



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 7 Issue: XII Month of publication: December 2019

DOI: <http://doi.org/10.22214/ijraset.2019.12083>

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Study and Implementation of Phase Noise Channels using Independant Oscillators for Mimo by using Unscented Kalman Filter

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Abstract: Multiple input and multiple output (MIMO) channels are widely used to increase the spectral efficiency in coherent communication system. The Phase Noise which is introduced by the independent - oscillator is heavy and not good for the system, for that purpose we are using EKF. Forward and backward kalman filter is used to estimate the phase vector by considering time instants. The suboptimal method with static loop gain as well as forward and reverse filter algorithm is used to reduce the complexity of system. To overwhelm the limitation in EKF we use UKF. The unscented Kalman Filter (UKF) is one of the best filter compared with EKF which it overcomes the drawbacks of EKF. In this paper we are proposing unscented Kalman Filter to track the phase noise introduced by independent transmit and receive oscillators in multiple-input multiple-output transmission.

Keywords: EKF-extended kalman filter, UKF-unscented kalman filter, PN-phase noise , MSE-minimum mean square error, BER-bit error rate, SNR-signal noise ratio

I. INTRODUCTION

The PN that is introduced by the oscillators reduces the performance of high speed communication and it is the major problem introduced by oscillator during the transmission of signals at the transmitter and receiver antennas in radio transmission this is discussed in paper [1]. In this paper [3] we have learned about comparison between EKF and UKF and their performances. There is an impact of PN in MIMO it is studied in [4] in this the multiple input and multiple output antennas are affected by PN. Especially it is considered at the transceivers where single oscillators drive RF circuits and also discussed about the placing of antennas [4]. The EKF is not very stable and many times, when it does converge to the "right" solution, it does it very slowly. In order to improve this filter, instead of using linearization to predict the behavior of the system under investigation, we are proposing the UKF for better performance. The Kalman Filter with Unscented transformation is called Unscented Kalman Filter. This filter has some advantages when compared to the EKF, because the Unscented transformation somehow describes the nonlinear system better than the linearization.

II. SYSTEM MODEL

In this system to convert from low data rates to high data rates we use OFDM. In this we are using signal processing techniques like FFT/IFFT at transmitter and receiver. Here the Bit error rate (BER) performance of 2*2 MIMO system for higher modulation techniques like BPSK or 64 QAM is used the UKF proposed here is capable of tracking phase noise and it is effectively applied to point to point communication over wide range of SNR. Let the lowercase character indicate possibly complex scalars and column vectors, the uppercase character indicate matrices and the uppercase calligraphic character indicate square matrices. Consider a MIMO $N_t \times N_r$ narrowband channel with independent oscillators at transmit and receive side are

$$\varphi_{k;r} = (\varphi_{k;r;1}, \varphi_{k;r;2}, \dots, \varphi_{k;r;N_r})^T, k = 1, 2, \dots, (1) \quad \text{and} \quad \varphi_{k;t} = (\varphi_{k;t;1}, \varphi_{k;t;2}, \dots, \varphi_{k;t;N_t})^T, k = 1, 2, \dots, (2)$$

Here the superscript T denotes transposition, be the vectors of the phases of receive and transmit oscillators at time k. The end result of the MIMO channel at time k is

$$y_k = R_k H T_k a_k + w_k, k = 1, 2, \dots, (3)$$

where T_k (R_k) is a diagonal $N_t \times N_t$ ($N_r \times N_r$) matrix that has on the diagonal the complex exponentials of transmit (receive) oscillators' phases at time k, matrix H, which is assumed to be fixed in time and known at the receive side, is the $N_r \times N_t$ MIMO channel matrix, a_k is the k-th sample of the i.i.d. input modulation complex vector data sequence with zero mean vector and covariance matrix.

III. EXTENDED KALAMAN FILTER

For estimating a dynamic system we use EKF. It is a recursive algorithm .Which is used to predict the past ,present and future values of the system.EKF is a non linear system in which we have to linearize it by using jacobian functions here is the state model and measurement mode given belowl.

$$x_{k+1} = f(x_k, u_k) + w_k \dots (4)$$

Where, x is the state model which was used to predict the state at each step. x_{k+1} is the next state.

u_k is the control data it is optional.

w_k is a Gaussian white noise.

$$z_k = h(x_k) + v_k \dots (5)$$

Where z_k is the measurement model. v_k Gaussian white noise

<p>Predicted state estimate:</p> $\hat{x}_{k k-1} = f(\hat{x}_{k-1 k-1}, u_k)$	<p>Kalman gain :</p> $k_k = p_{k k-1}^- H_k^T S_k^{-1}$
<p>Predicted covariance matrix:</p> $p_{k k-1}^- = F_k p_{k-1 k-1}^- F_k^T + Q_k$	<p>updated covariance matrix :</p> $p_{k k}^- = (I - K_k H_k) p_{k k-1}^-$

Kalman gain represents the accurate values of state model and measurement model .If the measurement matrix covariance is tends to 0,then the measurement variable is major accurate than state model .If previous state variance is 0,then it is vice versa . After this process based on the kalman gain value the estimated data is updated and the error covariance is updated for the next iterations. Therefore, all parameters are updated in the each iteration. Therefore the estimated data and predicted data continue to become more accurate.

Linearization is based on the $N_r \times (N_r + N_t)$ Jacobian matrix.

where ϕ_k denotes the phase predicted by the extended Kalman filter at time k, these are the jacobians show in the following.

$$\left[\frac{\partial f_{k;i}(\phi_k)}{\partial \phi_{k;r;i}} \right]_{\phi_k = \hat{\phi}_k} = j \sum_{n=1}^{N_t} h_{i,n} e^{j(\hat{\phi}_{k;r;i} + \hat{\phi}_{k;t;n})} a_{k;n}$$

$$= j \hat{y}_{k;i}, \dots (6)$$

$$\left[\frac{\partial f_{k;i}(\phi_k)}{\partial \phi_{k;t;l}} \right]_{\phi_k = \hat{\phi}_k} = j h_{i,l} e^{j(\hat{\phi}_{k;r;i} + \hat{\phi}_{k;t;l})} a_{k;l} \dots (7)$$

Given the prediction vector and the prediction error covariance matrix of the forward (backward) recursion ($\hat{\phi}(b), \hat{\Sigma}(b)$), from equation below one writes the prediction error covariance matrix and the prediction vector as

$$\hat{\Sigma} = (\hat{\Sigma}_f^{-1} + \hat{\Sigma}_b^{-1})^{-1},$$

$$\hat{\phi} = (\hat{\Sigma}_f^{-1} + \hat{\Sigma}_b^{-1})^{-1} (\hat{\Sigma}_f^{-1} \hat{\phi}_f + \hat{\Sigma}_b^{-1} \hat{\phi}_b)$$

$$= \hat{\Sigma}_b (\hat{\Sigma}_f + \hat{\Sigma}_b)^{-1} \hat{\phi}_f + \hat{\Sigma}_f (\hat{\Sigma}_f + \hat{\Sigma}_b)^{-1} \hat{\phi}_b,$$

The EKF can only provide first order approximations, that approximations introduces errors in the covariance matrix which may lead to suboptimal performances .so by using UKF we can rectify this problem by UKF.

A. Forward and Backward Filtering

Forward and backward kalman filter is used to estimate the vector of phases. By using weighted sum of covariance we can find the direction of pilot symbol carriers. The Weighted sum of phase estimates are produced by the forward and backward recursions, where the weights are derived from the forward and backward covariance.

Two specifications have been given below:

- 1) *Linear Interpolation*: Just by interpolating the forward and backward estimates linearly at the pilots we can obtain the phase estimation in symbols between two consecutive pilots. The LI pattern is near to the optimal performance.
- 2) *SGM*: It eliminates the need for updating the information matrix at each and every step of the forward and backward recursions. SGM shows slightly worse performance especially at high SNR. SGM helps to find the relationship between signal to noise ratio as well as symbol error rate.

$$\Sigma_{\infty}^{-1} - Q = \beta \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

IV. UKF

In UKF we used to produce several sampling points around the state estimates based on its covariance. When we propagate these points through the non-linear systems we get accurate estimations of mean and covariance. By this process we avoid calculating the jacobians. Sigma vector propagated through non linear function.

To propagate accurate mean and covariance of Random variable (RV) A through a non linear transform B=f(A). Assume A has a mean \bar{A} and covariance P_A to calculate B, we form a matrix A of 2L+1 sigma vectors A_i according to the following.

$$\begin{aligned} A_0 &= \bar{A} & (4.1) \\ A_i &= \bar{A} + (\sqrt{(L + \gamma)P_A})_i \\ A_i &= \bar{A} - (\sqrt{(L + \gamma)P_A})_{i-L} \end{aligned}$$

Where $\gamma = \alpha^2(L + K) - L$ here α is the scaling parameter where $(\sqrt{(L + \gamma)P_A})_i$ is the i_{th} column of matrix square roots.

The sigma vectors are propagated through the non-linear function like:

$$B_i = f(A_i) \quad i=0, \dots, 2L \quad (4.2)$$

Mean and covariance for B are approximated using weighted samples.

$$\bar{B} \approx \sum_{i=0}^{2L} W_i^{(m)} Y_i \quad (4.3)$$

$$P_B \approx \sum_{i=0}^{2L} W_i^{(c)} \{B_i - \bar{B}\} \{B_i - \bar{B}\}^T \quad (4.4)$$

Here the super script T denotes transposition matrix and with weights W_i is given by

$$W_0^{(m)} = \gamma / (L + \gamma) \quad (4.5)$$

$$W_0^{(c)} = \gamma / (L + \gamma) + (1 - \alpha^2 + \beta)$$

$$W_i^{(m)} = W_i^{(c)} = 1 / \{2(L + \gamma)\}$$

The superscript (m) and (c) represents the weighting coefficients.

In unscented transform it is easy to perform non-linear transformations and these points are called sigma points. Advantages of UKF is there is no need to calculate the jacobians. Better than linearization (KF). More computationally efficient than a particle filter. It gives better accuracy with faster response. It is easy to apply for higher order non linearities.

V. SIMULATION

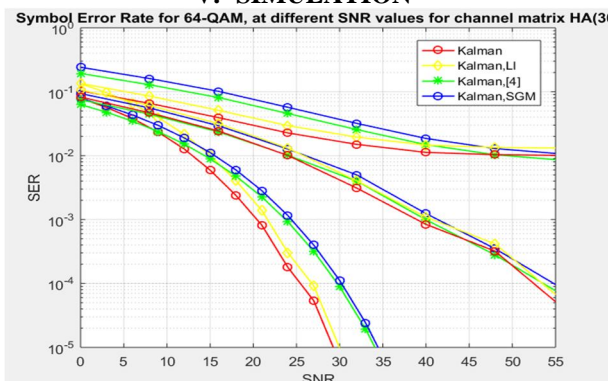


Fig.1 SER for 64-QAM at different SNR values are shown for channel matrix $H_A(30)$.

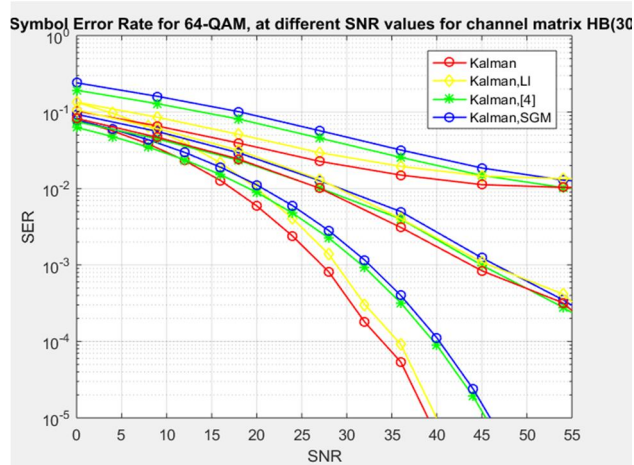


Fig.2 SER for 64-QAM at different SNR values are show for channel matrix $H_B(30)$.

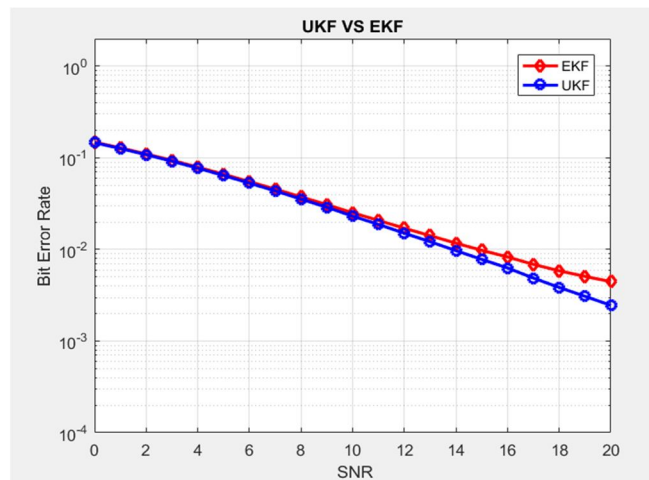


Fig.3 plotted between the BER AND SNR values for UKF vs EKF

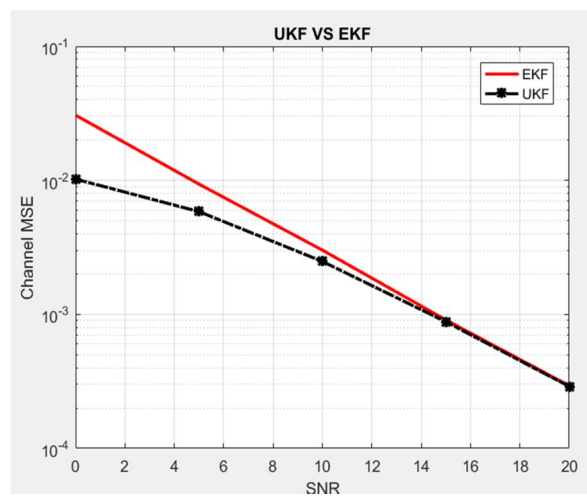


Fig.4 plotted between the channel MSE and SNR values for UKF vs EKF

Number of symbols used is 10000 and the channel size is 128. for 1 pilot symbol 52 bits are transmitted and the bits=8(tc_p/t_s) and carriers used is 15000. phase delay is 0.002 and 2 transmitters and 2 receivers is used. In this we used nakagami distribution with parameter values used $\mu=5$ and $\omega=2$ these are simulation values taken.

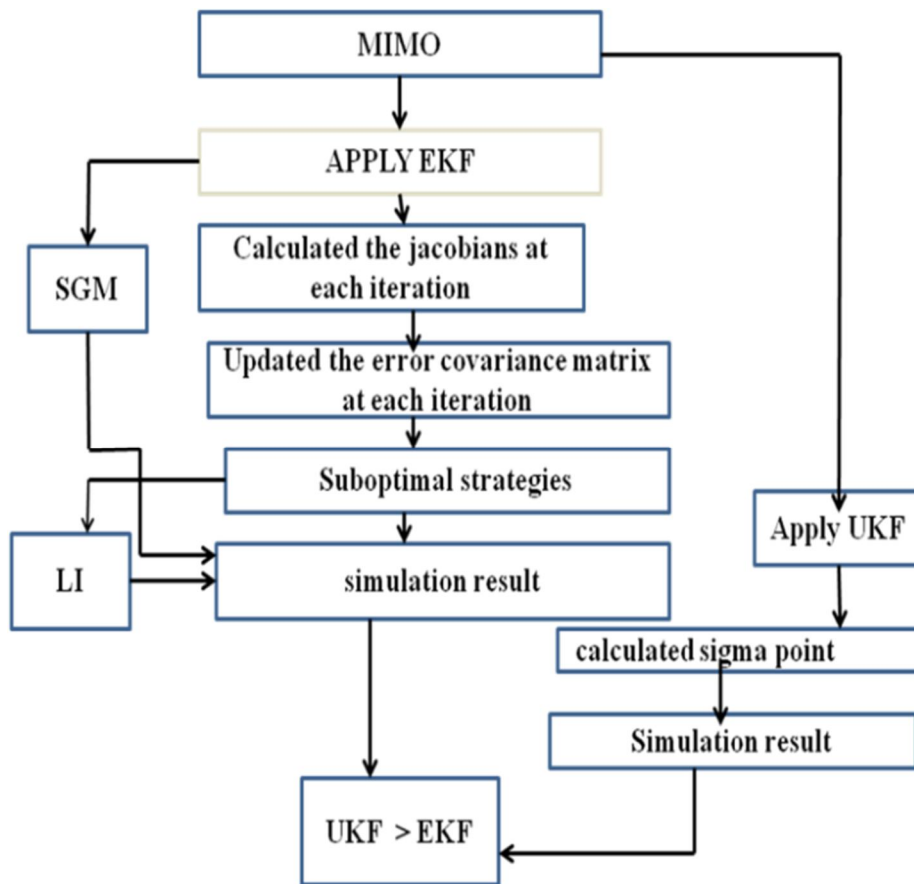


Fig.5. Algorithm for UKF

PARAMETERS	VALUES
Channel size	128
Number of bits per OFDM symbols	52
Multi carriers	5000
Number of data subcarriers	52
Number of symbols	10 ⁴
P1	0.5/2.3
P2	0.9/2.3
P3	0.7/2.3
P4	0.2/2.3

VI. CONCLUSION

In this paper to overcome limitations of EKF, we are using unscented filter. UKF achieves better accuracy compared with EKF shown in the plot. Graph plotted between signal to noise ratio (SNR) and bit error rate (BER) in this plot we get higher performance at low BER values leads to the better performances. And in this we also implemented for the technique like SGM, Linear-interpolation, oscillators and KF. SGM gives the better performance compared with the other techniques. We have explained this performance of gain in a number of application domains such as state-estimation, and parameter estimation. The performance of UKF and EKF is analyzed in terms of Mean Square Error (MSE) and Bit Error Rate (BER). The performance is evaluated from the results of MSE and BER against Signal to Noise Ratio (SNR). The simulation is performed using MATLAB and hence the results show that the performance of UKF is superior.

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