

Attitude Estimation And Compensation In Odometric Localization of Mobile Robot Using Low Cost IMU

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Abstract

The paper introduces the attitude estimation and compensation in odometric localization of a differential drive indoor mobile robot. A mobile robot navigates through an inclined indoor environment, wherein localization using only wheel encoder is erroneous. The robot uses inertial sensors such as gyroscope, accelerometer and magnetometer to calculate its attitude and acquires a three degree of rotational data. It is observed that the attitude update using gyroscopes alone are prone to diverge and hence error needs to be eliminated. The advantage of MEMS sensors is less-cost while complementary filter algorithm is low complexity in implementation.

The performance of the proposed complementary filter algorithm for attitude estimation and compensation in odometric localization are shown by experiment and analysis of results.

Keywords: Direction Cosine Matrix, Complementary Filter, Inertial Navigation System, Odometric Localization.

1. INTRODUCTION

A mobile robot is an autonomous machine that navigates in a given environment and recognises its surroundings using multiple sensors. The mobile robots are developed rapidly in various fields, such as national defence, medical, education, agriculture etc. Both position and attitude determination of a mobile robot are necessary for navigation, guidance and control of the robot. Dead-reckoning using the kinematic model of the robot and incremental measurement of wheel encoders are the common techniques to determine the position and orientation of mobile robots for applications in an indoor environment. However, the application of these techniques for localization of outdoor robots is limited [15], particularly when the robot has to traverse an uneven terrain or different types of surface such as gravel sand, grass etc. In spite of all these drawbacks, odometry is widely used for navigation on planar, low slippage surfaces, which are prototypical of the majority of two dimensional indoor environments.

In general, localization in outdoor scenario using inertial sensors and GPS are viable possibilities. They are entirely self-contained within the robot in the sense that they are not dependent on the transmission of signals from the robot or reception from an external source [8] [9]. Inertial sensors measurements are independent of robot physical parameters. However, inertial navigation

systems do rely upon the availability of accurate knowledge of robot position at the start of the navigation [4]. The inertial measurements are then used to obtain estimates of changes in position which takes place thereafter. An Inertial Navigation System based on utilization of multiple IMUs feedback is proposed in [7].

MEMS devices are one of the most exciting developments in inertial sensors. These devices overcome many of the features that have impeded the adoption of inertial systems by many potential applications, especially where cost, size and power consumption has been governing parameters.

Each mobile object that is free to move in space has six degrees of freedom or ways it can move. There are three linear degrees of freedom (x,y,z) that specify its position and three rotational degrees of freedom (theta (pitch), psi (yaw), and phi (roll)) that specify its attitude. If we know these six variables, we know where it is and which way it is pointed. In fact Navigation System is part of a mobile object to tell it where it is and what it is its' attitude.

Several approaches for localization have been proposed in the robotics literature and are currently an important research field. The Ultrasonic local positioning systems and infrared network systems are low cost, small, and are easy to interface [8] [9] [10]. However, these methods cannot measure far distances and have a difficulty in accuracy due to signal interferences. RFID requires additional equipment has a high cost. Global Positioning System (GPS) cannot be used in indoors and has a slow update rate. Nowadays, differential GPSs with centimetre-level accuracy are commercially available making them attractive for localization of outdoor mobile robots [5] [6].

Inertial navigation systems have been widely used in aerospace applications and now fancy in robotics applications. Integration of GPS and IMU has been proposed by many researchers using Kalman Filtering [11] [12] [13]. Camera along with IMU and GPS sensors provides better performance in attitude and position estimation [14].

In this paper, we discuss the attitude estimation and compensation in odometric localization of differential drive indoor mobile robot using low-cost, available off the shelf inertial measurement unit from Sparkfun. Attitude from tri-axial accelerometers and tri-axial gyroscopes are determined separately and fused using complementary filter. Filter gain is tuned experimentally to obtain much precise attitude.

The paper is organized as follows: In section 2, components of Inertial Navigation System are discussed. In section 3, Attitude estimation from accelerometers, magnetometers and gyroscope is presented. Also complementary filter algorithm, Direction Cosine Matrix and its features is mentioned. Section 4 provides description of attitude compensation in odometric localization while robot navigates on inclined ground is discussed. Section 5 includes experimental setup and results. Section 6 contains conclusion and future work.

2. INERTIAL NAVIGATION SYSTEM

The Inertial Navigation System described in this paper consists of IMU and navigation processor. The IMU include tri-axial accelerometers, tri-axial gyroscopes and tri-axial magnetometers. All three sensors along with Atmega 328 microcontroller is assembled in single breakout board by Sparkfun. ADXL345 accelerometer from Analog devices is low power, small with high resolution of 4 mg/LSB and measurement up to $\pm 16 g$. ITG-3200 from Invensense has resolution of 14.375 LSBs per deg/sec and measurement range of ± 2000 deg/sec. HMC5883L magnetometer from Honeywell is a magneto-resistive sensor with resolution of 0.73-4.35 milli-gauss and range of ± 8 gauss. The sensors communicate with the Atmega 328 microcontroller through Inter-Integrated Circuit protocol. Microcontroller uses these sensors data and processes the algorithm that estimates the orientation, velocity and position. The tri-axial accelerometers measure the absolute three dimension acceleration with respect to the body frame. The inclination of the

mobile robot is evaluated with three orthogonal accelerometers because they provide accurate information when the mobile robot is stationary. In addition, single and double integration of the accelerations provide the velocity and position respectively. The three orthogonal gyroscopes provide the angular rates of three respective axes. The integration of the angular rates provides the orientation of the mobile robot when it is stationary as well as in motion. Magnetometers give information of North Heading.

3. ATTITUDE ESTIMATION

The errors arises due to sensor misalignment has to be calibrated before proceeding onward. As such, the raw data of sensors won't read 0m/s^2 or 0radian/s even when they are still, except accelerometer which points in the direction of gravity vector and that too should be a constant value as per datasheet. This means, we need to calibrate them and calculate their zero offset. The calibration proposed here is simply taking a set of readings and averaging them to calculate the zero offset, which will then be subtracted from all consecutive readings.

3.1 Inclination of Robot With Respect To Gravity Vector

This method of determining the inclination of the robot is applicable when the net acceleration or force acting is gravity. Inclination sensing uses the gravity vector and its projection on the axes of the accelerometer to determine tilt angle. Let R be the gravity vector. The angles of interest are the angles between X, Y and Z axes and gravity force vector R .

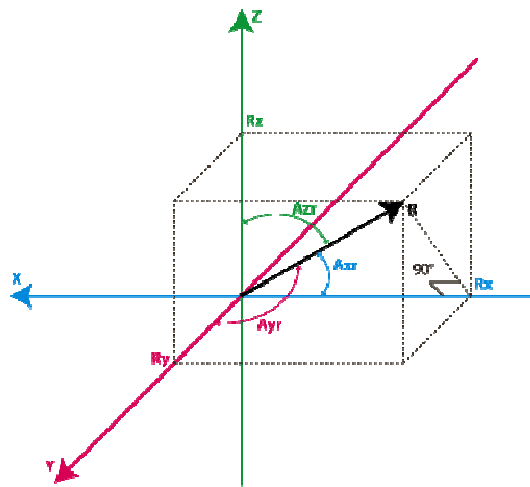


FIGURE 1: Angle Resolution of Gravity Vector.

Let these angles be A_{XR} , A_{YR} and A_{ZR} . Basic trigonometry can be used to show that the angles of inclination can be calculated using equation (1), (2) and (3).

$$A_{XR} = \cos^{-1}\left(\frac{R_x}{R}\right) \quad (1)$$

$$A_{YR} = \cos^{-1}\left(\frac{R_y}{R}\right) \quad (2)$$

$$A_{ZR} = \cos^{-1}\left(\frac{R_z}{R}\right) \quad (3)$$

where $R = \sqrt{R_x^2 + R_y^2 + R_z^2}$ and R_x , R_y and R_z are acceleration value of X, Y and Z axes respectively. In our case gravity vector act opposite to the direction of positive Z axis at rest and

using (1), (2) and (3) measures angles as 90° , 90° and 180° with respect to X, Y and Z axis respectively.

3.2 Initial Alignment Algorithm

Dead reckoning calculates a relative position from the initial position information and the initial orientation information of the mobile robot. The initial alignment process is used to calculate the initial orientation from the outputs of the inertial sensors when the mobile robot is stationary. We can assume that the starting point is the origin. The initial orientation can be calculated with three orthogonal accelerometers and dual magnetic sensors.

The acceleration (A^b) on the body frame is measured at a complete standstill in the following manner.

$$A^b = \begin{bmatrix} A_x \\ A_y \\ A_z \end{bmatrix} = C_n^b A^n = C_n^b \begin{bmatrix} 0 \\ 0 \\ -g^n \end{bmatrix}$$

$$A^b = \begin{bmatrix} g^n \sin \theta \\ -g^n \cos \theta \sin \phi \\ -g^n \cos \theta \cos \phi \end{bmatrix} \quad (4)$$

where C_n^b is the transformation matrix from the navigation frame to the body frame. A^n is the acceleration on the navigation frame and g is the gravity. ϕ and θ denote the roll angle and the pitch angle, respectively. From Eq. (4), the roll angle and pitch angle become:

$$\phi = \tan^{-1} \left(\frac{-g^n \cos \theta \sin \phi}{-g^n \cos \theta \cos \phi} \right) = \tan^{-1} \left(\frac{A_y}{A_z} \right) \quad (5)$$

$$\theta = \tan^{-1} \left(\frac{g^n \sin \theta}{g^n \cos \theta} \right) = \tan^{-1} \left(\frac{A_x}{\sqrt{A_y^2 + A_z^2}} \right) \quad (6)$$

The yaw angle (ϕ) may be obtained from the earth rotation angular velocity when stationary. However, it is quite difficult to measure the earth's rotation angular velocity because it demands gyroscopes with very high resolutions in order to measure this very small angular acceleration value.

Using the basic principle of compass (North) headings, the magnetometer provide yaw angle. The earth's magnetic field resembles that of a simple bar magnet. This magnetic dipole, Figure 2, has its field lines originating at a point near the South Pole and terminating at a point near the North pole. These points are referred to as the magnetic poles. These field lines vary in both strength and direction about the face of the earth. Magnetic angle of inclination (α) is the angle which field lines points downward toward north. The direction and strength of the earth's magnetic field (H_e) can be represented by the three axis values H_x , H_y , and H_z . The H_x and H_y information can be used to determine compass headings in reference to the magnetic poles.

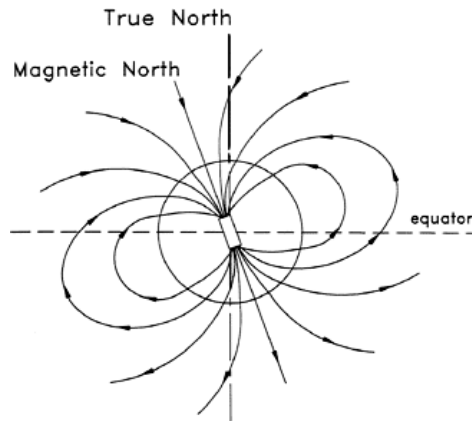


FIGURE 2: Earth's Magnetic Field.

It turns out that there is a discrepancy between the geographic poles and the magnetic poles. A value can be applied to the magnetic direction to correct for this called the declination angle (λ).

To determine compass headings using a magnetometer, the device must be level to the earth's surface, there should not be any ferrous materials interfering with the earth's field and the declination angle must be known. Various tilt compensation circuits and techniques can be used to normalize a magnetometer reading that is not level. There are also more sophisticated algorithms to account for nearby ferrous materials to correct for their effect on the earth's field.

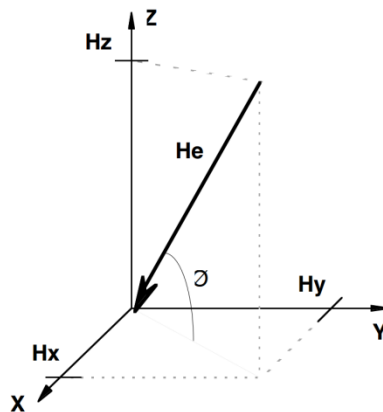


FIGURE 3: Earth's Magnetic Field Vector.

A compass heading can be determined by using just the X and Y component of the earth's magnetic field, that is, the directions planar with the earth's surface. Hold the magnetometer flat in an open area and note the X and Y magnetic readings.

The magnetic compass heading can be determined (in degrees) from the magnetometer's H_x and H_y readings by using the following set of equations:

$$\phi = \tan^{-1}\left(\frac{H_y}{H_x}\right) \quad (7)$$

To get yaw angle (ψ) add magnetic angle of inclination (ϕ) with angle of Declination (λ) i.e.

$$\psi = \lambda + \phi$$

3.3 Propagation of Direction Cosine Matrix

When the mobile robot is stationary, the angles obtained in initial alignment section are used to express initial value of Direction Cosines Matrix. Now when the robot starts moving, the angular velocity measured by tri-axial gyroscopes are utilised to update the direction cosine matrix [2]. The direction cosine matrix is also a transformation matrix that shows the relationship between the body frame and the navigation frame. This transformation is based on three consecutive rotations:

rotation around the gravity vector (z-axis) by ψ (yaw angle):

$$C_1 = \begin{bmatrix} \cos \psi & \sin \psi & 0 \\ -\sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

rotation around the y-axis by θ (pitch angle):

$$C_2 = \begin{bmatrix} \cos \theta & 0 & -\sin \theta \\ 0 & 1 & 0 \\ \sin \theta & 0 & \cos \theta \end{bmatrix}$$

rotation around x-axis by ϕ (roll angle):

$$C_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \phi & \sin \phi \\ 0 & -\sin \phi & \cos \phi \end{bmatrix}$$

ϕ , θ and ψ are euler angles. Thus a transformation inertial reference frame to body frame is expressed as: $C_n^b = C_3 C_2 C_1$.

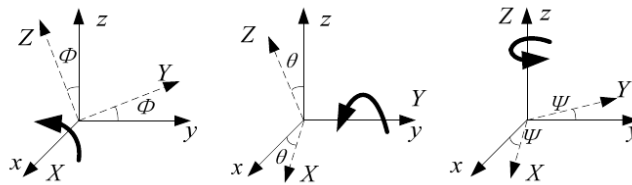


FIGURE 4: Rotation of Body Frame.

Similarly, the inverse transformation from body to inertial frame is given by:

$$C_b^n = C_n^{b^T} = C_1^T C_2^T C_3^T = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix}$$

$$C_b^n = \begin{bmatrix} c\psi c\theta & c\psi s\theta s\phi - s\psi c\phi & c\psi s\theta c\phi + s\psi s\phi \\ s\psi c\theta & s\psi s\theta s\phi + c\psi c\phi & s\psi s\theta c\phi - c\psi s\phi \\ -s\theta & c\theta s\phi & c\theta c\phi \end{bmatrix} \quad (8)$$

where $c = \cos$ and $s = \sin$.

The euler angles in terms of the direction cosine matrix components are:

$$\phi = \tan^{-1}\left(\frac{C_{32}}{C_{33}}\right) \quad (9)$$

$$\theta = -\sin^{-1}(C_{31}) \quad (10)$$

$$\psi = \tan^{-1}\left(\frac{C_{21}}{C_{11}}\right) \quad (11)$$

The propagation of direction cosine matrix with time using gyros [2] is given by:

$$\dot{C}_b^n = C_b^n \Omega \quad (12)$$

$$\Omega = \begin{bmatrix} 0 & -w_z & w_y \\ w_z & 0 & -w_x \\ w_y & w_x & 0 \end{bmatrix}$$

w_x , w_y and w_z are turn rate of X, Y and Z axes of inertial frame respectively.

3.4 Orthogonalization and Normalization Algorithms

To enhance the accuracy of the direction cosines, self consistency checks are emphasised after update algorithm. It is usually sufficient to carry put these checks at low frequency. The rows of the direction matrix represent the projection of unit vectors which lie along each axis of the orthogonal reference coordinate frame in the body frame. It follows therefore, that that the rows of the direction cosine matrix should always be orthogonal to one another and that the sum of the squares of the elements in each row should be unity. But, numerical errors could cause them to lean into each other.

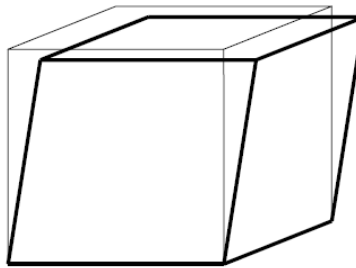


FIGURE 5: Orthogonality Feature of Direction Cosine Matrix.

To check the orthogonality of i th and j th rows of direction cosine matrix denoted by C_i and C_j , their dot product should be equal zero. In practice, that is not necessarily true, and we define:

$$\Delta_{ij} = C_i C_j^T$$

Where, Δ_{ij} is an orthogonality angle error defined about an axis perpendicular to C_i and C_j .

Since, either row, C_i or C_j is equally likely to be in error, the correction is weighted equally between them:

$$C_{i(\text{corrected})} = C_i - \frac{1}{2} \Delta_{ij} C_j \quad (13)$$

$$C_{j(\text{corrected})} = C_j - \frac{1}{2} \Delta_{ij} C_i \quad (14)$$

Normalisation errors can be eliminated by comparing the sum of the squares of the elements in a row with unity,

$$\Delta_{ii} = 1 - C_i C_i^T$$

And correction term is:

$$C_{i(\text{corrected})} = C_i - \frac{1}{2} \Delta_i \quad (15)$$

3.5 Complementary Filter

Complementary filter manages both high-pass and low-pass filters simultaneously. The low pass filter filters high frequency signals (such as the accelerometer in the case of vibration) and low pass filters that filter low frequency signals (such as the drift of the gyroscope). By combining these filters, a good signal, without the complications of the Kalman filter can be accomplished.

An accelerometer measures all forces that are acting on the system, more than just the gravity vector. Every small force working on the system will disturb the measurement completely. If working on an actuated system (like the mobile robot), then the forces that drive the system will be visible on the sensor as well. The accelerometer data is reliable only on the long term, so a “low pass” filter has to be used.

Also the angular position of a gyroscope undergoes integration over time, thus measured angle has the tendency to drift, i.e not returning to zero when the system went back to its original position. The gyroscope data is reliable only on the short term, as it starts to drift on the long term. Hence, “high pass filter” has to be used.

It can be concluded that on the short term, the attitude estimation from the gyroscope is very precise and not susceptible to external forces. While on the long term, attitude from accelerometer data doesn't drift. In its most simple form:

$$\begin{aligned} \text{attitude} = & K * (\text{angle} + \text{angle}_{\text{gyro}}) + \\ & (1 - K) * \text{angle}_{\text{accel+magneto}} \end{aligned} \quad (16)$$

Where, $0 < K < 1$ is filter gain and its value is chosen from experimental observation, $\text{angle}_{\text{gyro}}$ is obtained using expressions (9), (10), (11) and $\text{angle}_{\text{accel+magneto}}$ is obtained using expressions (5), (6), (7).

4. ATTITUDE COMPENSATION IN ODOMETRIC LOCALIZATION

The robot configuration is based on the incremental encoder data (odometry). Let $\Delta\phi_R$ and $\Delta\phi_L$ be the angular wheel displacements measured during the sampling time T_s by the encoders. Linear and angular displacements of the robot is given as

$$\Delta S = \frac{r}{2}(\Delta\phi_R + \Delta\phi_L), \Delta\psi = \frac{r}{d}(\Delta\phi_R - \Delta\phi_L) \quad (17)$$

where, r = radius of wheel and d = axial distance between wheels.

For a differential-drive robot the position can be estimated starting from a known position by integrating the movement (summing the increment travel distances). The estimate of Robot configuration at time t_k is computed as:

$$\Delta x = \Delta S \cos \psi; \Delta y = \Delta S \sin \psi$$

$$\begin{bmatrix} x_k \\ y_k \\ \psi_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \Psi_{k-1} \end{bmatrix} + \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta \psi \end{bmatrix} \quad (18)$$

Robot localization using the above odometric prediction (commonly referred to as *dead reckoning*) is accurate enough in the absence of wheel slippage, backlash and smooth ground surface.

While navigating on inclined ground robot starts wobbling and experiences roll (ϕ) and pitch (θ) angles. In such situation, if localization is based only on wheel rotation (motor encoders) then measured distance is different from the actual displacement of the robot. As a result of localization error, the trajectory planning and control of mobile robot gets affected. Therefore, incorporating attitude estimation from Inertial Measurement Unit in odometric localization can improve the accuracy of robot position configuration.

The odometric localization can be compensated using

$$\Delta x_{correction} = \Delta x \cos \theta + \Delta y \sin \phi \cos \theta$$

$$\Delta y_{correction} = \Delta y \cos \phi$$

$$\begin{bmatrix} x_k \\ y_k \\ \psi_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \Psi_{k-1} \end{bmatrix} + \begin{bmatrix} \Delta x_{correction} \\ \Delta y_{correction} \\ \Delta \psi \end{bmatrix} \quad (19)$$

5. EXPERIMENTAL RESULTS AND ANALYSIS

The experiments are performed using real data acquired by a mobile robot while traversing an outdoor environment. During the navigation of the robot, raw data from the sensors, angles and position estimated with and without filter are recorded and used to plot the same to make out the comparison. The robot used is a differential drive mobile robot designed and fabricated in-house. In order to compute attitude and position of the robot, IMU breakout board from Sparkfun is used. The sensor board is composed of three mutually orthogonal gyroscopes, three orthogonal

accelerometer, tri-axial magnetometer and Atmega 328 microcontroller. All three sensors are interfaced with microcontroller through I2C communication protocol.

Initially, 200 samples of each accelerometers and gyroscopes data are accumulated and then averaged to get sensor offset due to misalignment. These average values are compensated with consecutive samples of data. Attitude of robot before navigation is obtained using Initial Alignment algorithm and subsequently initial Direction Cosine matrix is constructed. Further, body turn rate from gyroscopes are used to update the Direction cosine matrix.

The data are sampled at 100Hz and the algorithm for both attitude and position estimation is also executed at the same frequency.

Figure 7 illustrates the main functions implemented within the navigation system; the processing of the rate measurements to generate body attitude, the resolution of the acceleration measurement into inertial reference frame, North heading from magnetometer, offset elimination and complementary filter algorithm.

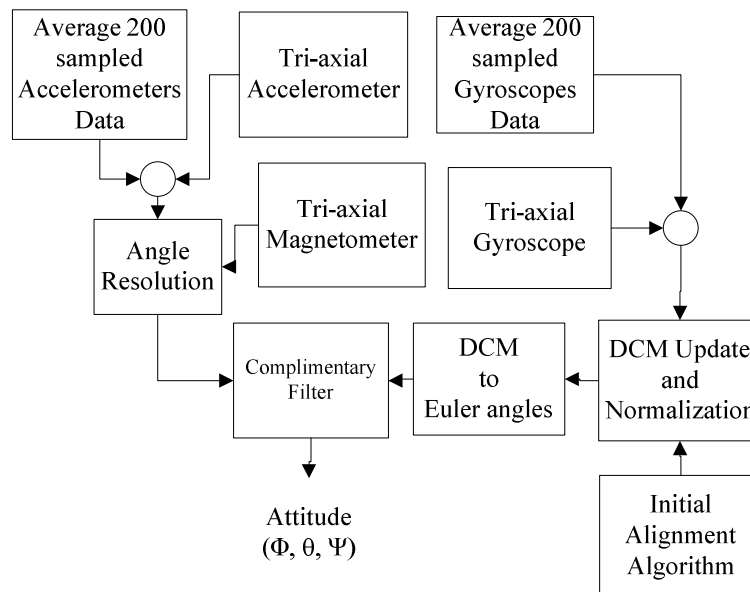


FIGURE 6: Block Diagram of Proposed Attitude Estimation.

Numerous experiments are conducted on sensor raw data, attitude estimation while robot is at rest as well as in motion. Comparisons are made to show effectiveness of proposed algorithm of complimentary filter for attitude estimation and fusion of IMU and encoders for precise localization on inclined ground conditions.

From the plot, it is observed that the attitude estimation from standalone Gyros drift over a period of time due to integration involved in estimation. These drawbacks can be overcome by incorporating complimentary filter algorithm as evident from the plots.

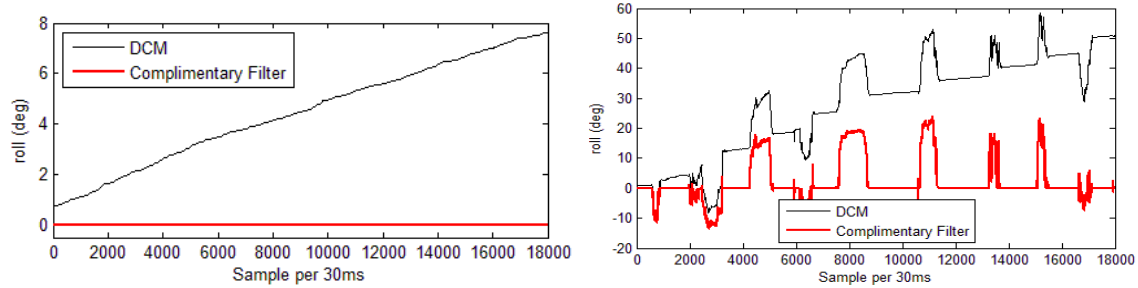


FIGURE 7: Roll measurements when the robot is at (a) stationary (b) motion.

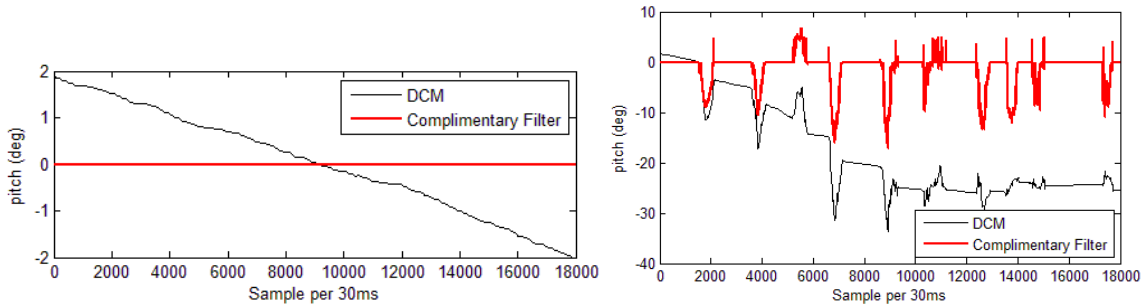


FIGURE 8: Pitch measurement when the robot is at (a) stationary (b) motion.

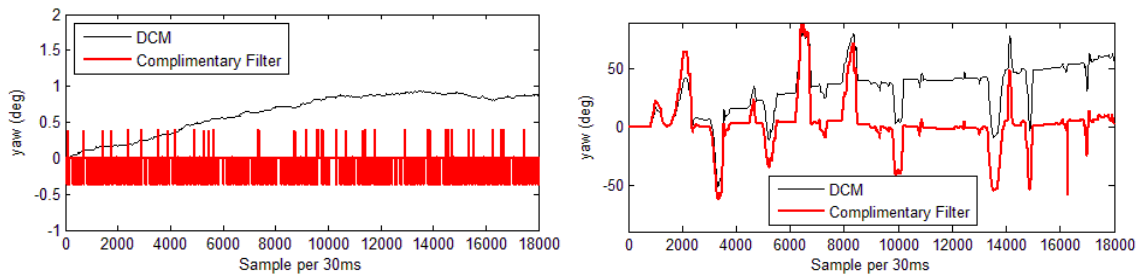


FIGURE 9: Yaw measurement when the robot is at (a) stationary (b) motion.

As the robot navigates on inclined ground it undergoes roll and pitch variations. These variations in roll and pitch result in overestimation and underestimation of the robot position. Although, the robot navigates on the inclined ground the estimation should be similar to the estimation on even ground. To achieve this attitude compensation has to be incorporated. The comparison of the robot position (x and y coordinates) with and without considering attitude obtained from IMU has been plotted as shown in the figure.

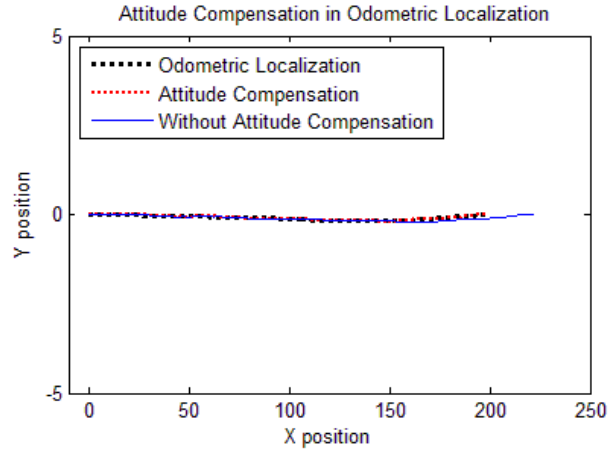


FIGURE 10: Navigation in X-direction Experiencing Pitch.

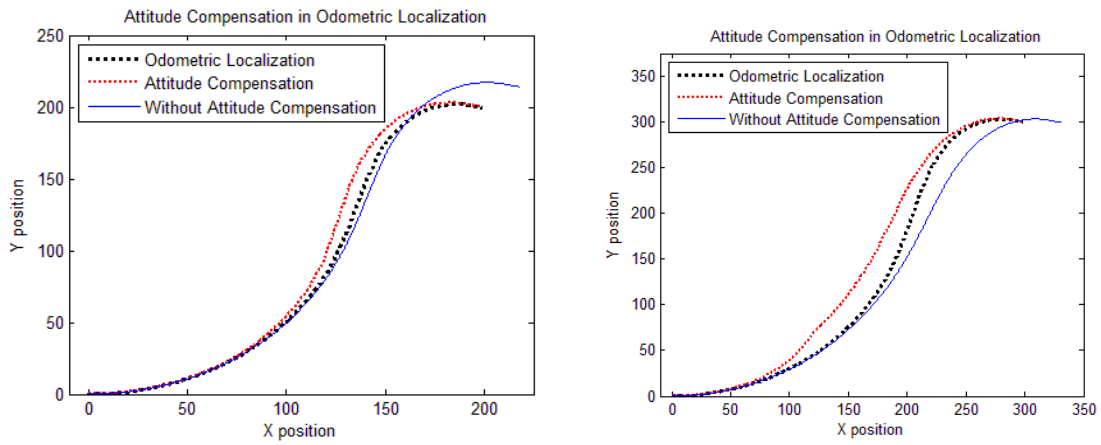


FIGURE 11: Navigation in XY-direction experiencing (a) pitch (b) roll.

It is observed that on inclined ground position estimation of the robot without incorporating attitude results different behaviour than the actual traverse trajectory.



FIGURE 12: Experimental Robot.

6. CONCLUSION AND FUTURE WORK

The proposed algorithm of Inertial Navigation System offers quick and accurate attitude estimation but position estimation of the robot deteriorates in long run. Errors are amplified due to integrating nature of INS, low frequency noise, sensor bias and other factors. Complementary filter is incorporated in attitude estimation wherein angles from accelerometer, magnetometer on one side and gyroscope on other side are fused, is not only simple in implementation but also consumes less computation unlike Kalman filter algorithm. Vibration of the robot during navigation has also accounted for the deterioration of actual position traversed. The most accurate and reliable value is yaw angle, mainly because of magnetometer, which made it possible to eliminate drift.

In order to further improve the attitude and position estimation for the mobile robot navigating in outdoor or uneven terrain, multi-sensor (viz. GPS, camera, pressure sensor, encoders) data fusion has to be considered. Two Inertial Navigation System combinations can also be utilized.

7. ACKNOWLEDGEMENT

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