selection

Selection in DE adopts Darwinian principle "Survival Of the Fittest". Here if the trail vector yields a better fitness value, it replaces its target in the next generation; otherwise the target vector is retained in the population. Hence the population either gets better (with respect to the fitness function) or remains constant but never deteriorates.

$$\overrightarrow{X_i}(t+1) = \overrightarrow{U_i}(t) \quad \text{If } f(U_i(t)) \le f(X_i(t)),$$
$$= \overrightarrow{X_i}(t) \quad \text{If } f(X_i(t)) < f(U_i(t))$$

DE mutation Schemes

The five different mutation schemes suggested by Price [5] as follows:

Scheme 1-DE/rand/1

In this scheme, to create a donor vector $\overrightarrow{V_i}(t)$ for each ith member, three other parameter vectors (say the o_1, o_2, and o_3th vectors) are chosen randomly from the current population. A scalar number F is taken. This number scales the difference of any two of the three vectors and the resultant is added to the third one. For the ith donor vector, this process can be given as

$$\overrightarrow{V_i}(t+1) = \overrightarrow{X_{o_1}}(t) + F * \left(\overrightarrow{X_{o_2}}(t) - \overrightarrow{X_{o_3}}(t)\right)$$

Scheme 2-DE/rand to best/1

This scheme follows the same procedure as that of the Scheme1. But the difference is the donor vector which is generated by randomly selecting any two members of the population (say $\overrightarrow{X}_{0_2}(t)$, and $\overrightarrow{X}_{0,3}(t)$ vectors) and the best vector of the current generation (say $\overrightarrow{X}_{best}(t)$). For the ith donor vector, at time t=t+1, this can be expressed as $\overrightarrow{V_i}(t+1) = \overrightarrow{X_i}(t) + \lambda * \left(\overrightarrow{Xbest}(t) - \overrightarrow{Xi}(t)\right) + F * \left(\overrightarrow{X}_{o_2}(t) - \overrightarrow{X}_{o_3}(t)\right)$

Where λ is a control parameter in DE and ranges between [0, 2] . To reduce the number of parameters, we consider λ =F.

Scheme 3-DE/best/1

This scheme is identical to Scheme 1 except that the result of the scaled difference is added to the best vector of the current population as $\overrightarrow{V}i(t+1) = \overrightarrow{X}best(t) + F * \left(\overrightarrow{X}_{o_1}(t) - \overrightarrow{X}_{o_2}(t)\right)$

Scheme 4-DE/best/2

In this scheme, the donor vector is formed by using two difference vectors as shown below

$$\overrightarrow{Vi}(t+1) = \overrightarrow{Xbest}(t) + F * \left(\overrightarrow{X}_{o_1}(t) - \overrightarrow{X}_{0_2}(t)\right) + F * \left(\overrightarrow{X}_{o_3}(t) - \overrightarrow{X}_{o_4}(t)\right)$$

Scheme 5-DE/rand/2

Here totally five different vectors are selected randomly from the population, in order to generate the donor vector. This is shown below

$\overrightarrow{Vi}(t+1) = \overrightarrow{X}_{o_1}(t) + F_1 * \left(\overrightarrow{X}_{o_2}(t) - \overrightarrow{X}_{o_3}(t)\right) + F_2 * \left(\overrightarrow{X}_{o_4}(t) - \overrightarrow{X}_{o_5}(t)\right)$ Here $F1$ and $F2$ are two weighing factors selected in the range from 0 to 1. To reduce the number of parameters we may choose $F1 = F2 = F$.

The experiment we conducted in this study uses Scheme 1-DE/rand/1

Procedure for DE

1. Randomly initialize the position of the particles
2. Evaluate the fitness for each particle
3. For each particle, create Difference-Offspring
4. Evaluate the fitness of the Difference-Offspring
5. If an offspring is better than its parent then replace the parent by offspring in the next generation;
6. Loop to step 2 until the criterion is met, usually a sufficiently good fitness or a maximum number of iterations.

The original DE algorithm has three control parameters namely the mutation scale factor F, the probability of recombination C_r and the population size NP. In the original DE algorithm [10, 11] these parameters are fixed values. Storn and Price in [12] have indicated that a reasonable value of NP could be chosen between 5-D and 10-D (D being the dimensionality of the problem), and a good initial choice of F was 0.5. The effective range of F is usually between 0.4 and 1. The probability of recombination is between 0.3 and 0.9. It has been found that the best setting of control parameters depend on the function and the requirements of consumption time and accuracy. If the size of the problems is increased then much more time is needed to perform preliminary testing and hand-tuning of the evolutionary parameters prior to commencing the actual optimization process. As can be perceived from various literatures available on DE, several claims and counter claims were reported with regard to the rules for choosing control parameters. Some objective functions are very sensitive to proper choice of the parameters settings in DE. Therefore, researchers started to consider some techniques such as self-adaption to automatically find an optimal set of control parameters. V. Price [13, 14]] proposed a algorithm, in which the control parameters are self-adapted by learning from their previous experiences of generating promising results. The parameter F, is approximated by a normal distribution with mean value 0.5 and the standard deviation 0.3. The F was found to maintain both exploration (with large F value) and exploitation (with small F value) throughout the entire evolution process due to its property of sampling random values of F from normal distributions. The F is adaptively updated by setting a lower bound of fitness value f and calculating f_{min} and f_{max} which are minimum and maximum values of objective function over the individuals of the populations, obtained in a generation. Recently, wenjing &Gao. [10] proposed a self-adaption scheme called JDE for the DE control parameters. They encoded control parameters into the individual and adjusted them introducing two new parameters $\tau_1$and τ_2. In our work we have proposed a new adaption scheme for F. In this scheme the F is updated based on the variance of the population fitness of all vectors in a generation. The mutation scale factor F is updated by finding the variance of the population fitness as

$$\sigma^2 = \sum_{i=1}^{M}\left(\frac{fi - favg}{f}\right)^2 \qquad (18)$$

Where f_{avg}=average fitness of the population of vectors in a given generation.
f_i =fitness of the ith vector in the population.
M=total number of vectors

$$f = \{\max(|fi - favg|)\}, \text{ i=1, 2, 3……M} \qquad (19)$$

Here, f is a normalizing factor to limit σ. A large value of σ will make the search random and whereas a small value of σ or $\sigma = 0$, the solution tends towards a premature convergence. To alleviate this phenomenon and to obtain optimal solution, the F is updated as

$$F(k) = \lambda F(k-1) + (1-\lambda)\sigma^2 \qquad (20)$$

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

$$F(k) = \lambda_1 F(k-1) + rand(\ )/2$$

Here $0 \le \lambda_1 \le 0.5$ .Where rand () is a random number between (0, 1).Here the influence of the past performance of the vector on the current vector is chosen to be random and the mutation scale factor 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 vectors.

4. Kalman Differential Evolution (KDE)

The Kalman- Differential Evolution (KDE) is a new hybrid approach that reduces the number of iterations required to reach an optimum solution. The new solution is predicted by observing the best solution in the neighborhood at each time step. The basic equations of KDE are summarized as follows:

$$K_t = \left(V\Sigma_{k-1}V^T + \Sigma_0\right)H^T\left(H\left(V\Sigma_{k-1}V^T + \Sigma_0\right)H^T + \Sigma_\zeta\right) \qquad (21)$$

$$\hat{\theta}_k = V\theta_{k-1} + K_k\left(\zeta_k - HV\hat{\theta}_{k-1}\right) \qquad (22)$$

$$\Sigma_k = \left(I - V\Sigma_{k-1}V^T + \Sigma_0\right) \qquad (23)$$

Where V and H are the transition and sensor characteristic matrices, $\Sigma_\theta, \Sigma_\zeta$ are the respective covariance matrices. The value of ζ is obtained from the observations and k is the time. The transition and observation matrices are

$$V = \begin{pmatrix} I & I \\ 0 & I \end{pmatrix}, \; H = \begin{pmatrix} I & 0 \end{pmatrix}$$

And the estimated solution vector $\hat{\theta}_k$ is obtained as

$$\hat{\theta}_k = \begin{pmatrix} \hat{x}_k \\ \hat{x}_k \end{pmatrix} \text{ , with initial value as } \hat{\theta}_0 = \begin{pmatrix} \hat{x}_0 \\ \hat{x}_0 \end{pmatrix},$$

And I is an unit matrix of appropriate dimension.
The covariances are defined as

$$\Sigma_0 = \in .diag\begin{pmatrix} w_1 \\ w_1 \end{pmatrix} \qquad (24)$$

$$\sum_\xi = \in .\text{diag } (w_1)$$

And $\Sigma_k = \in .diag\begin{pmatrix} w_1 \\ w_1 \end{pmatrix}$

Where $\in$ is chosen as 0.001 and w_1 depends on the size on the limits of vector range.
The filtered or true state of the vector is determined from a distribution

$$\hat{\theta}_{k+1} = \begin{bmatrix} \hat{x}_{k+1} \\ \hat{\dot{x}}_{k+1} \end{bmatrix} = Normal\left(V\hat{\theta}_k, \Sigma_k\right) \qquad (25)$$

The position information in the K-DE algorithm is used to set the new position of the vector. The mutation scale parameter F is updated by finding the variance of the population fitness as described in equation (18).

5. Simulation Results

The following case studies on frequency of the non stationary signals in noise are presented to highlight the KDE performance over EKF through MATLAB simulation considering a situation where the frequency change in signal is like a Ramp Variation i .e the angular frequency w is varied linearly as

For $0 \le k \le 300$, $w(k) = w_0$ for $300 \le k \le 700$, and $w(k) = w_1$ *for* $k \ge 700$ up to 1000 samples the angular frequency will be w_1 for the simulated test signal considering noise of 10 db and 30 db in four stages of EKF and KDE for the signal $y(k) = \sin(kwT_S + \phi) + n(t)$

In four different cases of ramp variations in signal frequency in noisy conditions in the simulation figure 1.(A)EKK 10db,(B) KDE 10db ,(C)EKF 30db and (D)KDE 30db are Compared.

In our simulation the dimension chosen is 2 and hence the population size in KDE is 25. The initial values of mutation scale parameters $F_{\max}$, $F_{\min}$ are chosen as, $F_{\max} = 1$, $F_{\min} = 0.4$, lower and upper bound of Q and R are lb=0.0005, ub=0.01, $iter_{max}$=100. The above equation represents a time varying frequency from w_0= 49 Hz to w_1=51 Hz.

A 1 kHz sampling frequency is chosen. The time varying frequency, amplitude, and phase of the signal are generated for different SNR (signal to noise ratio) of the white noise varying from 30 db to 10 db. The errors between the tracked parameters and the actual parameters are shown in the table specified. In the sub figures of A, B, C or D of fig 1 the X axis represents the number of sample over which the measurements were made. The y axis plots the frequency variation, errors and the percentage of errors in db. For larger variation of frequency ramping over time may not be tracked with greater accuracy further requires tuning of proper covariance matrices.

Table 1: Comparisons

item	*Frequency error*	*Frequency error (db)*
EKF(10db)	0.04	1.12%
KDE(10db)	0.01	0.73%
EKF(30 db)	0.08	0.8%
KDE(30db)	0.05	0.1%

Conclusions

In this paper, we have presented an extended KDE filtering technique with optimized noise covariance matrices by a new variant of DE called KDE wherein we have proposed a new approach to adapt the mutation scale factor of DE and hybridization of Kalman and DE optimization techniques to estimate the frequency of a signal, whose frequency is ramped . This adaptability provides an optimum solution of the noise covariance matrices Q and R in a smaller number of iterations in comparison to the conventional DE algorithm. Both large and small variations along with harmonics and noise are considered for signal frequency estimation and frequency error is found to be within 0.01 to 0.05% in noisy conditions. On the other hand the error in frequency is found to be 0.1 to 1.12% using a simple EKF without Q and R optimization. However the analysis and estimation of frequency in variation such as Step, frequency modulation, Signal with Harmonic Distortion and Parabolic Frequency Variations are the proposed work. However lots of works are proposed by using hybrid differential Evolution for estimation of phase angle and amplitudes of time varying power signals in the presence of white noise.

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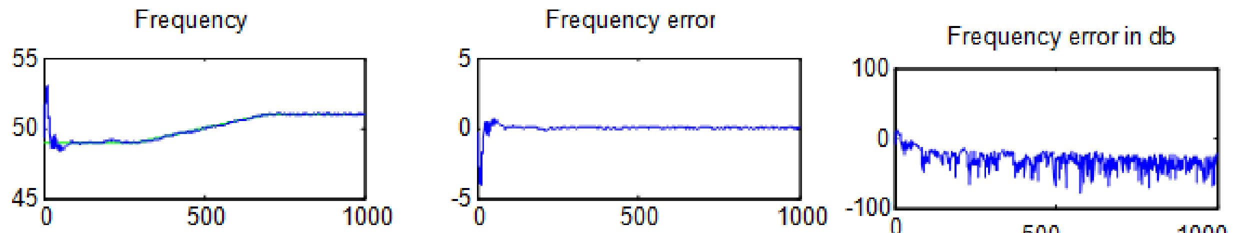
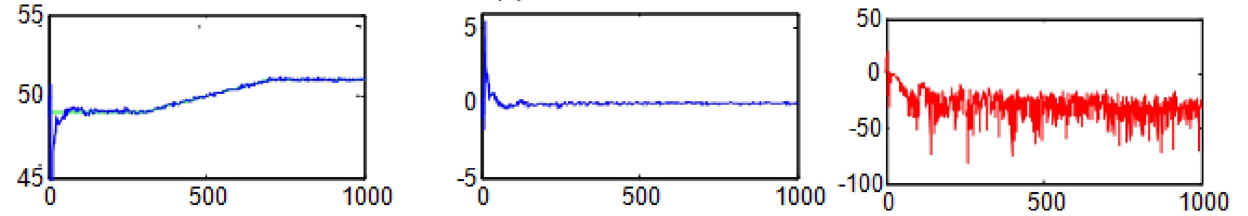
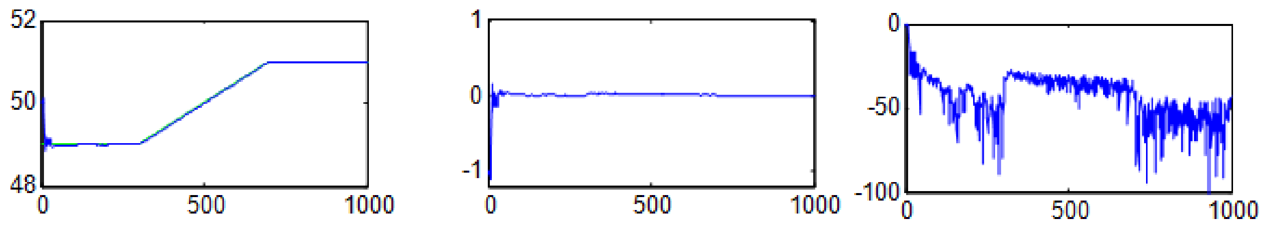


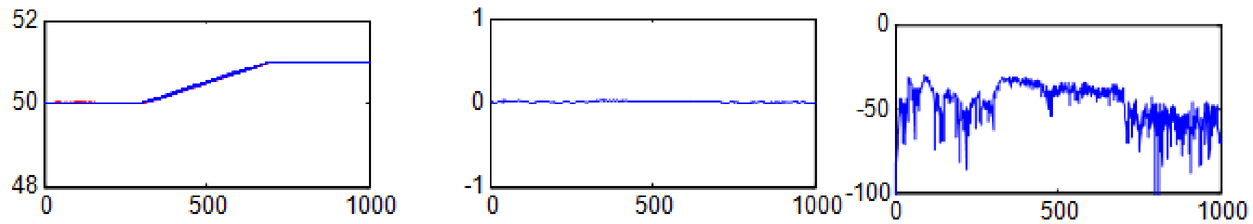
(A) EKF with 10 db noise



(B) KDE with 10 db noise



(C)EKF with 30db noise



(D) KDE with 30db noise