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Kalman Filter based Adaptive Attitude Estimation of Rigid Body

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ABSTRACT

This paper mainly focuses on rigid body attitude estimation under the effect of external acceleration with the help of accelerometer and gyroscope. The paper proposes a Kalman filter based estimation algorithm for detection of dynamic cases in which external acceleration occurs. Covariance matrix of the external acceleration is estimated to tune the filter gain. Model of the system involves inertial sensor made up of triaxial accelerometer and a triaxial gyroscope along with Kalman filter. Based on the effect of external acceleration, the system is able to estimate accurate attitudes with minimal errors. The proposed scheme is implemented and tested in Matlab/ Simulink.

Keywords

Accelerometer, Attitude estimation, Kalman filter, Simulink.

I. INTRODUCTION

MEMS Sensors are mainly used to collect data from surrounding environment and convert it into useful electrical signals for interpretation and analysis. Such sensors are modeled and used in this system for attitude estimation. Proper tracking of rigid body attitude, i.e., determining the three dimensional orientation with the help of MEMS sensors is main requirement in many applications like unconstrained walking [1], pedestrian localization [2, 3], indoor navigation [4, 5], and human body trackers [6, 7]. The main use of gyroscope is to measure angular velocity whereas accelerometer to measure the sum of external acceleration and gravity. To improve the estimation accuracy, fusion of the sensors is preferred rather than using them individually. Filtering is essential in many situations to remove noise without disturbing the useful information. Kalman filter is one such tool used to estimate the states of a linear system and when compared with all possible filters, it is the one which minimizes the variance of the estimation error [8]. Though it is developed mainly for use in spacecraft navigation, it turns out to be good for other applications also.

According to literature survey, many attitude estimation methods have been proposed with different filtering techniques such as Kalman filters [9, 10], extended Kalman filters (EKFs) [11], or nonlinear observers [12, 13]. All these performed well during static cases but failed to do same in dynamic cases. Even the effect of external acceleration is not considered. So to deal with the same issue, some works explicitly considered effect of external acceleration [14, 15, 16]. Authors in [14] added the diagonal matrix to the observation covariance matrix to reflect accurately the external effects but failed to get accurate results. A switching architecture was proposed in [16] to differentiate between the low and high acceleration modes. Thus all the approaches in [14, 15, 16] need the threshold setting which is really a tricky job in practice. To view this problem in a different angle, some authors proposed an external acceleration model which works well for short periods and was filled with errors for long duration. Some of the disadvantages of the existing system are complex algorithms, inaccurate detection system, long time for processing and more power consumption. From all these studies, we can conclude that whatever may be the level of effect and duration of external acceleration, efficient methods are yet to be modeled.

In the proposed work, firstly raw accelerometer and gyroscope data are collected which are then extracted and calibrated in the Matlab file and sent to the Simulink model. The data is fed to the kalman filter continuously and there occurs the adaptive tuning of the filter gain producing the more accurate estimate. The model is capable of distinguishing the static and dynamic cases which can be used for energy consumption by switching off the gyroscope when not in use i.e., in static cases. However, gyroscope is more prone to drifts which will alter the output readings. To compensate this effect magnetometer can be used along with the other two inertial sensors.

The rest of the paper is organized as follows: In Section II the theoretical background is explained. Section III includes the Simulink model development with results being presented. Finally, Section IV concludes the paper.

II. THEORETICAL BACKGROUND

In this section, we describe the basics of sensors used like accelerometer, gyroscope along with Kalman filter theory.

A. Accelerometer

"An accelerometer is a device used to measure the physical acceleration experienced by an object due to inertial or mechanical excitation". Conceptually, it can be seen as a damped mass on a spring. Whenever the accelerometer experiences the acceleration, mass is displaced accordingly and this displacement is measured in order to get the acceleration. The working principle of an accelerometer can be explained with the help of a seismic/proof mass attached to a spring which is in turn attached to outer casing as in Fig. 1.

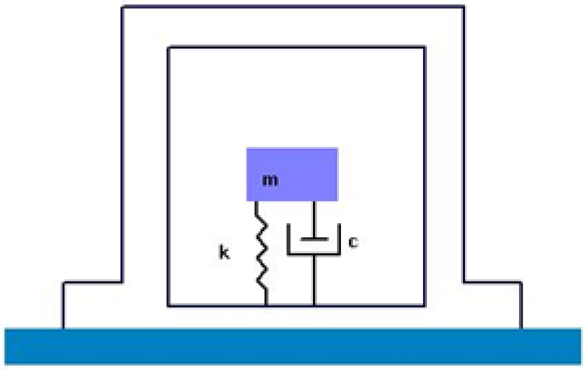

Fig. 1. Schematic of an accelerometer

To derive the respective governing equations, Newton's second law is used. From the stationary observer‟s point of view, the sum of all forces in the z direction is,

$$F_{applied} - F_{damping} - F_{spring} = m\ddot{x}$$

$$m\ddot{x} + F_{damping} + F_{spring} = F_{applied}$$

$$m\ddot{x} + kx + \dot{c}x = F \tag{1}$$

where

m = mass of the proof-mass

x = relative movement of the proof-mass with respect to frame

c = damping coefficient

k = spring constant

F = force applied

B. Gyroscope

Gyroscope is a device which measures the rate of change of the angular position over time i.e., angular velocity with unit [deg./s] which means to get the derivative of the angular position over time.

$$\dot{\theta} = \frac{d\theta}{dt} \tag{2}$$

To get the angular position back simply integrate the above equation. It is very much important to select proper sampling period as faster changes in the gyroscopic data over sampling frequency causes drifting which cannot be detected. Basic working schematic of a MEMS gyroscope is as shown in Fig. 2.

MEMS gyroscopes work by transferring vibration from one mode to another. Also, Corilis effect and angular acceleration are used as the methods to transfer energy.

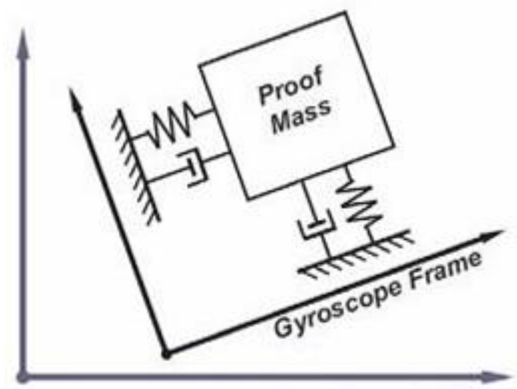

Fig. 2. Schematic of a MEMS gyroscope

C.Kalman Filter

R.E. Kalmanin 1960, published a famous paper that describes the recursive solution to linear filtering problems.Kalman filter is nothing but a set of mathematical equations which provide good computational means in order to have proper estimation of state of the process to minimize the mean squared error [17]. The two main tasks in Kalman filtering are predicting and updating which are shown with their respective governing equations in Fig. 3.

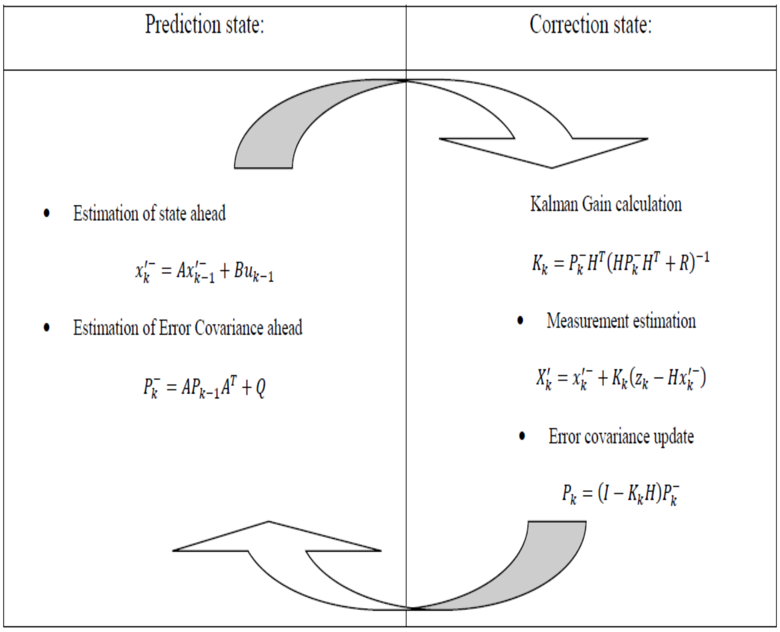

Fig. 3. Governing equations of Kalman filter

The first task in updating is to determine the Kalman gain K_k. Then after each pair of operation, the process is repeated making use of previous a posteriori estimates to predict the new a priori estimates. Thus, Kalman filter is used as a feedback system.

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III. SIMULINK MODEL DEVELOPMENT

In this section, proposed system model for attitude estimation is presented along with the obtained results.

A. Proposed system model

The block diagram of the proposed system is as shown in Fig. 4.

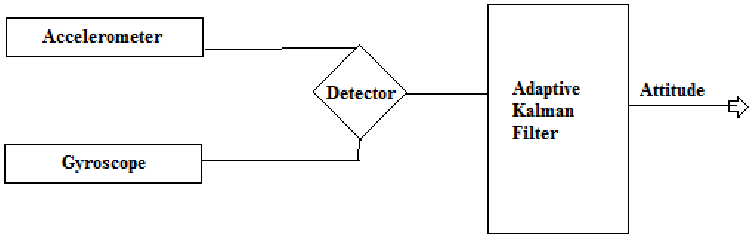

Fig. 4 . Proposed system model for attitude estimation

According to fig. 4, the simulated accelerometer and gyro data recorded for both static and dynamic cases are considered. These are later calibrated and the output of which is applied to an adaptive Kalman filter for attitude determination. There occurs the tuning of covariance matrix accordingly with respect to changes in external acceleration resulting in adaptive process.

Raw data extraction and Kalman filter gain calculation is done through Matlab code. One such set of raw data indicating the dynamic case is depicted below in Fig. 5.

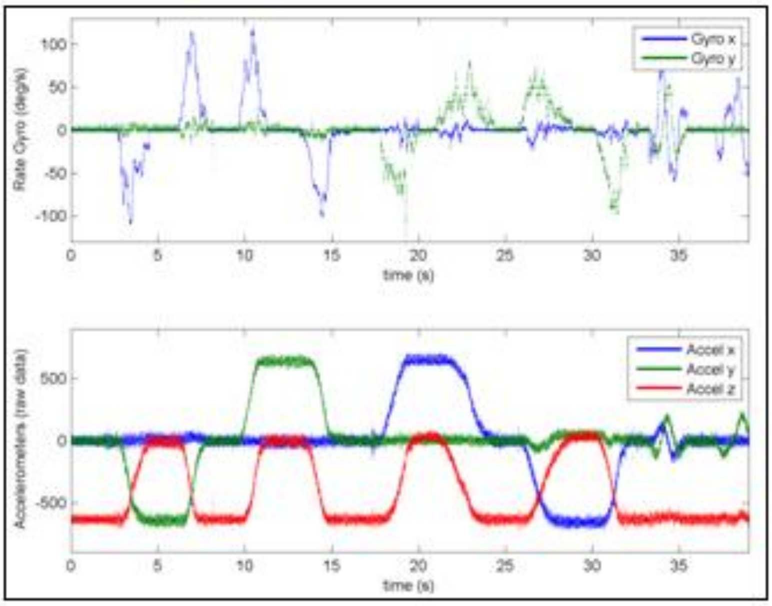

Fig. 5. Set of raw data for dynamic case

B. Implemented model

The complete model with various subsystems for attitude estimation which detects static and dynamic cases is as shown in Fig. 6. Here, firstly five set of accelerometer and gyroscope data recorded over different time period for both static and dynamic case are considered. These are then fed to the sensor calibration unit where necessary bias is added. The output from which is given to the Adaptive Kalman filter block for accurate attitude estimation. Kalman filter block produces the estimated angles and speed rate along X and Y axes as the output.

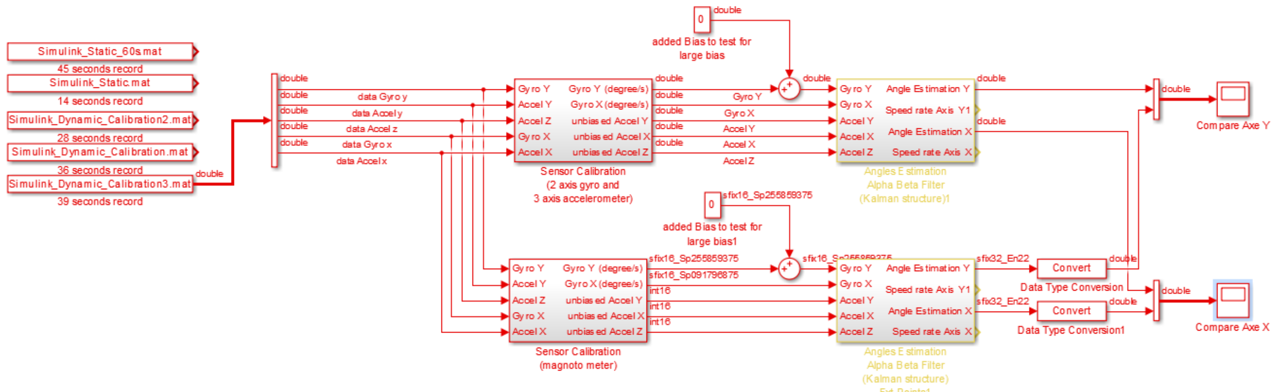

Fig. 6. Complete model of proposed work

The Simulink block diagram shown in Fig 6., is executed using MATLAB/ Simulink toolbox. Simulink is a software package which helps to model, simulate and analyze the time varying systems. Simulation of such dynamic systems is a two- step process. First, a model is created in model editor which depicts the mathematical relationships among the various inputs, states and outputs. Then, behaviour of the system is simulated over specified time period. There is integration between the Matlab and Simulink environment allowing the use of Matlab algorithms into model and export back the simulation results to workspace for further analysis.

Figure 7 and 8 shows the graphs when dynamic cases is detected and angles estimated along X and Y axis are presented through graphs. From the graphs, it is observed that, with the use of Kalman filter, more accuracy is obtained when compared with non-filter output.

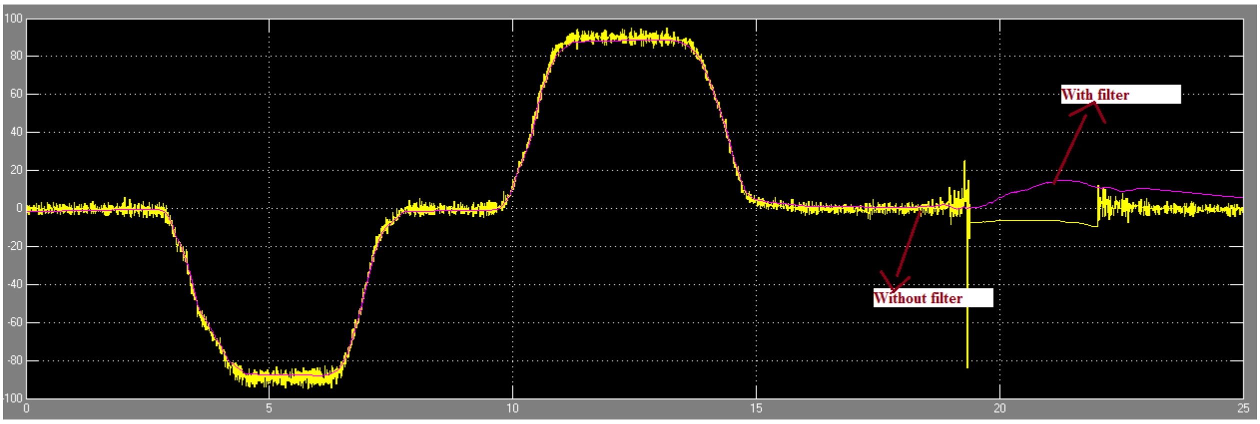

Fig. 7. Comparision of angles along X-axis in dynamic case

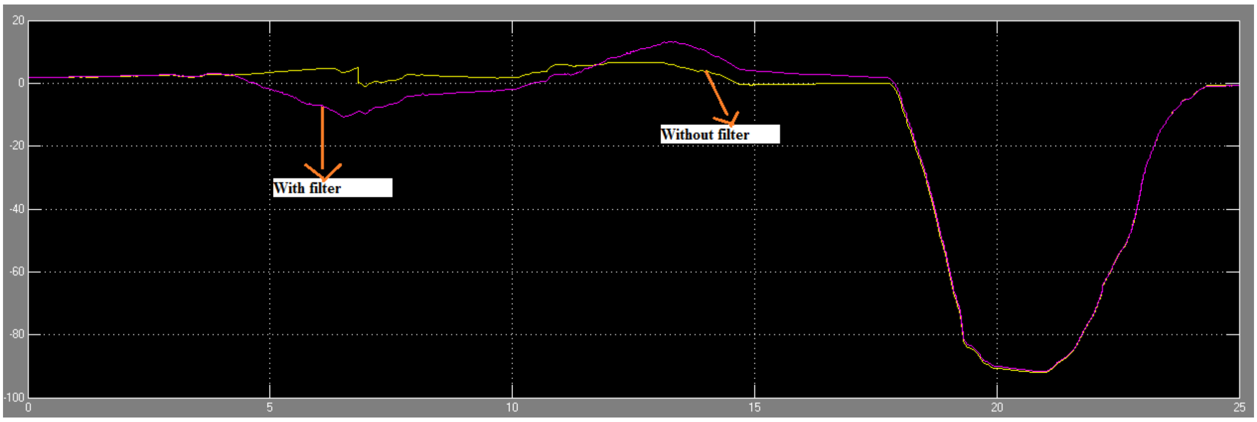

Fig. 8. Comparision of angles along Y-axis in dynamic case

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Graphs shown in Fig.9 and Fig. 10 indicate that the static cases are not being detected since random noise like signals appear at output of both axes. Thus, the proposed algorithm is capable of estimating the angles along the axes in dynamic cases.

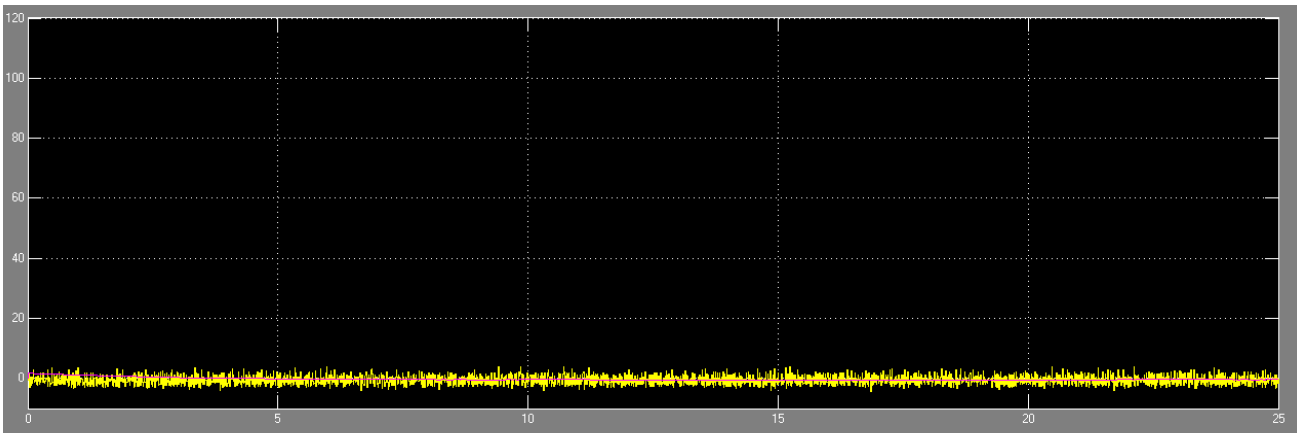

Fig. 9. Comparision of angles along X-axis in static case

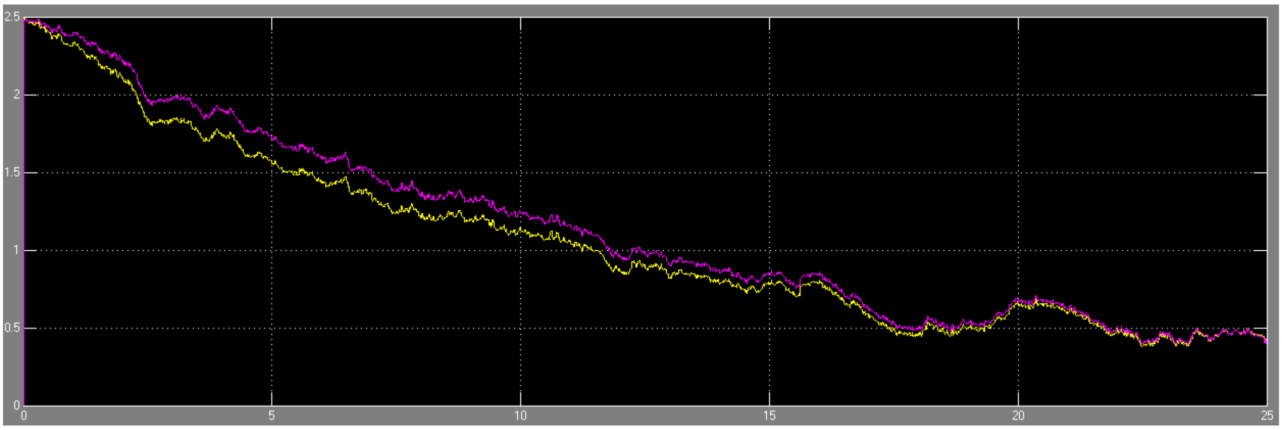

Fig. 10.Comparision of angles along Y-axis in static case

IV. CONCLUSIONS

In this paper, modelling and some simulation results of adaptive Kalman filter (AKF) for rigid body attitude estimation is presented. The filter was designed with a goal of reducing the effect of external acceleration and distinguishing between the static and dynamic cases. There is tuning of covariance matrix for optimal compensation of error. In this process, the effect of magnetic disturbances for attitude estimation is not being considered which affects the yaw angle calculation. This issue acts as a problem for future studies.

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