KALMAN FILTER: An Optimal Estimator – A Tracker Development Approach

A Dissertation submitted

By Pooja Archana

to

Department of Electronics and Communication Engineering

In partial fulfilment of the Requirement for the
Award of the Degree of

Master of Technology in Electronics and Communication Engineering

Under the guidance of
Asst. Prof. Gunjan Gandhi

LOVELY PROFESSIONAL UNIVERSITY
PHAGWARA, PUNJAB
MAY-2015

CERTIFICATE

This is to certify that Pooja Archana bearing Registration no. 11305390 has completed thesis titled, **"Kalman Filter: An Optimal Estimator-A Tracker Development Approach"** under my guidance and supervision. To the best of my knowledge, the present work is the result of her original investigation and study. No part of the thesis has ever been submitted for any other degree at any university.

The thesis is fit for submission and the partial fulfilment of the conditions for the award of M.Tech.

Signature and Name of the Research Supervisor

Designation

Lovely Professional University

Phagwara, Punjab

Date:

Examiner 1 Examiner 2

ACKNOWLEDGEMENT

It is with great satisfaction and pride that I present my dissertation on the topic **Kalman Filter: An Optimal Estimator-A Tracker Development Approach**, for partial fulfilment of my Master of Technology degree at LPU Phagwara.

I would like to thank LPU Phagwara for giving me the opportunity to use their resources and work in such a challenging environment. First and foremost I take this opportunity to express my deepest sense of gratitude to my guide **Asst. Prof. Gunjan Gandhi**, for his able guidance during my dissertation work. This project would not have been possible without his help and the valuable time that he has given me amidst of his busy schedule. I am also very much grateful to my parents and my elder sister without their constant encouragement and motivation it could not be possible.

Last but not the least I would like to thank Almighty God and my friends and roommates who have been very cooperative with me throughout my work.

DECLARATION

I, Pooja Archana, student of M.Tech (ECE) under guidance of Asst. Prof. Gunjan Gandhi of Lovely Professional University, Phagwara hereby declare that all the information furnished in this dissertation report is based on my own intensive research and is genuine. To the best of my knowledge, the matter embodied in this dissertation report has not been submitted to any other university/institute for the award of any degree or diploma.

Date: Pooja Archana

Reg no. 11305390

ABSTRACT

Tracking of maneuvering target is an important area of research with wide application may be in military or civilian domains etc. Constant gain Kalman filter is performing good in this area but still outstanding performance is not obtained. Though constant gain Kalman filter is better than traditional Kalman filter as this filter seeks to work directly with gains instead of the state and measurement noise covariance. A lot of uncertainties can also be removed by this method but still detection of target is not accurate. This problem is overcome by implementation of extended Kalman filter which works very well with nonlinear cases giving a very good result. Extended Kalman filter is modified version of Kalman filter having some extra features which helps us to track maneuvering target. First of Kalman Filter using different models are simulated and then extended Kalman filter is implemented. Simulation shows that the target is tracked more accurately by the extended Kalman filter and also this filter is highly suitable for nonlinear cases for maneuvering target. Now-a-days estimation or detection of any target is very important as it gives us the idea about the outcome. Tracking is a challenge for maneuvering target just because of the presence of noise which corrupts the signal and makes our detection poor. So all the noise should be filtered out properly for the exact position of the target. Wireless communication is very much affected by the noise whether it may be Gaussian noise or thermal noise or may be any type of noise. So noise should be dealt with great care. All the initial parameters of the Kalman filter should be set very accurately to start the system and later on these are updated while the new signals are coming and finally optimal point is received which gives the exact position or location of the target. For proper detection of the target various estimation techniques are developed, some proved well while some like LMS, RMS suffer from some drawbacks like computational complexity, higher convergence rate etc, Kalman filter is a very good estimator as it is recursive in nature and it not only gives the idea of present and past state of the target but also future state. Just because of several advantages it is widely used in electronics and communication companies. Extended Kalman filter is also easy to design having many parameters similar to Kalman filter. The major two steps are initialize and update. As new measurements are coming older one is updated according to the new measurement and like this filter reaches to the exact position of the target minimizing the errors.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

APA	Affine Projection Algorithm
DWNA	Discrete White Noise Acceleration
DWPA	Discrete Wiener Process Acceleration
CT	Coordinated Turn
EA	Evolutionary Algorithm
EKF	Extended Kalman Filter
FIS	Fuzzy Interference system
GKF	General Kalman Filter
HC	Colour Histogram
HOG	Histogram of Orientation Gradient
HOGC	Histogram of Orientation Gradient and Colour
MTT	Multi Target tracking
MTT	Multi Target tracking
K.F	Kalman Filter
RFID	Radio Frequency Identification
SIFT	Scale Invariant Feature Transform
UWB	Ultra Wideband

Chapter 1

INTRODUCTION

1.1 Kalman Filter

In Kalman filter, filtering means actually estimating the state vector at the present time which is based upon the past observed data. On the other hand prediction is estimating the state vector at the future time [1]. Kalman filter forms the basis of most state estimation algorithms. We use this state estimation just because it is the key for obtaining the best possible navigation solution from the various measurements available with us. Kalman filter uses all the measurement informations that are input to it over time, not just the most recent set of measurements. It is actually an estimation algorithm, rather than a filter. It also maintains real time estimates of a number of parameters. Estimates are updated using a series of measurements that are subject to noise. It uses knowledge of the deterministic and random properties of system parameters and the measurements for obtaining the optimal estimates of the information available. It is also called Bayesian estimation technique.[1]

For the real time applications, such as navigation, the recursive approach is more processor efficient, as only the new measurements data need to be processed on each iteration. We can discard the old measurement data [1]. The Kalman filter is also called a tool for estimating the variables of a wide range of processes. In mathematical terms we can say that a Kalman filter estimates the states of a linear system. The Kalman filter not only works well in practice, but it is theoretically attractive too because it can be shown that of all possible filters, it is the one that minimizes the variance of the estimation error. Kalman filters are often implemented in embedded control systems because in order to control a process, we first need an accurate estimate of the process variables [1]. For enabling optimal weighting of the data, a Kalman filter maintains a set of uncertainties in its estimates and a measure of the correlation between errors in the estimates of different parameters. This is carried forward from iteration to iteration alongside the parameter estimates. Non-recursive estimation algorithms derive their parameter estimates from whole set of measurement data without any prior estimates. [1]

1.2 Following are the elements of Kalman filter:-

1) **State vector:-** It is a set of parameters which describe a system, known as states, which the Kalman filter estimates. Each state may be constant or may be time varying. For many navigation applications, the state includes the components of position or position error. Velocity, altitude and navigation sensor error states may also be estimated.

   Along with the state vector there is an error covariance matrix which represents the uncertainties in the Kalman filter's state estimate and degree of correlation between errors in those estimates. This correlation information within the error covariance matrix is important for the following 3 reasons.

   a) It enables the error distribution of the state estimates to be completely represented.
   b) There is not always sufficient information from the measurement to estimate the Kalman filter states independently. The correlation information enables estimates of linear combinations of these states to be maintained while awaiting further measurement information.
   c) Correlations between errors can build up over the integral between measurements. Modeling this can enable us to determine one from the another.

   As the Kalman filter is an iterative process, so the initial values of the state vector and covariance matrix must we need to set or determined from another process.[2]

2) **System model:-** This model is also called the process model or time propagation model which describes how Kalman filter states and error covariance matrix vary with time.

   Example- A position state will vary with time as integral of a velocity state, the position uncertainty will increase with time as the integral of velocity uncertainty, the position and velocity estimation errors will become more correlated. The system model is deterministic for the states, as it is based on known properties of the system.

   A state uncertainty should also be increasing with time to account for unknown changes in the system which causes the state estimate to go out of data in the absence of new measurement information. These changes may be unmeasured dynamics or random noise on an instrument output.[2]

   Example- A velocity uncertainty must be increasing over time if acceleration is unknown. This variation over the true values of the states is called as **system noise or process noise** and its assumed random properties are usually defined by K.F designer.

3) **Measurement vector:-**It is a set of simultaneous measurements of properties of system which are functions of state vector.

Along with the measurement vector is a measurement noise covariance matrix that describes the statistics of noise on the measurement. For many applications, new measurement information is input to K.F at regular intervals. But in some other cases the time interval between measurements can be irregular.[2]

4) **Measurement model :-** It describes how the measurement vector varies with the function of true state vector in the absence of measurement noise [2].

The Kalman filter is a set of mathematical equations which provides us an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error. The filter is very powerful in various aspects: it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown to us.

5) **Kalman Filter Algorithm:-**The Kalman Filter estimates a process simply by using feedback control like form. The operation may be described as the process is estimated by the filter at some particular point of time and the feedback is obtained in the form of noisy measurements. The Kalman filter equations can be divided into two categories: time update equations and measurement update equations. To obtain the a priori estimates for the next time step the time update equations project forward (in time) the current state and error covariance estimates. The measurement update equations get the feedback to obtain an improved *a* posteriori estimate which incorporates a new measurement into the a priori estimate.[3]

1.3 System Model

Discrete time linear systems are generally represented in a state variable format given by the expression:

$$x_j = ax_{j-1} + bu_j \qquad [1]$$

where;

$x_j =$ state (scalar); a,b=constant; u_j=input; j=time variable.

Now imagine some noise is added.

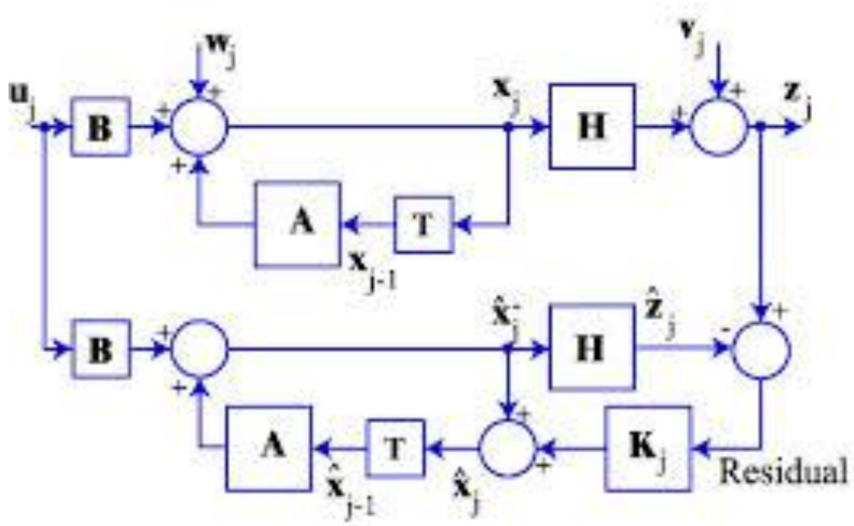

Fig. 1.1-System model of Kalman Filter [3]

If some noise is added to the process such that:

$$x_j = ax_{j-1} + bu_j + w_j \qquad [2]$$

Here the noise, w, is white noise source with zero mean and covariance Q and is uncorrelated with the input.

Let us assume that the signal x is measured, and the measured value is z.

$$z_j = hx_j + v_j \qquad [3]$$

The measured value z depends on the current value of x, as determined by the gain h. Along with this measurement it has its own noise, v, associated with it. The noise, v, is the white noise source with zero mean and covariance R which is uncorrelated with the input or with the noise w. The two noise sources are independent of each other and independent of the input. The original estimate of x_j is now called $\hat{x}_j$,we refer to this as the a priori estimate [3][4][5][6].

$$\hat{x}_j^- = a\hat{x}_{j-1} + bu_j \quad [4]$$

We use this a priori estimate to predict an estimate for the output, $\hat{z}_j$. The difference between this estimated output and the actual output is called the residual, or innovation.

$$Residual = z_j - \hat{z}_j \quad [5]$$

If the residual is small, it generally means we have a good estimate; if it is large the estimate is not so good, we can use this information to improve our estimate of x_j; we call this new estimate the a posteriori estimate $\hat{x}_j$.

If the residual is small, so is the correction to the estimate. As the residual grows, so does the correction. The relevant equation from block diagram 1.1 is

$$\hat{x}_j = \hat{x}_{j-1} + k \text{ (residual)} \quad [6]$$

The only task now is to find the quantity k that is used to improve our estimate, and it is this process that is the heart of Kalman filtering. We are trying to find an optimal estimator and thus far we are only optimizing the value for the gain k.

For finding k, first of all we need to define the errors of our estimate. There will be two errors, an a priori error, e_{j-1}, and an a posteriori error, e_j each one is defined as the difference between the actual value of x_j and the estimate.[6]

$$e_{j-1} = x_j - \hat{x}_{j-1} \quad [7]$$

$$e_j = x_j - \hat{x}_j \quad [8]$$

Along with these errors is a mean squared error, or variance:

$$p_j^- = E\{(e_j^-)^2\} \quad [9]$$

$$p_j = E\{(e_j)^2\} \quad [10]$$

A Kalman filter minimizes the a posteriori variance, p_j, by suitably choosing the value of k.

$$p_j = E\{(x_j - \hat{x}_j)^2\} \quad [11]$$

$$p_j = E\{(x_j - \hat{x}_j^- + k(z_j - hx_j^-))^2\} \quad [12]$$

To find the value of k that minimizes the variance we differentiate this expression with respect to k and set the derivative to zero.

$$\frac{\delta p_j}{\delta k} = 0 \quad [13]$$

$$= \frac{\delta E\{(x_j - \hat{x}_j^- + k(z_j - h\hat{x}_j^-))2}{\delta k} = 0 \quad [14]$$

$$k = hp_j^- / h^2 p_j + R \quad [15]$$

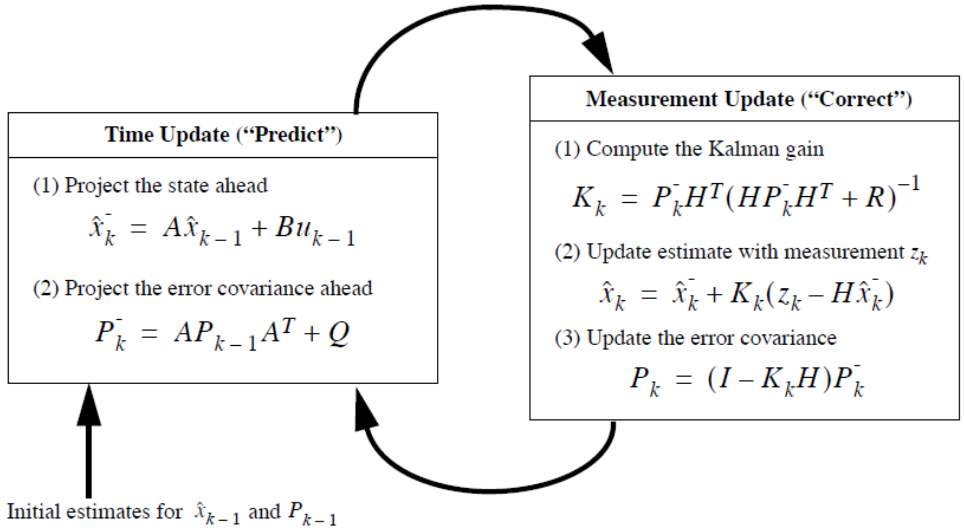

Fig. 1.2 A complete picture of the operation of the Kalman filter [7]

1.4 Application of Kalman Filter includes:-

1) Tracking objects (e.g., balls, faces, heads, hands)
2) Channel estimation.
3) Orbit determination
4) Navigation
5) Structural health monitoring
6) Weather forecasting
7) Radar Tracker etc.

1.5 Extended Kalman Filter

Extended Kalman Filter which comes in the field of estimation theory, is actually the nonlinear version of the Kalman Filter which linearizes about an estimate of the current mean and covariance. It is also considered de facto standard in the theory of nonlinear state estimation, navigation system and GPS.[8]

1.6 Formulation of EKF [8]

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1} \quad [16]$$

$$z_k = h(x_k) + v_k \quad [17]$$

where;

w_k=process noise

v_k=observation noise

u_k=control vector

Both these noises are assumed to be zero mean multivariate Gaussian noises with covariance Q_k and R_k respectively.

Here f and h are the two functions which are used to compute the predicted state from the previous estimate and similarly the function h can be used to compute the predicted measurement from the predicted state. However, f and h cannot be applied to the covariance directly. A partial derivatives (the Jacobian) matrix is computed. Jacobian is evaluated at each time with current predicted states. In the Kalman Filter equation these matrices can be used. This process linearizes the non-linear function around the current estimate.

Discrete-time predict and update equation

Predict

Predicted state estimate

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k-1}) \quad [18]$$

Predicted covariance estimate

$$P_{k|k-1}=F_{k-1}P_{k-1|k-1}F_{k-1}^{T}+Q_{k-1} \quad [19]$$

Update

Innovation or measurement residual

$$\hat{y}_k=z_k\text{-h}(\hat{x}_{k|k-1}) \quad [20]$$

Innovation (or residual) covariance

$$S_k=H_k P_{k|k-1}H_k^T+R_k \quad [21]$$

Near-optimal Kalman gain

$$K_k=P_{k|k-1}H_k^T S_k^{-1} \quad [22]$$

Updated state estimate

$$\hat{x}_{k|k}=\hat{x}_{k|k-1}+K_k\hat{y}_k \quad [23]$$

Updated covariance estimate

$$P_{k|k}=(\text{I-}K_k H_k)P_{k|k-1} \quad [24]$$

Where the state transition and observation matrices are defined to be the following Jacobians

$$F_{k-1}=\frac{\delta f}{\delta x}|x_{k-1|k-1},u_{k-1} \quad [25]$$

$$H_k=\frac{\delta h}{\delta x}|\hat{x}_{k|k-1} \quad [26]$$

1.7 Constant Gain Kalman Filter

It is a type of Kalman Filter which seeks to work only with the gains instead of the state and measurement noise covariance. This filter solves the problems associated with using a Kalman Filter for tracking a maneuvering target with unknown system and measurement noise statistics. This filter also decreases the computational complexity of the system. Constant gain Kalman filter is a better approach than other estimation techniques like Least Mean Square (LMS) and Root Mean Square (RMS). The problems associated with the conventional estimation techniques are higher computational complexity, higher convergence rate etc. Estimations received by these techniques are also not so much accurate ad also not matches with the actual position of the target. A constant gain Kalman filter tracks maneuvering targets using different models like Discrete White Noise Acceleration (DWNA) model and Discrete Weiner Process Acceleration (DWPA) model. But the outcome is still not so well to rely upon it completely because even a small change in position can affect a lot. To over this problem extended Kalman filter is used along with the constant gain Kalman filter for fine and accurate location of the target. In this filter once the optimum value of gain has been determined there is no use of employing R (measurement noise covariance which describes noise which is assumed to be white and may be correlated), Q (process covariance matrix which describes process noise added at each measurement. This is the clock noise), P (parameter covariance matrix which describes uncertainties in the state vector estimates. P^{+} and P^{-} is the matrix after and before the measurement update. [9]

1.8 Motivation

Tracking of maneuvering targets is an important area of research with applications in both the military and civilian domains. One of the most fundamental and widely used approaches to target tracking is the Kalman filter and the most significant problem in target tracking is state estimate. In presence of unknown noise statistics there are difficulties in the Kalman filter yielding acceptable results. In the Kalman filter operation for state variable models with near constant noise and system parameters, it is well known that after the initial transient the gain tends to a steady state value. Hence working directly with Kalman gains it is possible to obtain good tracking results dispensing with the use of the usual covariance. In the multi sensing environment, some noisy signals are obtained along with the desired signal which corrupts the data because of the changing surroundings. But we need to obtain correct data. Though there are so many algorithms to combat the problem but they have some problems like high convergence rate, computational complexity. So some other techniques should be developed that fulfill the need to accurately measure and predict the correct position of the object even if the object is not directly accessible to the GPS or other similar devices.
For example if the object is passing through the tunnel.

- Now-a-days communication systems are facing a lot of problems in getting the accurate position of any object whether stationary or non-stationary due to increasing congestion, noise etc.
- Some estimation techniques like LMS, RMS have computational complexity and high rate of convergence.

1.9 Organization of report

Chapter 2 discuss about literature review that is work done in the past. Rationale and scope of the study has been discussed in chapter 3. Chapter 4 contains objective of the study. Materials and research methodology is discussed in chapter 5. Chapter 6 consists of results and discussion. Experimental work and performance evaluation have also been discussed in this section. Conclusion and future scope have been discussed in the chapter no. 7. Last but not the least list of references, bibliography and appendix have been discussed after chapter 7.

1.10 Terminology

1) State estimation—It is the key which is used to obtain the best possible navigation solution from the various measurements available and Kalman filter uses all the measurement information input to it over time, not just the most recent set of measurements to track the target.[10]
2) State vector (x_t)—This is actually a set of parameters describing a system, known as states, which the Kalman filter estimates. Each state may be constant or time varying. For most navigation applications, the state consists of the components of position or position error velocity, altitude and navigation sensor error states may also be estimated.[10]
3) Error covariance matrix—This is associated with state vector which represents the uncertainties in the Kalman filter's state estimate and degree of correlation between errors in those estimates.[10]
4) System model—This is also called process model or time propagation model which describes how Kalman filter states and error covariance matrix vary with time.[10]
5) Measurement vector—This vector is a set of simultaneous measurements of properties of system which are function of state vector. This is actually the information from which all of the state estimates are derived after initialization.[10]
6) Measurement noise covariance matrix (R)— It is associated with measurement vector which is a set of simultaneous measurements of properties of system which are function of state vector. This matrix actually describes the statistics of noise on the measurements. For many applications new measurement information is input to Kalman filter at regular intervals. In other cases the time interval between measurements can be irregular.[10]
7) Measurement model—This model describes the measurement vector which varies as a function of true state vector in the absence of measurement noise.[10]
8) Parameter covariance matrix (P)—This describes the uncertainties in the state vector estimates. P^+ and P^- is the matrix after and before the measurement update.[10]
9) Process covariance matrix (Q)—This matrix describes process noise added at each measurement. This is the clock noise.[10]

10) State Transition Matrix (F_t)– This matrix applies the effect of each system state parameter at time t-1 on the system state at time t. For example the position and velocity at time t-1 both affect the position at time t. [10]

11) Control vector (u_t)—Vector containing any control input (steering angle, braking force).

12) Control input matrix (B_t)—This applies the effect of each control input parameter in the vector u_t on the state vector. Example- applies the effect of the throttling setting on the system velocity and position[10].

13) Process noise vector (w_t)—Vector containing the process noise terms for each parameter in the state vector.[10]

14) Measurement vector (z_t)—Consists of vector of measured values

15) Measurement noise vector (v_t)—This is a vector containing the measurement noise terms for each observation in the measurement vector.[10]

Chapter 2

REVIEW OF LITERATURE

This section includes related work done in the past

2.1 Related Work

In [11] a method for tracking multiple moving humans with the help of Ultra-Wideband (UWB) radar is shown. UWB radar can complement other human tracking technologies in the form that it works well in poor visibility conditions. In this research paper tracking approach is shown as a point process interpretation of the multi-path UWB radar scattering model for moving humans. Based on this model, a multiple hypothesis tracking (MHT) framework is shown for tracking the ranges and velocities of a variable number of moving human targets. The multi-target tracking (MTT) problem for UWB radar differs from traditional applications just because of the complex multipath scattering observations per target. Finally in this paper MHT framework is introduced for UWB radar-based multiple human target tracking, which can simultaneously solve the complex observation clustering and data association problems with the help of Bayesian inference.

In [12] paper an algorithm is proposed to project the trajectory of any moving object using Kalman Filters. An algorithm is developed which fulfills the need to accurately measure and predict the correct position and velocity. The approach which is used in this paper includes using an initial estimated position and then recursively calling the Kalman Filter equations to reduce the error in position and velocity and correctly predict the position and velocity. After successive recursions the predicted and actual trajectories are found to be nearly the same with a very low margin for error.

In [13] an improved Kalman filter method is introduced to reduce noise and obtain correct data. Performance of Kalman Filter is determined by a measurement and system noise covariance which are usually called the R and Q variables in the Kalman filter algorithm. Choosing a correct R and Q variable is one of the most important design factors for better performance of the Kalman filter. For this reason in this paper an improved Kalman filter is improved to advance an ability of noise reduction of the Kalman filter. With this method, more accurate data can be obtained with smart RFID tags.

In [14] the use of Kalman filter methods to make optimum use of the incoming range and Doppler information in forming the track is introduced.

The [15] uses multiple independent object tracking algorithms as inputs to a single Kalman filter. A function to estimate each algorithm's error from related features is trained using linear regression. This error is used as the algorithm's measurement variance. With a dynamic measurement error covariance computed from these estimates, they attempt to produce an overall object tracking filter that combines each algorithm's best-case behavior while diminishing worst-case behavior. This filter is intended to be robust without being programmed with any environment-specific rules.

In [16] the neural extended Kalman filter (EKF) is applied simultaneously to three separate classes of targets each with different maneuver capabilities. The result shows that the approach is well suited for use within a tracking system without prior knowledge of the target's characteristics. An important benefit of the technique is its versatility because little if any a priori knowledge of the target dynamics is needed. This allows the neural extended Kalman filter to be used in a generic tracking system that will encounter various classes of targets.

In [17] investigates the performance of speaker verification system in mobile environment and the techniques used to improve the robustness of the verification system. The paper demonstrates by corrupting the speech signal with additive white Gaussian noise in simulated environment. A comparative study of the three front-end noise reduction techniques namely spectral subtraction, Wiener filter and Kalman filter have been made independently as well as combining spectral subtraction with other two methods alternatively and their performances have been evaluated for the clean speech as well as contaminated speech with different level of white Gaussian noise. It has been shown that spectral subtraction plays an important role in reducing low power Gaussian noise whereas Kalman filter is efficient in reducing noise when noise power is high. Wiener filter improves the performance at all levels of noise. No considerable performance improvement has been observed when spectral subtraction is combined with other two methods.

In [18] a combined feature is used which is a set of color histogram and histogram of orientation gradients, called histogram of color and orientation gradient, for object tracking. The combined feature set is the evolvement of color, edge orientation histograms and SIFT descriptors. In this paper SURF detector is shown as the best detector.

In [19] sensor nodes are stationary and they identify the movement of the person who has a valid RFID tag within their coverage area. When several people are close to the sensor node, the RFID reader may not interpret the tag correctly. Hence, there might be an ambiguity in sensing the location of the person. Also, when more than one sensor detects the same RFID tag, there is an ambiguity in determining the location of the person. The Kalman filter based prediction scheme proposed in this paper overcomes the above mentioned problems.

In [20] as electricity demand continues to grow and renewable energy increases its penetration in the power grid, real-time state estimation becomes essential for system monitoring and control. Recent development in phasor technology makes it possible with high-speed time-synchronized data provided by phasor measurement units (PMUs). In this paper, we present a two-stage Kalman filter approach to estimate the static state of voltage magnitudes and phase angles, as well as the dynamic state of generator rotor angles and speeds. Kalman filters achieve optimal

performance only when the system noise characteristics have known statistical properties (zero-mean, Gaussian, and spectrally white). However, in practice, the process and measurement noise

models are usually difficult to obtain. Thus, we have developed the adaptive Kalman filter with inflatable noise variances (AKF with InNoVa), an algorithm that can efficiently identify and reduce the impact of incorrect system modeling and/or erroneous measurements. In stage one, we estimate the static state from raw PMU measurements using the AKF with InNoVa; then in stage two, the estimated static state is fed into an extended Kalman filter to estimate the dynamic state. The simulations demonstrate its robustness to sudden changes of system dynamics and erroneous measurements.

In [21] development of a robust Kalman filter for uncertain stochastic systems under persistent excitation and unknown measurement model is presented. The given discrete-time stochastic formulation does not require the knowledge of any bounds on parametric uncertainties and excitations. When there are no system uncertainties, the performance of the proposed robust estimator is similar to that of the traditional Kalman filter and the proposed approach asymptotically recovers the desired optimal performance in the presence of uncertainties and/or persistent excitation.

In [22] Kalman filter is recognized as an outstanding tool for dynamic system state estimation, whose performance depends upon its parameter R called the measurement noise covariance matrix. But it is very difficult to get the exact value of R before starting up of the filter and also value of R keep on changing with the measurement environment when filter is in working mode. For solving this problem, a new parameter adaptive Kalman filter is proposed in this paper. In this case R is kept offline which is decided by Evolutionary A Algorithm and value of R is decided by EA is online updated by Fuzzy Interference System (FIS). The result based on target tracking is carried out and shows that the new adaptive Kalman filter proposed in this paper has a stronger adaptability to time-varying measurement noises than regular Kalman filter.

In [23] the Kalman filter which is called as the minimum variance state estimator for linear dynamic system with Gaussian noise. Not only this, even if the noise is non- Gaussian, the Kalman filter is the best linear estimator. But in the case of non-linear it is not possible, so some modifications are needed which include the unscented Kalman filter and the particle filter. Kalman filter and its modifications are powerful tools for state estimation, we might have information about a system that Kalman filter does not incorporate. If we take example then we may know that the states satisfy equality or inequality constraints. For this case, kalman filter is modified to exploit this additional information and get better filtering performance than the Kalman filter provides. This paper provides an overcome of various ways to incorporate state constraints in Kalman filter and its no-linear modifications. So if both the system and state constraints are linear, then all of these different approaches result in the same state estimate. If either the system or constraints are non-linear, then constrained filtering is not optimal and different approaches give different results.

In [24] comparison of two types of filtering methods are done for localization of an underwater robot: Kalman filter and particle filter are major filters for estimation of robot pose on the ground. These filters are used for underwater robot localization. Kalman filter is used for linear processes and measurement system while the particle filter can be used for non-linear cases also. Also the uncertainty of Kalman filter is restricted to Gaussian distribution, while the particle filter can deal with non-gaussian noise distribution. When sesor noise exhibits jerky error Kalman filter results in location estimation with hopping while particle filter still produces robot localization. The paper also compares he performance of these filters under various measurement uncertainty and process uncertainty.

In [25] Kalman filter is also known as very interesting signal processing tool, used in widely in many practical application. In this paper, Kalman filter is used in the context of echo cancellation. Contribution of this work is threefold. First of all different form of the Kalman filter is derived by considering, at each iteration, a block of time samples instead of one time sample as it is the case in the conventional approach. Secondly, general Kalman filter is shown which is connected with some of the most popular adaptive filters for echo cancellation i. e normalized Least Means Square algorithm, the affine projection algorithm and its proportionate version (PAPA), thirdly a simplified Kalman filter is developed to reduce the computational load of the general Kalman filter. This algorithm behaves like a variable step-size adaptive filter.

In [26] target tracking in wireless sensor network is discussed which is a very important area of research these days with applications in both the military and civilian domains. Kalman filter is also one of the most fundamental and widely used approach. Presence of noise creates problem in target tracking. After initial transients, gains tends to be steady state values. Using Kalman filter directly, it is possible to get good tracking results dispensing with the use of the usual covariance. Innovations based cost function minimization approach is used to target tracking problem in wireless sensor network. For obtaining the constant Kalman gain for both the stand-alone and data fusion modes. Numerical study show that the constant gain Kalman filter gives good comparative performance in both the stand-alone and data fusion modes for target tracking problem.

In [27] “Comparison of Cubature Kalman Filter and Unscented Kalman Filter is discussed. CKF has more stable performance and uses a third-degree spherical-radial cubature rule to numerically compute the integrals encountered in non-linear filtering problems. But third degree cubature rule-based filter is not accurate enough in many real-life applications. Spherical cubature formula which is used to develop the CKF has some demerits in computation, generally its inconvenient properties in high-dimensional state estimation problems. To overcome all these problems square root embedded cubature Kalman filter is proposed.

Chapter 3

RATIONALE AND SCOPE OF THE STUDY

3.1 Scope of the study

Kalman Filter plays a very important role in the field of tracking, whether it is object tracking, vision tracking, video tracking, target tracking etc. We study it for the accurate tracking of the object without any noise. It also gives the prediction of the object about its future location. More and more advancement in the conventional Kalman filter is taking place only due to its efficiency. Advanced version of Kalman filter are extended Kalman filter, constant gain Kalman filter. Unscented Kalman filter etc. all these versions of Kalman filter carry extra features in them which are proving really fruitful in the area of tracking. In some places exact position of the object is very2 essential to find out for many reasons. We need to have the correct position of the enemy objects for the safety of the people. For all these reasons and many more it has become the area of extensive research. The advantages of the Kalman filter over other estimation algorithm like LMS, RMS are less computational complexity, short equations, recursiveness, optimality etc. Kalman filtering was very popular in the research field of navigation and aviation because of its magnificent accurate estimation characteristic. Since then, electrical engineers manipulate its advantages to useful purpose in target tracking systems. Consequently, today it had become a popular filtering technique for estimating and resolving redundant errors involves in tracing the target.

The *Extended Kalman Filter* (EKF) has become a standard technique used in a number of nonlinear estimation and machine learning applications. These include estimating the state of a nonlinear dynamic system, estimating parameters for nonlinear system identification *(e.g.*, learning the weights of a neural network), and dual estimation *(e.g.*, the Expectation Maximization (EM) algorithm) where both states and parameters are estimated simultaneously. The UKF consistently achieves a better level of accuracy than the EKF at a comparable level of complexity. Kalman filter is used for the location of moving targets. For simplicity we use constant gain Kalman filter. In constant gain Kalman filter the gain becomes constant after the initial transients. Kalman filter is used in wireless sensor network. The Kalman filter is a very powerful tool when it comes to controlling noisy systems. Also with the help of Kalman filter we can project trajectory of any moving object. When a sensor network is used to track moving objects, the task of local data aggregation in the network presents a new set of challenges, such as the necessity to estimate, usually in real time, the constantly changing state of the target based on information acquired by the nodes at different time instants. To address these issues, we propose a distributed object tracking system which employs a cluster-based Kalman filter in a network of wireless cameras. When the senor measurements are nonlinear in the target state, Extended Kalman filtering is a commonly used method to deal with the nonlinearity. When data travel along unreliable communication channels in a large, wireless, multi hop sensor network, the effect of communication delays and loss of information in the control loop cannot be neglected. We address this problem starting from the discrete Kalman filtering formulation, and modeling the arrival of the observation as a random process.

This technique is used in radar 3-D tracking modeling, sensor networking, Multi sensor data fusion, chemical processing industries (process and error estimation), satellite imagery and communication, wireless networking.

Chapter 4

OBJECTIVES OF THE STUDY

4.1 Objective of the study

1) Develop an insight to provide better technique on target kinematics modeling

In this case, maneuvering target is tracked using various models like Discrete White Noise Acceleration (DWNA) model which is used for linear motion or non-maneuvering target. Discrete Wiener Process Acceleration (DWPA) model which is used for maneuvering target or jerk target. Jerk model, Coordinated Turn (CT) model. Though various types of models have been implemented but still the closeness between the estimated and actual measurements are not 100%. To overcome all these drawbacks an extended Kalman filter is also implemented in the second case, which is also very much suitable for non-linear case. Here we are dealing directly with the gain because after the initial transients the gain tends to be a steady state value. So there is no need to work with the state and measurement noise covariance.

2) Also to find better approach method to develop a generic model for minimization of error in process in various fields.

This is the improved version of the work done in the first case. In this apart from the work done earlier, some new technique has been added for better target detection. Along with the Kalman filter, improved version of Kalman filter that is extended Kalman filter has been added for detecting the maneuvering target precisely. Extended Kalman filter is implemented along with the Kalman filter implementation. Implementation is done taking into the consideration constant gain. In this case we are getting the result with more accuracy and more closely.

Chapter 5

MATERIALS AND RESEARCH METHODOLOGY

5.1 Initialization of Kalman matrices

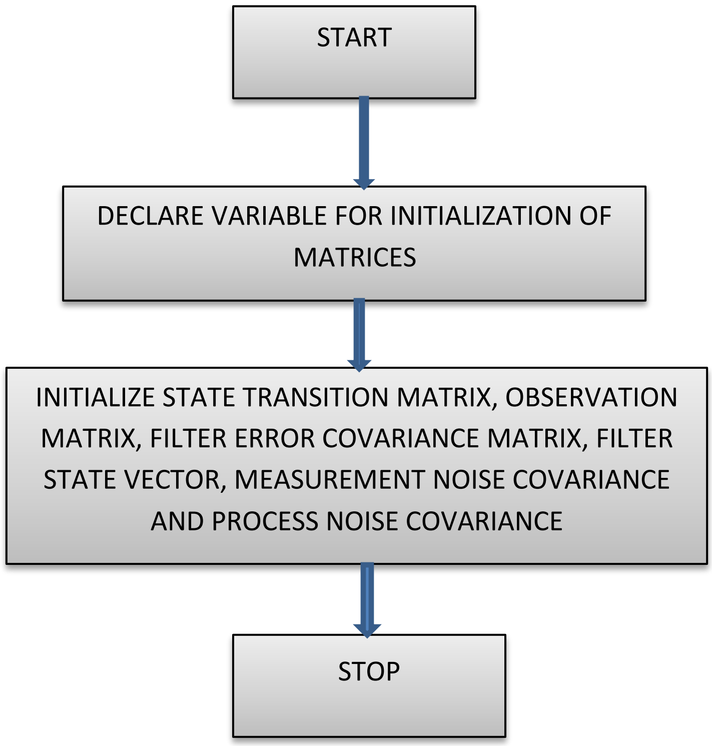

Fig. 5.1-Flow Chart for Initialization of Kalman Matrices

For the initialization of Kalman filter we set the initial values of the parameters of Kalman filter as mentioned in the flow chart like state transition matrix, observation matrix, filter error covariance, filter state vector, measurement noise covariance, and process noise covariance. According to the signals we are receiving from the target, we can change the initial values accordingly. The initial values should be set very carefully and within some range. A Kalman Filter is an iterative process, so the initial values of the state vector and covariance matrix must be set by the user or determined from another process.[7]

State Transition Matrix – This matrix applies the effect of each system state parameter at time t-1 on the system state at time t. For example the position and velocity at time t-1 both affect the position at time t.

Filter state vector – A set of parameters are described which is known as states, which the Kalman filter estimates. The state may be constant or time varying. For example in navigation applications, the state include the components of position or position error velocity, altitude and navigation sensor states may also be estimated.

Filter Error Covariance matrix- This matrix represents the uncertainties in the Kalman filter's state estimate and also the degree of correlation between errors in those estimates. The correlation information within the error covariance matrix is important because of the following reasons.

i) It enables the error distribution of the state estimates to be fully represented.

ii) There is not always enough information from the measurement to estimate the Kalman filter states independently. The correlation information enables estimates of linear combinations of those states to be maintained while awaiting further measurement information.

iii) Also correlations between errors can be built up over the intervals between measurements. Modeling of this can enable one state to be determined from another. For example velocity from a series of position.

Measurement noise covariance matrix- It is associated with measurement vector which is a set of simultaneous measurements of properties of system which are function of state vector. This matrix actually describes the statistics of noise on the measurements. For many applications new measurement information is input to Kalman filter at regular intervals. In other cases the time interval between measurements can be irregular.[2]

5.2 Update of Kalman filter equations

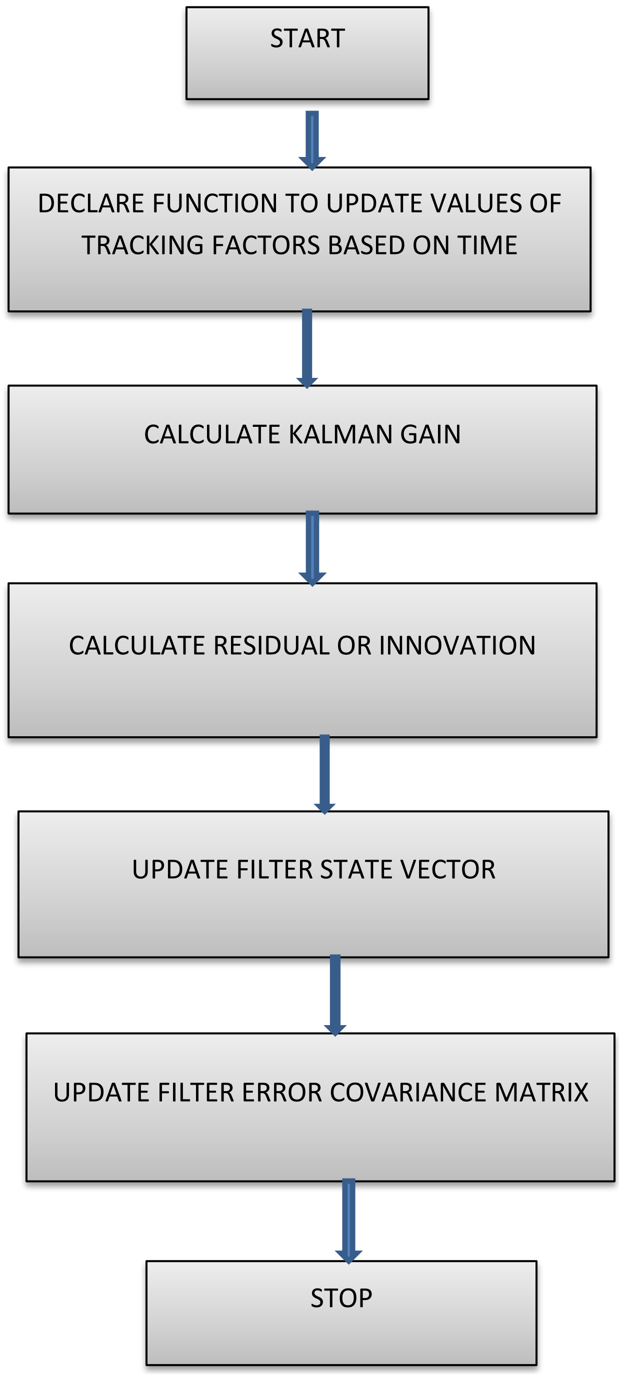

Fig. 5.2-Flow Chart for Kalman Filter Update Equation

To update the Kalman filter first of all we have to declare all the function that need to be updated each time we are getting new information.[7]

For this case we need to define Jacobian matrix, error jacobian matrix, a priori state, posteriori state. After that Kalman gain is updated. All the matrix which are defined earlier are updated along with all types of error. All the previous state which are initialized are also updated. After the update step we reach at an optimal point where we get the actual position of the target filtering out the noises.

Chapter 6

RESULTS AND DISCUSSION

6.1 Experimental work

Constant Gain Kalman Filter is implemented using MATLAB: DWNA model

Constant Gain Kalman filter is implemented using MATLAB: DWPA model

Gain K and error covariance matrix P is implemented using MATLAB

Extended Kalman Filter is implemented using MATLAB

Equations used:

State-error Jacobian

W=1 0; 0 0

Measurement- state Jacobian

H=1 0; 0 1

Measurement-error Jacobian

V=1 0; 0 1

No. of iterations =1000

True state

x=zeros(2,N)

A priori state estimate

x_apriori=zeros(2,N)

A posteriori state estimate

x_aposteriori=zeros(2,N)

A priori error covariance estimates

P_apriori=zeros(2,2,N)

A posteriori error covariance estimates

P_aposteriori=zeros(2,2,N)

Measurements

z= zeros(2,N)

Kalman gain

k=zeros(2,2,N)

True initial state

x(:,1)=0 3*pi/50

Initial a posteriori state estimate

x_aposteriori(: , 1)=1 1*pi/500

Process noise covariance

Q=0.001 0; 0 0

Measuremet noise covariance

R=0.1   0; 0 0.01

Initial a posteriori error covariance estimate

P_aposteriori (: , :, 1)=1 0; 0 1

Update true state

x(:, i)=[sin(x(2,i-1)*(i-1)); x(2,i-1)]+sqrt(Q)*[randn;randn]

update measurements

z(: , i)=x(: ,i)+sqrt(R)*[randn;randn]

update apriori estimate

x_apriori(; , i)=[sin(x_aposteriori(2,i-1)*(i-1));x_aposteriori(2,i-1)]

update state Jacobian

Ai=[0 (i-1)*cos(x_aposteriori(2,i-1)*i-1)); 0 1]

Update apriori error covariance estimate

P_apriori(:, :, i)=Ai*P_aposteriori(:,:,i-1)*Ai+W*Q*W

Update Kalman gain

k(:,:,i)=P_apriori(:,:,i)*H’/(H*P_apriori(:,:,i)*H’+V?*R*V’)

update aposteriori state estimate

x_aposteriori(:,1)=x_apriori(:,i)+k(:,:,i)*(z(:,i)-x_apriori(:,1));

update aposteriori error covariance estimate

P_aposteriori(:,:,i)=(eye(2)-k(:,:,i)*H)*P_apriori(:,:,i)

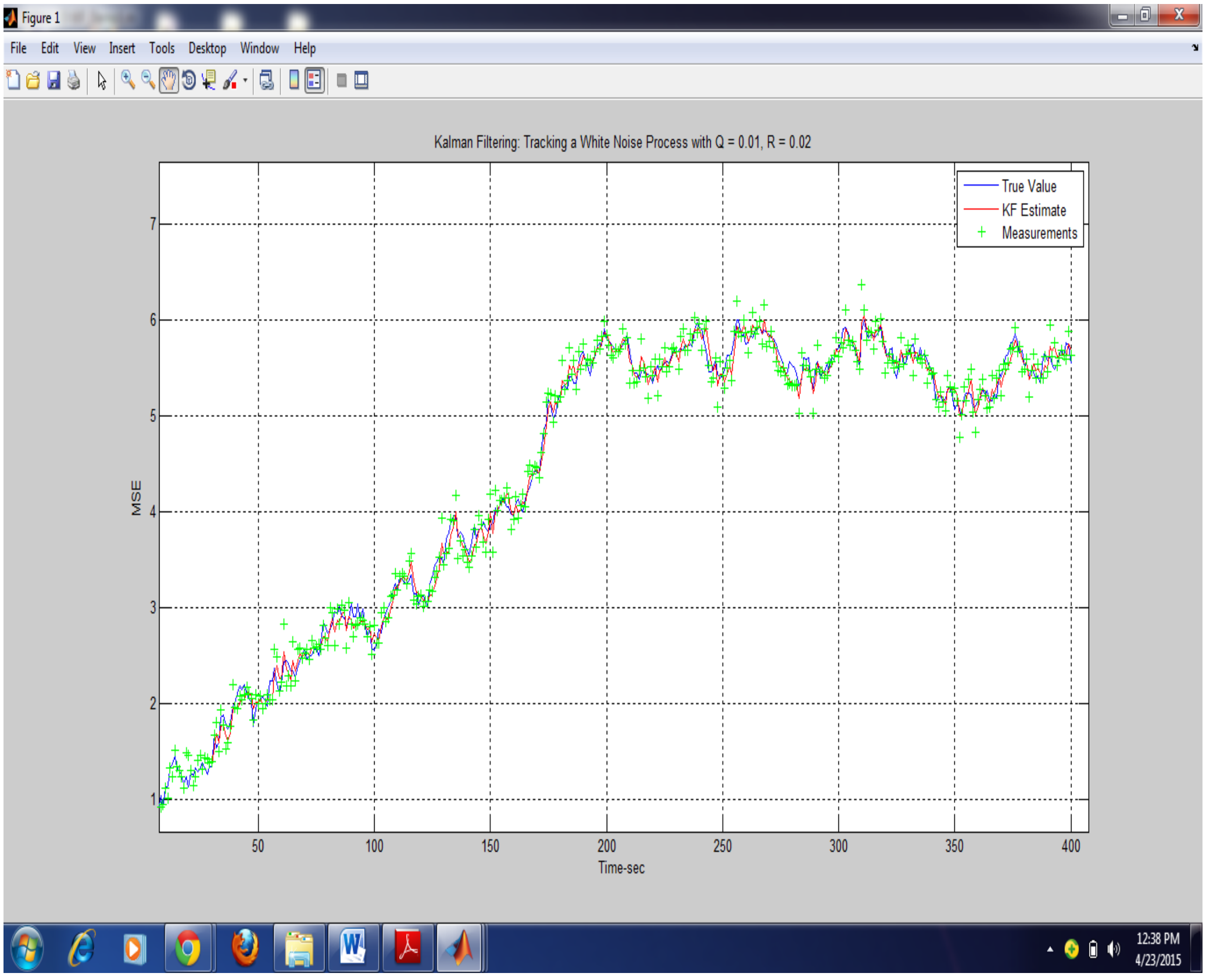

Fig.6.1 Graph showing the behavior of process noise

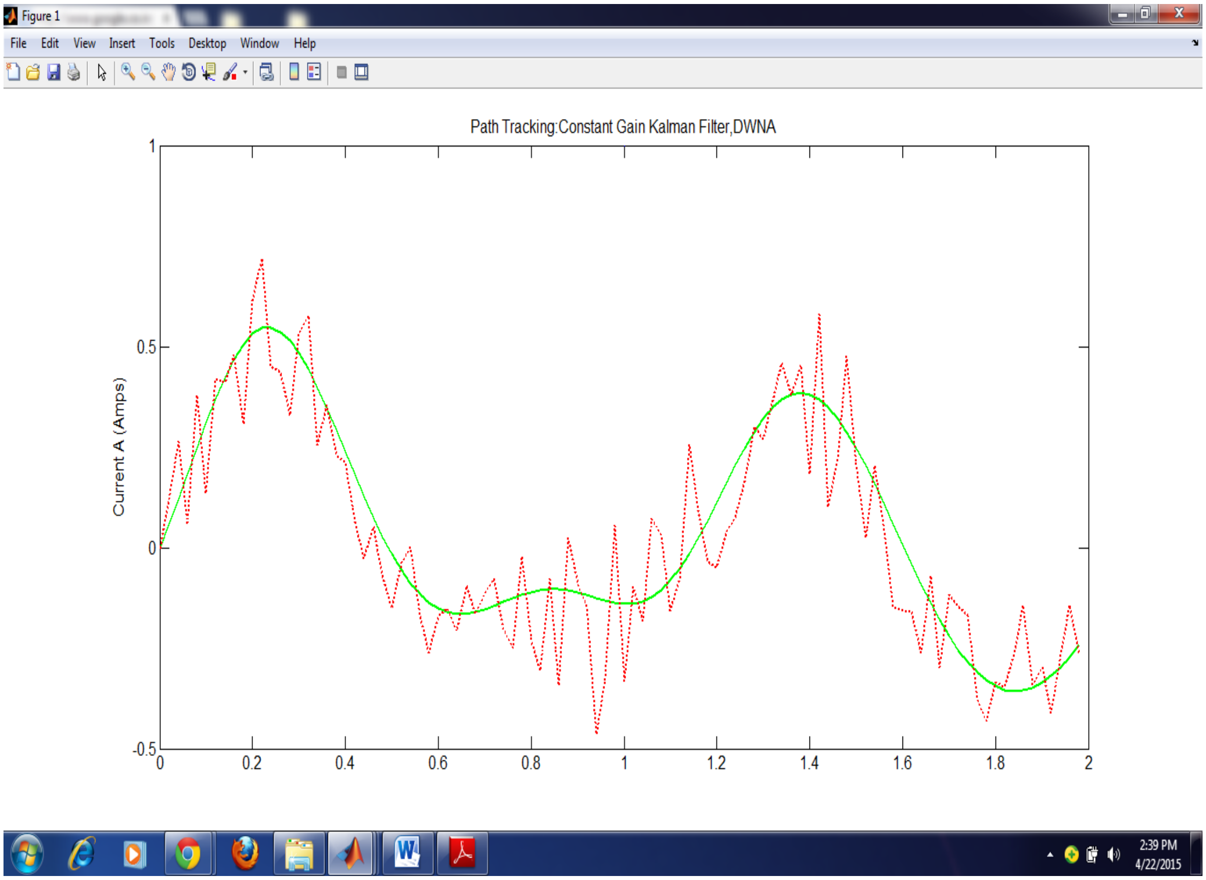

Fig. 6.2 Graph showing actual and estimated position using DWNA model.

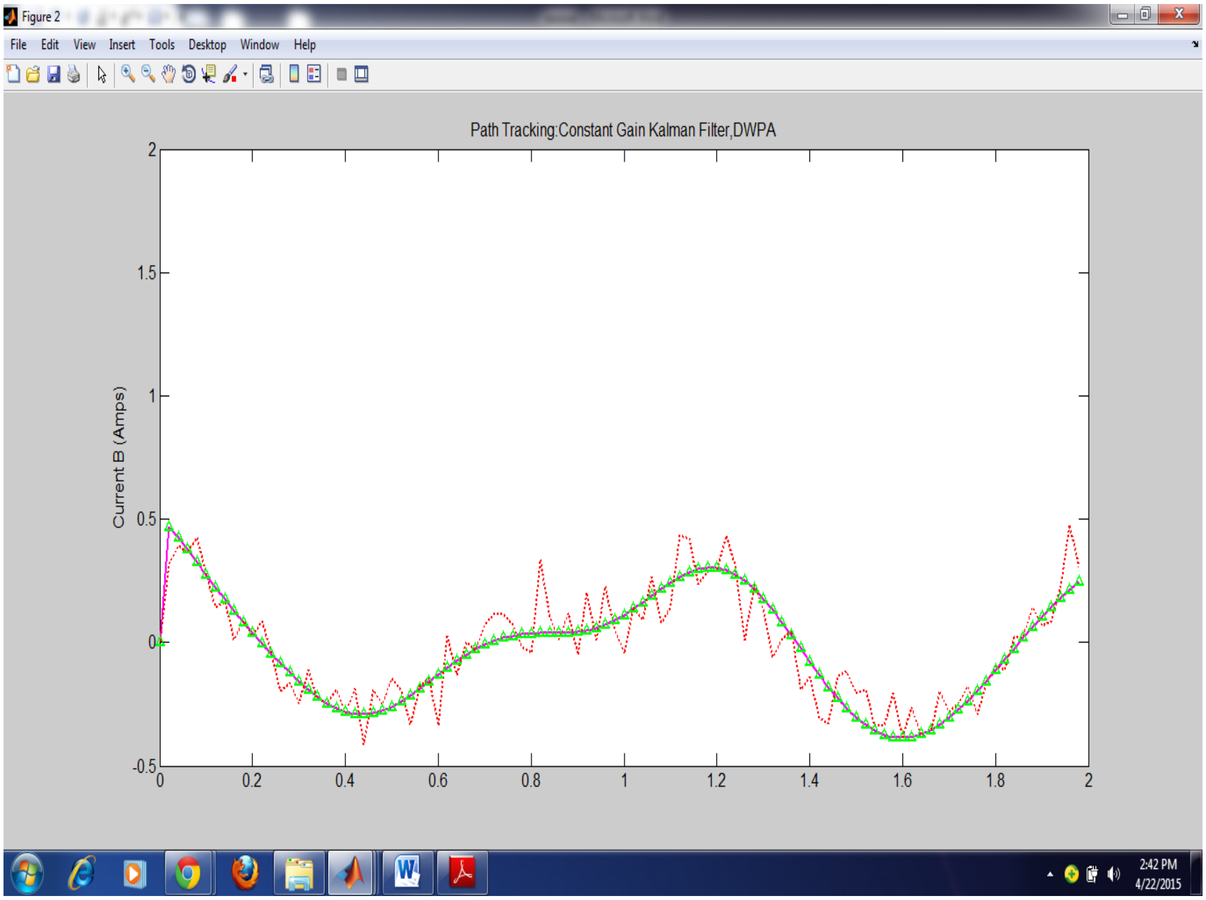

Fig. 6.3 Graph showing actual and estimated position using DWPA model

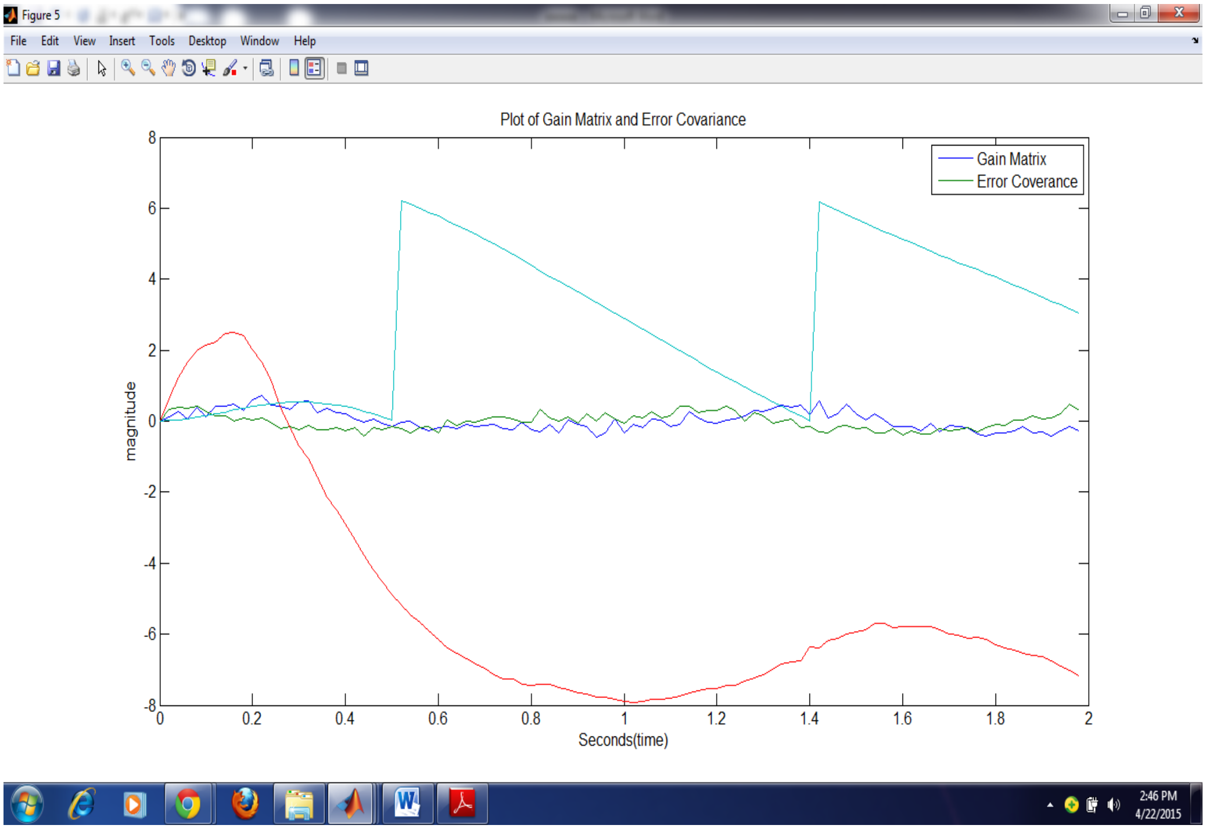

Fig. 6.4 Graph showing gain and error covariance

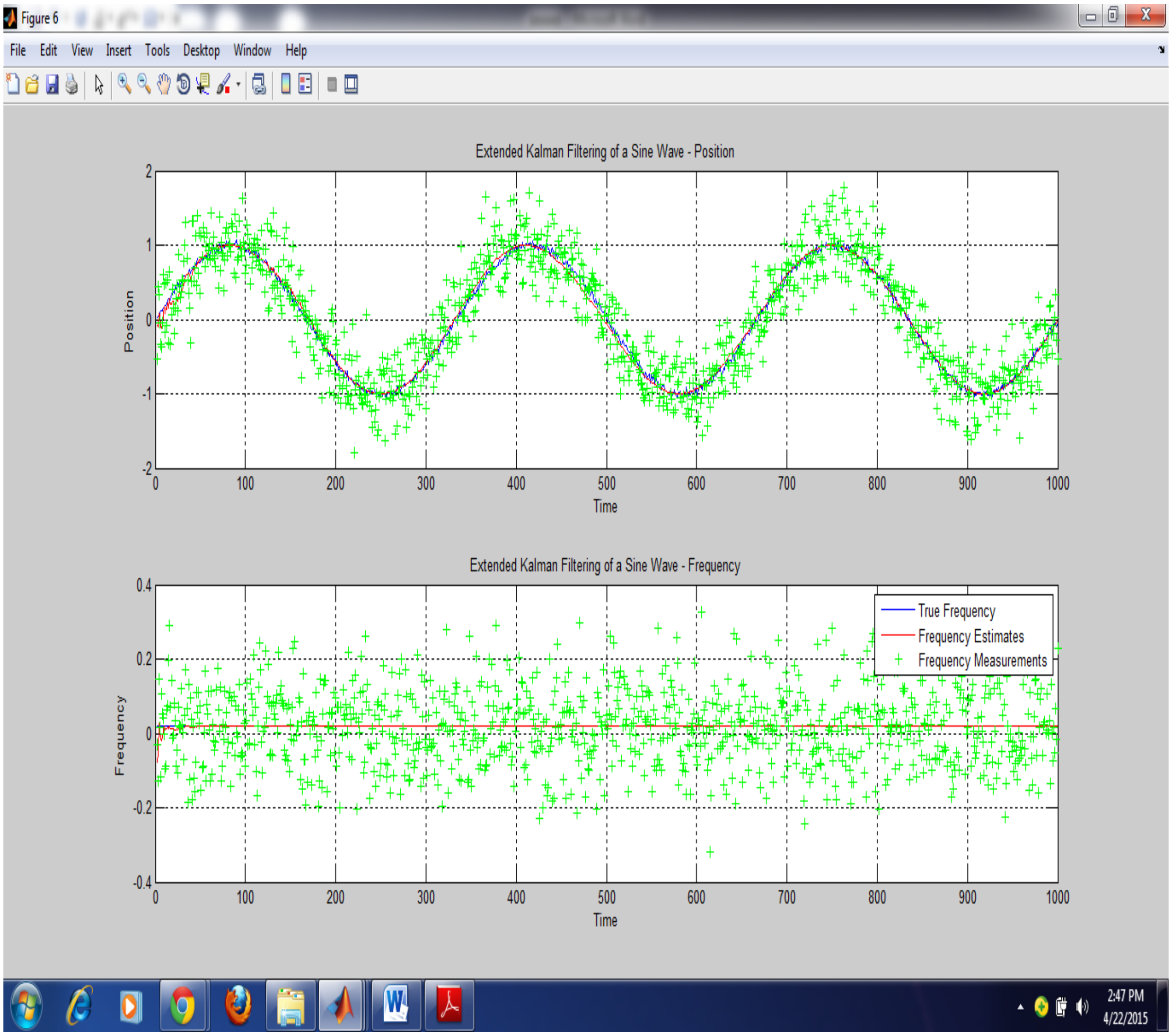

Fig. 6.5 Implementation of improved version of Kalman filter.

6.2 Performance evaluation

In figure 6.1, 6.2, 6.3 and 6.4 implementation of Kalman filter has been done. The graph shows the actual and estimated position of the target. From the graph it is clear that the estimated and actual position of the target is not overlapping on each other. This means that target is not accurately detected. Exact location of the target is not obtained. This implementation is carried out by initializing the Kalman parameters and then updating the received values. Finally optimum point is reached. In this implementation we are dealing with the constant gain instead of the state and measurement noise covariance. Figure 6.1 is showing the implementation of Kalman filter for DWNA model. This model is used for tracking non maneuvering target. Figure 6.2 showing implementation of DWPA model which is used in the case of maneuvering target. Figure 6.3 shows the gain is constant verses error-covariance.

The implementation of improved version of Kalman filter is shown in figure 6.4. Here the actual and estimated position of the target is completely overlapping on one another showing the exact location of the target. In the field of estimation the important thing is how exactly the target is being detected. We need to have exact position of the target so that we can take any type of action accordingly. If this type of graph is obtained on the display of the system means the exact position of the target is detected very nicely which is very-very important in various fields like radar 3D tracking modeling, sensor networking, multi sensor data fusion, chemical processing industries for process and error estimation, satellite imagery and communication, wireless networking etc.

For the implementation of improved version of Kalman filter that is extended Kalman filter we need to initialize a priori state estimate and a posteriori state estimate along with the parameters of the Kalman filter and later on these are updated. A priori state estimate find out the frequent patterns repeating on the channel whereas posteriori state estimate count the pattern formed in the previous case and then recycle them. Extended Kalman filter is also very much suitable for the nonlinear case where we have maneuvering target. Also he maneuvering target is detected better by the extended Kalman filter estimation mechanism.

Chapter 7

CONCLUSION AND FUTURE SCOPE

Target tracking using constant gain Kalman filter mechanism with the help of different models like DWPA and DWNA are good but close estimation is still not obtained. But after making some improvement like application of Extended Kalman filter in the previous work we are getting closer graph. Target is detected very accurately. Also the efficiency is increased. We deal with the Kalman gains instead of the state and measurement noise covariance. Also the extended Kalman filter is more suitable for exact detection of the position of target. Some features of extended Kalman filter helps to achieve actual position of the maneuvering target. Extended Kalman filter works by linearizing the nonlinear states. There is hardly any difference between the actual position and estimated position which was not the case in Kalman filter. By applying extended Kalman filter both the graph (actual and estimated) are overlapping on each other giving us the accurate data.

As far the matter of future scope is concerned, extended Kalman filter has a very wide scope in the field of radar 3D tracking modeling, sensor networking, multi sensor data fusion chemical processing industries (process and error estimation), satellite imagery and communication, wireless networking etc. In all these fields estimation through extended Kalman filter plays a very vital role and also helps to get the desired result without any loss. In some field if accurate position of the target is not achieved then a lot of widespread loss can occur. In military domain or civilian domain tracking of maneuvering target is an important area of research. The major problem in tracking any target is the noise which are comes along with the signal and corrupt the actual data. And this noise is filtered out to a greater extent with the help of extended Kalman filter.

REFERENCES

I. Books

[1] Signal Detection and Estimation “Maurad Barkat”.

[2] An introduction to Kalman Filter, G Welch and G Bishop

[3] Handbook of Digital Signal Processing, D Elliot ed, Academic Press, 19986.

[4] Digital and Kalman filtering: an introduction to disdrete-time filtering and optimum linear estimator, SM Bozic, Halsted Press 1994.

[5] An Engineering Approach to Optimal Control and Estimation Theory, GM Siouris, John Wiley and Sons, 1996.

[6] Statistical and Adaptive Signal Processing, DG Manolakis, VK Ingle, SM Kogon, McGraw Hill, 2000.

II. Research Papers

[7] “Implementation of Kalman Filter in Radar Tracking using MATLAB”. Arghya Das. Int C and IEEE.

[8] Courses, E.; Surveys, T. (2006). "Sigma-Point Filters: An Overview with Applications to Integrated Navigation and Vision Assisted Control". *Nonlinear Statistical Signal Processing Workshop, 2006 IEEE*: 201–202. doi:10.1109/NSSPW.2006.4378854. ISBN 978-1-4244-0579-4. Retrieved 2008-07-14.

[9] “A Constant Gain Kalman Filter Approach to track Maneuvering Target”,Ashwin Yadav, 2013 IEEE International Conference on Control Applications(CCA)

[10] “Understanding the Basis of Kalman Filter via a Single and Intuitive Derivation”, Ramsey Faragher

[11] “People Tracking with UWB Radar Using a Multiple-Hypothesis Tracking of Clusters (MHTC) Method”. SangHyun Chang, Rangoli Sharan, Michael Wolf, Naoki Mitsumoto, Joel W. Burdick. Int J Robot (2010) 2:3-18. DOI 10.1007/s1269-009-00399-x.

[12] “Implementation of Kalman filter for Radar Tracking Using MATLAB”, Arghya Das, IEEE

[13] “Improved Kalman Filter Method for Measurement Noise Reduction in Multi sensor RFID systems”. Ki Hwan Eom, Seung Joon Lee, Yeo Sun Kyung, Chang Won Lee, Min Chul Kim and Kyung Kwon Jung. Sensors 2011, 11, 10266-10282;doi:10.3390/s111110266

[14] “An Adaptive Kalman Filter Tracker for Multi-Mode Range/Doppler Sonar”. Dr. C. Nicholas Pryor. Aspects of signal processing, NATO Advanced study institutes series volume 33-1, 1977, ppp265-278.

[15] “Robust Object Tracking Using Kalman Filters with Dynamic Covarience”.Sheldon Xu and Anthony Chang, Cornell University

[16] “Tracking of Multiple Target Types with a Single Neural Extended Kalman Filter”. Kathleen A. Kramer, Stephen C. Stubberud. Intelligent Techniques and Tools for Novel System Archtecture Studies in Computational Intelligence Volume 109,2008,pp495-512

[17] “Performance Evaluation of Wiener Filter and Kalman Filter Combined with Spectral Subtraction in Speaker verification System”. Utpal Bhattacharjeeand Pranab Das, Int J of Innovative Technology and Exploring Engineering (IJITEE), ISSN:2278-3075, Volume-2, Issue-2, January 2013.

[18] “Person tracking Using Kalman Filter in Wireless Sensor Network”. Vadehi.V, S.Vasuhi, K.Sri Ganesh, C. Theanammai,. Naresh Babu N T, N Uthiravel, P. Balamuralidhar, Grish Chandra. Parallel Processing Lab, Department of Electrical Engineering, Madras Institute of Technology,Anna University, TCS, Bangalore.

[19] “Online Feature Evaluation for Object Tracking Using Kalman Filter”. Zhenjun Han, Qixiang Ye, Jianbin Jiao, Graduate University of Chinese Academy of Sciences, Beijing, China.

[20] “A Two-Stage Kalman Filter Approach for Robust and Real-Time Power System state Estimation”Jinghe Zhang, Greg welch, Member,IEEE, IEEE Transaction on Sustainable Energy, vol.5,No-2, April 2014

[21] “Robust Kalman Filtering for Discrete-Time Uncertain Stochastic System” Jemin George, 2013 American Conrol Conference (ACC), Washington, DC,USA,June 17-19-2013

[22] “A new Adaptive Kalman Filter by Combining Evolutionary algorithm and Fuzzy Inference System”, 2014. IEEE

[23] “ Kalman Filtering with State Constraints: a survey of Linear and Nonlinear Algorithm”, IEEE

[24] “Comparison of Kalman Filter and Particle Filter used for Localization of an Underwater Vehicle”, Nak Yong Ko, Chosun University, IEEE

[25] “Study of the General Kalman Filter for Echo Cancellation”, Constantin Paleologu, Jacob Banesty, Member, IEEE,

[26] “A Constant Gain Kalman Filter Approach to Target Tracking in Wireless Sensor Network”, Yadav, A; Dept. of Electr. Eng, Indian Institute of Technology, Kanpur, India

[27] “A Novel Cubature Kalman Filter for Nonlinear State Estimation”, Xin-Chun Zhang, 52nd IEEE Conference on Decision and Control December 10-13, 2013, Florence, Italy

BIBLIOGRAPHY

Pooja Archana is pursuing Master of Technology in Wireless Communication from Lovely Professional University, Phagwara, Punjab. She has published her paper in Scopus named "Extended Target Tracking Constant Gain Kalman Filter in Error Covariance" and IJISET named "Kalman Filter: An Optimal Estimator-A Tracker Development Approach"

APPENDIX

Wireless Communication is a type of communication to transfer information between two or more points that are not connected by an electrical conductor. Radio is used by most common wireless technologies. Distance can be short with radio waves such as a few meters for television or as far as thousands or even millions of km for deep space radio communication. It covers various types of fixed mobile and portable application including two-way radios, cellular telephones, personal digital assistants (PDAs) and wireless networking. Application of radio wireless technology include GPS units, garage door openers, wireless computer mice, keyboards and headsets, headphones, radio receivers, satellite television, broadcast television and cordless telephones. It is the fastest growing segment of the communication industry. It has also captured the attention of the media and the imagination of the public. Cellular systems have experienced exponential growth over the last decade and there are currently around two billion users worldwide. Cellular phones have become business tool and part of everyday life. Wireless local area network replace wired network in many homes, businesses and campuses. If we consider its new applications then wireless sensor network, automated highways and factories, smart homes and appliances and remote telemedicine comes into our mind. Wireless local area networks are developed in the family of IEEE 802.11 standard. There are various advantages of wireless communication. Wireless networks are cheaper to install and maintain. We can alert people or organization in urgent situations. Information can be conveyed to consumers very easily. Wireless communication has many disadvantages also. It has led to many security threats to mankind. Hackers can grab the wireless signal that are spread in the air. Wireless networks should be secured so that the information cannot be exploited by unauthorized users. Security protocols must be created to save data. There are various types of wireless services like WiFi, cordless telephone, satellite television, global positioning system etc. Wireless communication system is robust, viable voice and data transport mechanism. The wide spread success of cellular has led to the development of newer wireless systems and standards for many other types of telecommunication traffic besides mobile voice telephone calls. WLANs and Bluetooth use low power levels and do not require a license for spectrum use. The evolving Bluetooth modem standard promises to replace troublesome appliances communication cords.