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Schmidt-Kalman Filter for Target Tracking with Reducing Navigation Errors

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ABSTRACT: - **In tracking a target error may exist only in target calibration with respect to its velocity known as velocity error. The velocity error can be removed by using an extended kalman filter. If the sensor capturing is also under motion then their exist an error due to sensor position report called position error. These navigation errors can be removed by designing a new filter called Schmidt-kalman filter (SKF) taking kalman filter as a reference. Schmidt-kalman filter is capable of tracking a target reducing position error and velocity error. In order to track an object filter PREDICTS the input and error. MEASURMENT is the input coming. The difference between the predict and measurement is called the consider covariance. Consider covariance is probabilistic process to predict the incoming input or matrix. The SKF does not estimate the navigation errors explicitly but rather takes into account (i.e., considers) the navigation error covariance provided by an on-board navigation unit in the tracking filter formulation. Including the navigation errors leads to the so-called "consider covariance." By exploring the structural navigation errors, the SKF is not only more consistent but also produces smaller mean squared errors than regular Kalman filters. Monte Carlo simulation results are presented in the paper to demonstrate the operation and performance of the SKF for target tracking in the Presence of navigation errors. In real time scenario ON BOARD NAVIGATION is supposed to give the input form sensor network. A cosine wave is considered as an input to the Schmidt kalman filter with error matrix super imposed on the wave. The root mean square position and velocity of the Extended Kalman Filter (EKF) and SKF are compared. The convergence speed of the Schmidt-kalman filter is also plotted.**

Keywords: Target tracking formulation, Consider covariance in tracking filter, filter design for above navigation, filter implementation.

I. INTRODUCTION

There are also many examples in engineering goal is to determine the relative location of a target for such applications as a homing missile. However, for other applications such as sensor data fusion or weapons cueing, the sensor/platform location accuracy is critical for high speed maneuvering target tracking as the target's relative location has to be transferred into a global reference frame and the sensor navigation errors get magnified into the target position solution. For tracking mission success, it requires the use of such techniques as the Schmidt-Kalman Filter (SKF) to account for navigation errors. In this project the Schmidt-Kalman filter (SKF) is formulated for target tracking with navigation errors. The Schmidt Kalman filter does not estimate the navigation errors explicitly (it could if external reference data were available) but rather takes into account (i.e., consider) the navigation error covariance, provided by an on-board navigation unit, into the tracking filter formulation. By exploring the structural navigation errors, the SKF are not only more consistent but also produces smaller mean squared errors than regular Kalman filters.

II. "KALMAN FILTER"

The Kalman Filter is an estimator for what is called the *"linear quadratic problem"*, which focuses on estimating the instantaneous "state" of a linear dynamic system perturbed by white noise. This is a complete characterization of the current state of knowledge of the dynamic system, including the influence of all past measurements. The reason behind why it is much more than an estimator is because it propagates the entire probability distribution of the variables it is tasked to estimate. These probability distributions are also useful for statistical analyses and the predictive design of sensor systems.

A.Adaptive Filters:

An adaptive filter is a filter that self-adjusts its transfer function according to an optimizing algorithm. Because of the complexity of the optimizing algorithms, most adaptive filters are digital filters that perform digital signal processing and adapt their performance based on the input signal. Adaptive filter, which uses feedback to refine the values of the filter coefficients and hence its frequency response. Generally speaking, the adapting process involves the use of a cost function, which is a criterion for optimum performance of the filter (for example, minimizing the noise component of the input). Here is a related general problem in the area of linear systems theory generally called the observer design problem. The basic problem is to determine (estimate) the internal states of a linear system, given access only to the system's outputs.

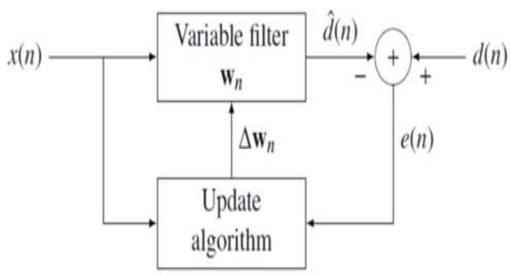

Fig 1. Adaptive Filter Block Diagram

III. "SCHMIDT KALMAN FILTER"

B. Multi sensor Track-to-Track Association:

Target tracking is an important element of surveillance, guidance or obstacle-avoidance system whose role is to determine the number position &movement of targets.

The fundamental building block of a tracking system is filter for recursive target estimation.

Fusion of data from multiple sensors can be hindered by systematic bias errors. This may lead to severe degradation in data association and track quality and may result in a large growth of redundant and spurious tracks. Multi-sensor networks will generally attempt to estimate the relevant bias values (usually, during sensor registration), and use the estimates to debias the sensor measurements and correct the reference frame transformations. Unfortunately, the biases and navigation errors are stochastic, and the estimates of the means account only for the "deterministic" part of the biases. The remaining stochastic errors are termed "residual" biases and are typically modeled as a zero-mean random vector. Residual biases may cause inconsistent covariance estimates, disassociation, multiple track swaps, and redundant/spurious track generation; we therefore require some efficient mechanism for mitigating the effects of residual biases.

B. Non Linear Filtering:

A key advantage of this approach is that it maintains the cross-correlation between the state and the bias errors, leading to a realistic covariance estimate. This paper is comprehensive survey of maneuvering target tracking without addressing the so-called measurement-origin uncertainty. It covers theoretical results of density-based exact nonlinear filtering for handling the uncertainties induced by potential target maneuvers as well as nonlinearities in the dynamical systems commonly encountered in target tracking. An emphasis is given to the results of significance for practical considerations, especially those of good potential for tracking applications.

This text is the most comprehensive compilation of practical algorithms for the estimation of the states of targets in surveillance systems operating in a multitarget-multisensor environment. This problem is characterized by measurement origin uncertainty, typical for low observables. Explicit consideration is given for measurements obtained from different sensors under realistic assumptions --- lack of synchronicity and different detection and accuracy characteristics. The modeling accounts for target maneuvers, detection probability, false alarms, interference from other targets and the finite resolution capability of sensors. The problems of track initiation, track maintenance and track-to-track association and fusion in a multisensory situation are considered.

Non linear filtering has been the focus of interest in the stastical &engineering applications. The problem is to estimate sequentially the state of a dynamic system using a sequence of noisy measurements made on the system.

C. States-Space Model:

The state-space approach to modeling dynamic systems and focus on the discrete time formulation of the problem. Thus difference equations will be used to model the evolution of the system over time and measurements are assumed to be available at discrete times.

For dynamic state estimation discrete-time approach is both widespread and convenient. The state-space approach is convenient for
Handling multivariate data and nonlinear/non-Gaussian processes. In order to analyze a dynamic system at least two models required: first model requiring the evolution of the state with time and second model relating the noisy measurements to the state. These models are available in probabilistic form. The probabilistic state-space formulation and the requirement for the updating of information on receipt of new measurements are ideally suited for the Bayesian approach.

In the Bayesian approach to dynamic state estimation one attempts to construct the
Posterior probability density function (pdf or density) of the state, based on available information, including the sequence of received measurements. If either the system is or measurement model is nonlinear the posterior pdf will be Gaussian. Since this pdf embodies, all available stastical information it may be regard to the complete solution to the estimation problem. In principle optimal estimate of the state may be obtained from posterior pdf.

A measure of the accuracy of the estimate may also be obtained. For many problems an estimate is required every time when a measurement is received. In this case a recursive filter is convenient solution. A recursive filtering approach means that received data can be processed sequentially rather than a batch, so that it is not necessary to store the complete data set or to reprocess existing data if a new measurement becomes available. Such a filter consists of two stages: prediction and update.

The prediction stage uses the system model to predict state pdf forward from one measurement time to the next. Since the state is usually subject to unknown disturbances (modeled as random noise).The update operation uses the latest measurement to modify the state prediction pdf. This is achieved using Bayes theorem, which is the mechanism for updating knowledge about the target state in the light of extra information from new data.

D. The Schmidt Kalman Filter Works In The Following Way:

Firstly, it estimates a process by using a form of feedback control loop whereby the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, these equations for the Kalman filter fall into two groups: **"Time Update equations"** and **"Measurement Update equations".**

The responsibilities of the time update equations are for projecting forward (in time) the current state and error covariance estimates to obtain the priori estimates for the next time step. The measurement update equations are responsible for the feedback i.e. for incorporating a new measurement into the priori estimate to obtain an improved posteriori estimate.

The time update equations can also be thought of as *"predictor"* equations, while the measurement update equations can be thought of as *"corrector"* equations.

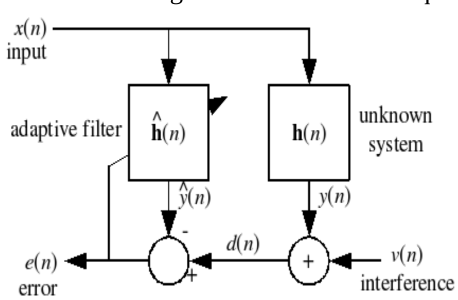

Fig 2. LMS Filter Block Diagram h (n) is the Impulse Response Of the Unknown System, v (n) Is Interference)

IV. "RESULTS &DISCUSSIONS"

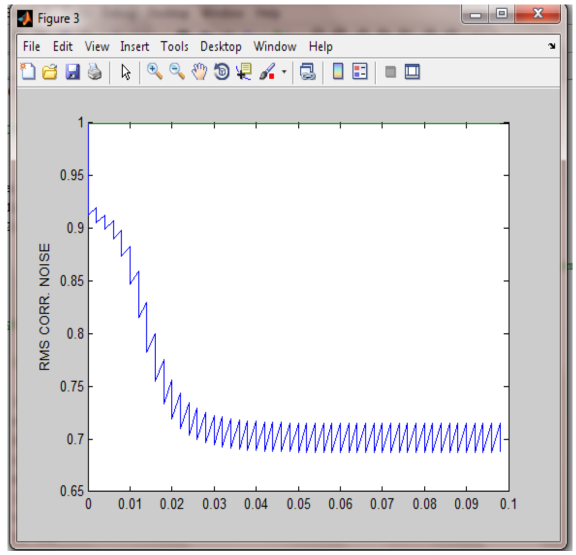

Fig 3 The Convergence of the Kalman Filter

In fig 3.7.0 shows that Root Mean Square value versus Noise. It means that the convergence of the filter it takes less time to reach stable value. After 0.02 value means with fewer amounts of time &with less value it reaches stable state

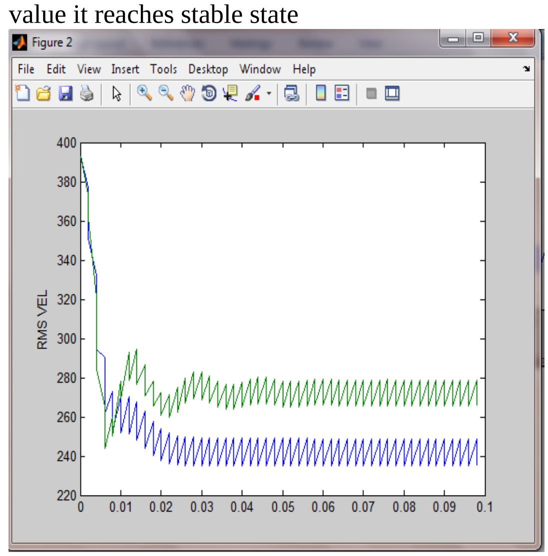

Fig 4 The root means analysis of the kalman filter

In fig 3.7.1 shows that the difference between kalman & Schmidt kalman filter with X-axis as RMS value and Y-axis is taken as velocity error. The velocity error gets whenever to track the target an error occurred. With in the less time it reaches constant values as compared to kalman filter. It reaches constant values means it has less errors.

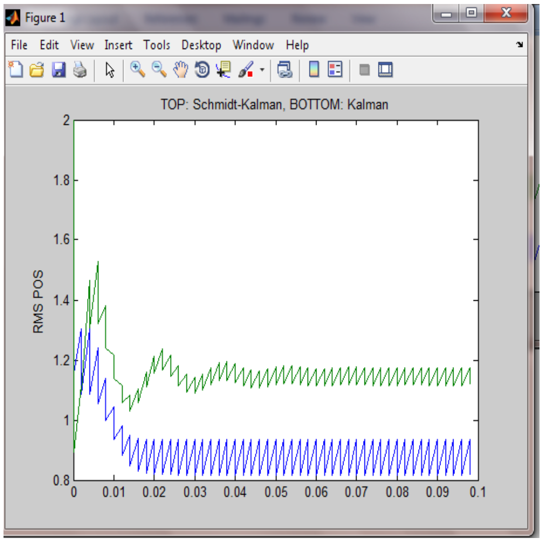

Fig 5 The root means analysis of the kalman filter

This figure shows that sensor position errors of kalman and Schmidt kalman filter-axis taken as Rms value & Y-axis taken as values of Positional errors. The Schmidt kalman filter reaches constant values with less time .It means that it has less positional errors.

V. "CONCLUSIONS"

We investigated the effect of sensor location errors (navigation errors) for Non linear filtering/non Gaussian filtering &also filtering in a typical target tracking system. To reduce these errors regular kalman filters only optimistic, so use Schmidt kalman filters. The Schmidt-Kalman filter (also known as the consider Kalman filter), which incorporates the navigation error covariance, was shown not only to be *more consistent* but also to produce *smaller* estimation errors. One aspect of our ongoing work is to extend the formulation to maneuvering targets using such algorithms as the interacting multiple model (1MM) estimator. Another effort is to apply the consider covariance for track-to-track fusion. Yet another effort is to develop a track bias calibration and removal algorithm. Finally, we will investigate the proactive approach to sensor management with consider covariance in the presence of navigation errors.

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