Two Stage Kalman Filtering for Position Estimation Using Dual Inertial Measurement Units

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***Abstract*— Herein a two stage Kalman filter based algorithm is proposed for processing of Inertial Measurement Unit (IMU) data to obtain accurate position estimation over a short period of time. The proposed algorithm uses a novel sensor placement strategy on rigid body. An Extended Kalman filter algorithm incorporates these placement constraints to achieve accurate position estimation. The results show 30% improvement in position estimation as compared to a conventional Dead Reckoning(DR) approach. To the best of the authors' knowledge, the proposed technique is the first which employs spatially separated dual IMUs on a single rigid body for position estimation.**

I. Introduction

Inertial Measurement Units (IMUs), consisting of miniature MEMS accelerometers and gyroscopes, offer a sourceless, self contained and inexpensive means for Position and Orientation (P&O) estimation [1]. IMUs are often used in conjunction with a primary ranging system to form a hybrid motion tracking system. The IMU subsystem provides P&O estimates under the conditions of Non-Line-of-Sight in primary ranging subsystem. Unfortunately, the nature of the fabrication of the IMU units renders their measurements to be noisy and have varying DC offset. Due to inherent noise, unstable bias and inaccurate compensation for the gravity component, these position estimates derived from the IMUs become inaccurate and unusable after a short period of time. The proposal reported herein improves IMU position estimation accuracy by using two IMUs on a single rigid body and two stage Extended Kalman Filtering (EKF). The approach uses a novel sensor placement strategy and a customized EKF which incorporates the placement constraints. The approach allows for greater accuracy when using Dead Reckoning (DR) in hybrid motion tracking systems during Non-Line-of-Sight conditions for the primary ranging subsystem.

The rest of the paper is organized as follows. Section II provides a brief survey of previous position estimation techniques using IMUs. Section III outlines the approach used in the current work. Section IV presents the simulation and the experimental results. Conclusions and future work are presented in section V.

II. Background

Position and orientation estimation from IMUs can be performed using integration of angular velocity measurements from gyroscopes and double integration of accelerometer data [5]. The literature shows frequent use of acceleromters for inclination measurements and as a add-on to gyroscopes for orientation estimation, as reported in [6], [2], [7]. Position and orientation estimates from inertial sensors, with manual bias tuning, have been reported with accuracies of 6 cm and 0.2 degrees during human locomotion task over 12 seconds [4]. Orientation estimates with 3 degree rms error, using only IMUs are reported in [7]. Gyrofree inertial P&O systems have been investigated in the past consisting of 6 or 9 accelerometers in [9], [8]. Three different sensor assemblies were compared for a 4 second movement in [3]. The gyro-accelerometer assembly yielded minimum error.

III. Approach

A. Overview

The sensor placement strategy is shown in Figure 1. It employs two IMUs (S_1 and S_2) on a single rigid body, with body-fixed frame of reference (O_B), so that their relative 3D separation and relative orientation remains fixed. The dual stage Kalman filter processes the IMU data as shown in Figure 2. In the first stage, orientation estimates are obtained in the global frame of reference (O_G) by integration of angular velocity measurements from gyroscopes. These are corrected using accelerometer signals during a quasi static phase. This stage of filtering is based on the work reported in [7]. A second stage employing EKF based position estimation is introduced which uses the estimated orientation for deriving the observation vector and uses the constraint of the fixed inter-sensor separation for correction of the two independent DR position estimates. Two stages of processing are needed because the observation vector of the Kalman filter in second stage, is derived from the corrected orientation estimates from the first stage. The procedure for prediction and observation vector derivation is described in the next section. The predicted estimates are corrected using standard Kalman filter equations.

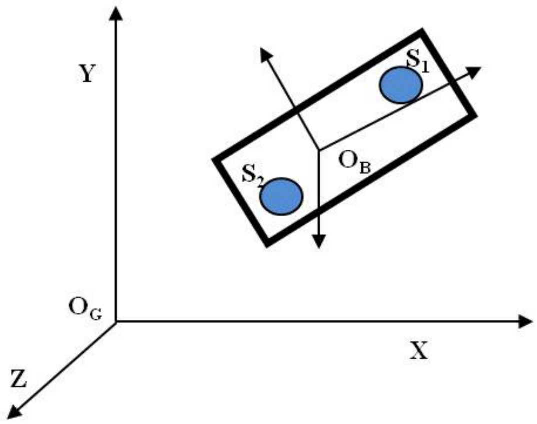

Fig. 1: Sensor Placement

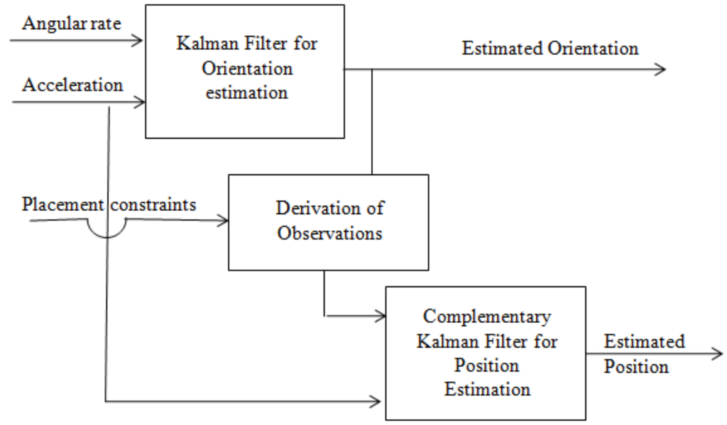

Fig. 2: Approach

B. Proposed Estimation Algorithm

A Kalman filter is a statistical, recursive estimation technique using noisy measurements [10]. The proposed approach uses an Extended Kalman filter due to the non-linear nature of the placement constraints. The process model and the derivation of the observation vector is described in the following sections.

a) Process model and Measurement model: The state vector of the Kalman filter is a vector consisting of each the x, y and z co-ordinates, their velocities and the acceleration along the respective axes.

$$S = \begin{bmatrix} x_i & vx_i & ax_i & y_i & vy_i & ay_i \end{bmatrix}'$$

Q is process noise covariance matrix, σ is the standard deviation of the accelerometer noise floor and t is the time interval between successive updates.

$$Q = \begin{bmatrix} I_Q & I_Q \\ I_Q & I_Q \end{bmatrix}$$

where,

$$I_Q = \begin{bmatrix} \frac{\sigma^2 t^4}{4} & \frac{\sigma^2 t^3}{2} & \frac{\sigma^2 t^2}{2} \\ \frac{\sigma^2 t^3}{2} & \sigma^2 t^3 & \sigma^2 t \\ \frac{\sigma^2 t^2}{2} & \sigma^2 t & \sigma^2 \end{bmatrix}$$

The State transition matrix is A is given by

$$A = \begin{bmatrix} I_A & I_A \\ I_A & I_A \end{bmatrix}$$

where,

$$I_A = \begin{bmatrix} 1 & t & \frac{t^2}{2} \\ 0 & 1 & t \\ 0 & 0 & 1 \end{bmatrix}$$

$$h = \begin{bmatrix} x_i - x_{i-1} \\ y_i - y_{i-1} \\ z_i - z_{i-1} \\ \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2 + (z_i - z_{i-1})^2} \end{bmatrix}$$

The observation matrix (H), is the Jacobian matrix of partial derivatives of the observation vector (h) with respect to S, i.e.

$$H_{(i,j)} = \frac{\partial h_i}{\partial S_j} \tag{1}$$

b) Derivation of Observation Vector: Let R_n be the rotation matrix obtained from stage 1 of P & O estimation. The unit vector along x-axis of the body-fixed frame of reference ($\hat{x}_b$) is given by the column of R_n. If the global x-unit vector is ($\hat{x}_g$), the angle between the vector is given by

$$\theta_x(n) = \cos^{-1}(\hat{x}_b \cdot \hat{x}_g) \tag{2}$$

The X_{sep}(n) is given by:

$$X_{sep}(n) = X_{b_{sep}} \cos\theta_x(n) \tag{3}$$

Where, $X_{b_{sep}}$ is the prior known x separation in the body-fixed frame of reference. The observation vector is thus given as:

$$Z(n) = (X_{sep}, Y_{sep}, Z_{sep}, norm(X_{sep}, Y_{sep}, Z_{sep}))$$

IV. Results

The proposed algorithm was tested and compared with a conventional DR approach for 10,000 iterations of 30 seconds circular motion, linear motion and rest, at rates of 2m/s, with a data acquisition frequency of 50 Hz. Stable bias and

Motion (m)	**Error (DR)**	**Error (Kalman)**	**Improvement %**
Circular	0.78	0.57	26.9
Linear	0.79	0.55	30.9
Rest	0.76	0.52	31.5

TABLE I: Simulation Results

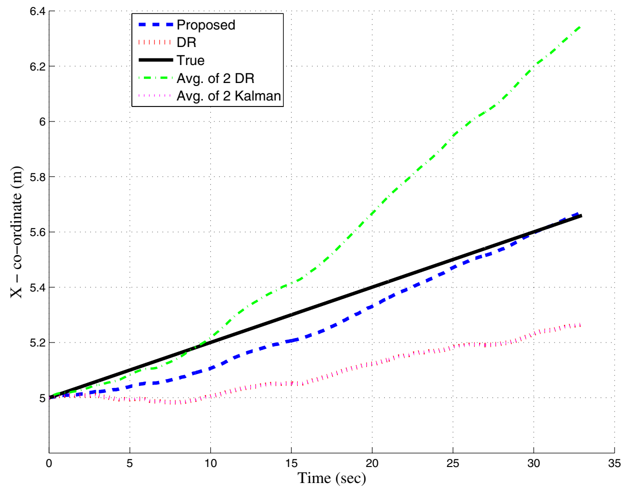

Fig. 3: Linear motion

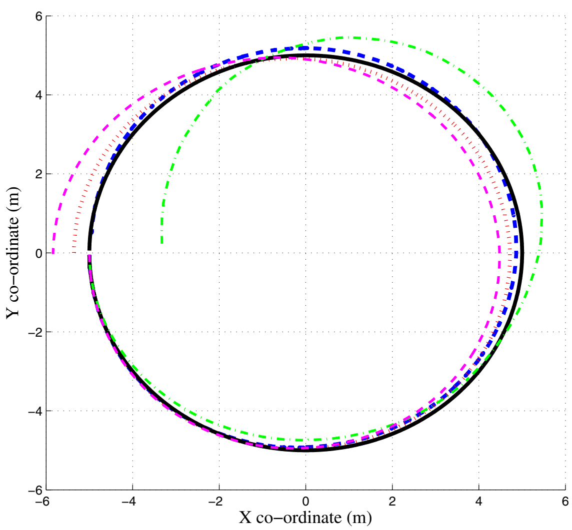

Fig. 4: Circular Motion

accurate gravity correction are assumed in the simulation. The figures 3 and 4 compare the proposed method, DR using one sensor, DR by averaging two sensors and Kalman filtering using the average of two sensors. Table 1 shows the mean squared error (in meters) for each motion. Position estimates for linear motion were previously reported with rms error of 6 cm over 12 seconds [4]. The effect of inter-sensor separation was investigated. It was found that the inter-sensor separation is lower-limited by measurement accuracy, as shown in Figure 5. Experimental results for the Shimmer research platform, containing the Freescale MMA7361 MEMs accelerometer, moving in a rectangular trajectory are depicted in Figure 6. The overall results show a 30% improvement in position estimation accuracy as compared to a conventional DR approach.

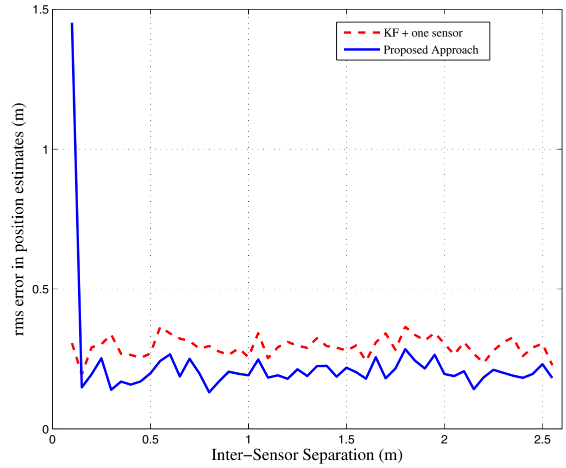

Fig. 5: Effect of inter-sensor separation in trajectory

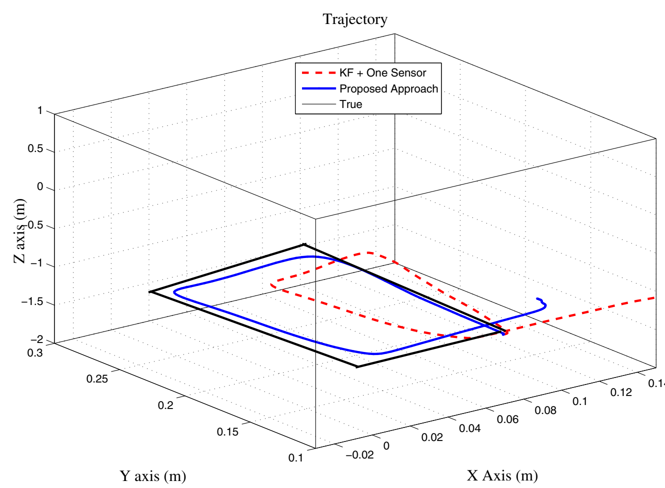

Fig. 6: Experimental Result

V. Conclusions and Future work

The proposed estimation procedure allows for greater accuracy in position estimation obtained from inertial measurements. The rate at which accuracy of position deteriorates is reduced by use of dual sensor and incorporation of placement constraint in the position estimation algorithm.

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