IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834, p- ISSN: 2278-8735.
PP 30-34
www.iosrjournals.org

Calibration Of U-Tube Manometer Using Kalman Filter and ECKF

Pearly Jacob
Department of Electronics and Communication Engineering SNGCE, Ernakulam
pearlyjacob1@gmail.com

***Abstract**: A capacitive level sensor is used in the U-Tube Manometer to measure the level of the mercury in terms of capacitance. The sensor is used as part of an oscillator circuit which produces the sinusoidal signal. The abnormal data obtained from the system may cause noises and disturbances as well as affect the accuracy of calibration in the manometer. The Kalman filter and Extended Complex Kalman Filter (ECKF) algorithm are employed to suppress the abnormalities from minute capacitance change of measurements for promoting efficiency in frequency estimation and amplitude estimation of the distorted signal.*
***Keywords**- Kalman Filter, ECKF, Frequency Estimation, U-Tube Manometer, LabVIEW.*

I. INTRODUCTION

In a sinusoidal signal, frequency plays an important role since it is generally used to indicate the system operation state. It can be used as a base for estimating other parameters such as amplitude and phase of the signal. Various estimation methods have been proposed such as Discrete Fourier transforms [1], Prony's Estimation [2], Least Square Error technique [3], adaptive notch filters and multiple frequency tracker [4], recursive Newton- type algorithm [5], Kalman filtering [6], a new variant of the extended Kalman filter [7]. In these methods, the higher order terms in the Taylor's expansion were neglected. Therefore, frequency estimation of distorted signals may occur incorrectly or take longer time to converge and even diverge.

A complex form of state variables has been considered to be applied to the extended Kalman filter [8] for frequency estimation of corrupted signals with higher noises. However, in practice the real and imaginary signals cannot be obtained simultaneously. Therefore, the signal model has been modified and the output equation is rewritten to calculate the real signal.

II. SIGNAL MODEL

An observation signal y_k at time t_k be a sum z_k of M sinusoids with white noise v_k

$$y_k = z_k + v_k \qquad k = 1,2,3,\dots,N \tag{1}$$

where

$$zk = \sum_{n=1}^{M} a_n \sin(w_n t_k + \emptyset_k) \tag{2}$$
$$w_n = 2\pi f_n \tag{3}$$
$$t_k = kT_s \text{ ,Ts is the sampling time} \tag{4}$$

The signal in (2) can be simplified and represented as a complex type, i.e.,

$$z_k = a_1 \sin(k\omega_1 T_s + \emptyset_1) = (-0.5i)\left(a_1 e^{j(kw_1 T_s + \emptyset_1)}\right) + (0.5i)\left(a_1 e^{-j(k\omega_1 T_s + \emptyset_1)}\right) \tag{5}$$

where
ω_1 fundamental of angular frequency
ϕ_1 fundamental of phase angle
a_1 fundamental amplitude of the signal

The complex types of state variables are described to represent the state variable x_k of a time varying single sinusoid signal. The measured value of the signal can be written as

State equation : $x_k = f(x_{k-1})$ (6)

Measurement equation : $y_k = h(x_k) + v_k$ (7)

A. *ECKF for frequency estimation*

The ECKF is suitable for describing state variables. The ECKF is divided into state prediction and state filter. The former performs prediction processing with reference to the history data and latter is used to find the optimal estimate.

State Prediction

$$\tilde{x}_k = f(\hat{x}_{k-1}) \quad (8)$$

Predicted error covariance

$$M_k = F_k P_{k-1} {F_k}^{*T} + Q_k \quad (9)$$

where

$$F_k = \frac{\partial f(\hat{x}_{k-1})}{\partial \hat{x}_{k-1}} \quad (10)$$

In (8), the symbols ~ and ˆ stand for the predicted and estimated values, respectively.

State filter

$$\hat{x}_k = \tilde{x}_k + K_k(y_k - H\tilde{x}_k) \quad (11)$$

Kalman gain K_k

$$K_k = M_k H^{*T}[HM_k H^{*T}]^{-1} \quad (12)$$

The filtered error covariance Pk for updating the estimation is written as

$$P_k = M_k(1 - K_k H) \quad (13)$$

where

$y_k - H\tilde{x}_k$ innovation vector

III. METHODOLOGY

The overall block diagram of the project is shown in the Fig. 1. When pressure is applied to one leg of the U-Tube Manometer, there is change in level of mercury. To one leg of the manometer, capacitor plates are placed which measures the change in mercury level. The measured capacitance is given to the capacitance frequency converter. The capacitance to frequency converter converts the capacitance value into frequencies which are given to LabVIEW through DAQ. The counter counts the frequencies change and stores the values. The output of the counter is given to the frequency estimator which estimates the frequency to calibrate the manometer

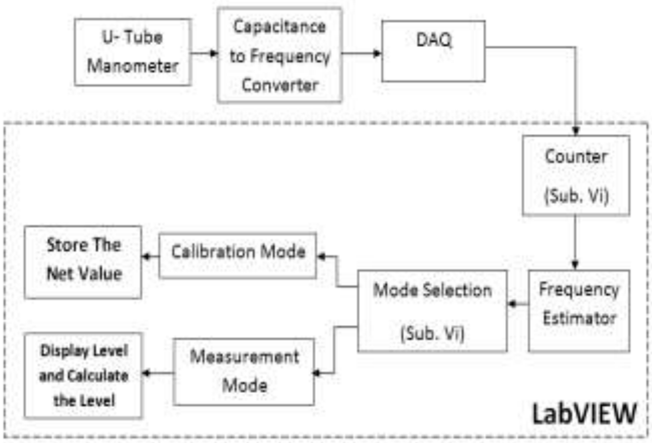

Figure 1. Block Diagram

The mode selection sub.vi has two modes such as calibration mode and measurement mode. In the calibration mode, training is done for level and the corresponding frequency values from the counter sub.vi. The trained values are stored in MATLAB file. These trained values are used in the measurement mode and the level is obtained for the intermediate values. Finally the calculation is done to find the pressure of the corresponding level.

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IV. FREQUENCY ESTIMATOR

The frequency estimator is used to estimate the frequency of the signal. The algorithm used to estimate the frequency and amplitude are Kalman filter and ECKF. As the frequency varies for each level of mercury, it is been counted by the counter sub vi and stored. The stored frequencies are estimated using the frequency estimation techniques.

A. Kalman Filter

The Kalman Filter is a recursive prediction algorithm to remove high gain noise in a signal or system. Mathematically, the filter estimates the states of a linear system. The gain, noise covariance and prediction covariance are assumed initially. Using these values, the Kalman gain has been calculated and it predicts the estimated value to update the covariance's.

B. ECKF

The ECKF simultaneously estimates the complex sinusoidal signal and its frequency corrupted by white noise. The state space representation of the distorted sinusoidal signal has been modeled under the assumption that the number of sinusoids are known. The system is to be linearized to apply ECKF to generate a nonlinear recursive filter for estimating a single complex sinusoid and its frequency in white noise. Therefore, the Kalman gain K_k and the covariance matrix P_k depend on the estimate of state filter.

V. MATLAB AND LABVIEW SIMULATION

A. Matlab Simulink Model

The process identification has been done to obtain the state transition matrix, the process noise covariance matrix and the measurement matrix. These values are loaded into the Kalman filter block parameter to estimate the sine wave corrupted with Gaussian noise generator as shown in the Fig.2.

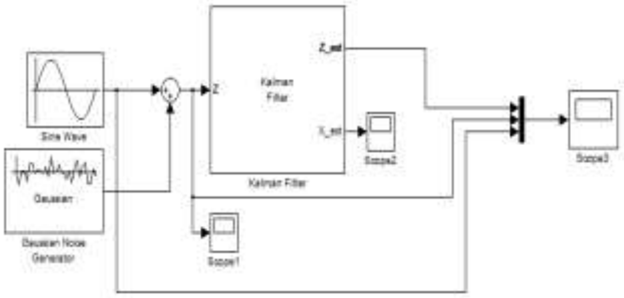

Figure 2. Kalman Filter

The amplitude of the distorted signal has been reduced from 3 V to 2V. The faster tracking of frequency is limited to 40 Hz at the lower end and 60 Hz at the higher end. The output estimated measurement of the Kalman filter is shown in the Fig.3.

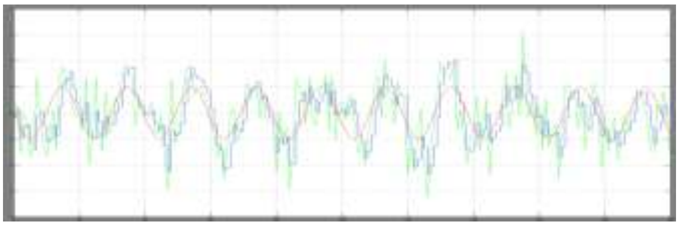

Figure 3. Output Estimated Measurement

B. Change In Amplitude .

The second case is one where there is a sudden change in amplitude. The simulation has been performed in LabVIEW where the amplitude can changed as per user's constraint. The output of the Kalman filter algorithm with change in amplitude is portrayed in Fig.4. During the change in amplitude, oscillations were exhibit in the frequency.

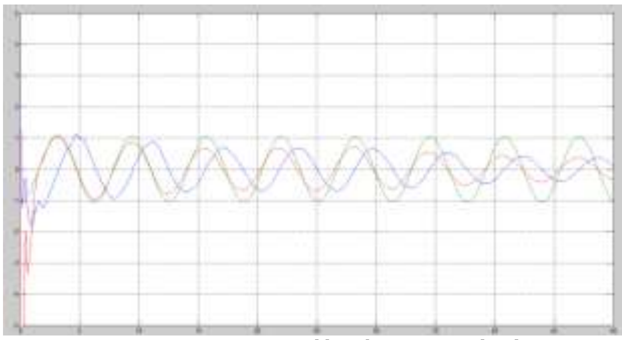

Figure 4. Sudden change in amplitude

C. Change In Frequency and Amplitude

Since oscillations were present in the frequency as mentioned above, we consider ECKF algorithm to observe the frequency and amplitude estimation. The desired amplitude are set to 1 V and the frequency to 0.5Hz. When the frequency and amplitude is varied randomly, there is a variation in the estimation. The amplitude was varied from 2V to 1V is shown in the Fig. 5 and the frequency was varied from 0.04 Hz to 0.08 Hz.

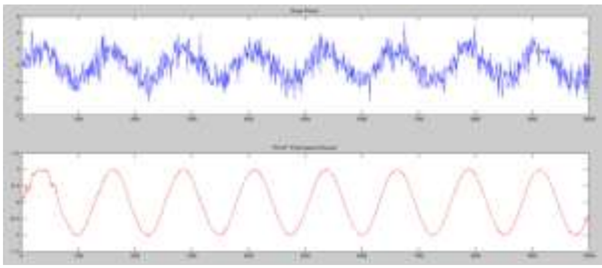

Figure 5. Amplitude estimation using ECKF

As the amplitude varies, there is a little oscillation in frequency and the tracking of the frequency is faster which settles at the desired frequency as depicted in Fig.6.

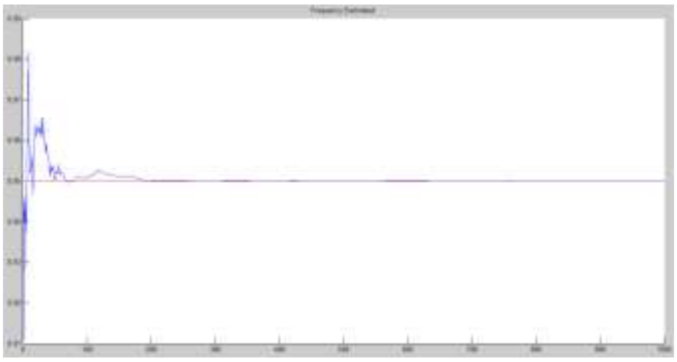

Figure 6. ECKF Frequency estimation

VI. CONCLUSION

This Paper examines both the amplitude and frequency approximation of the distorted signal using Kalman filter and ECKF algorithm. The hysteresis method are used to reset the covariance matrix, which enables fast tracking of frequency. The ECKF offers better performance with less number of oscillation when compared to Kalman filter algorithm. The computation of the filter is less which is more suitable for real time implementation. This approach is to found to be very stable and yields a significant frequency estimation accuracy of the order of 0.04 - 0.05 Hz in the presence of noise, less than 50 dB. The obtained results indicate that the algorithm works very well for step changes and decay or rise in the system.

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