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DEVELOPMENT OF ERROR COMPENSATION METHOD AND ALGORITHM IN DEAD RECKONING FOR IMPROVING PRECISION OF GPS NAVIGATION

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ABSTRACT

Global Positioning System (GPS) is a network of 24 satellites which orbits around the earth. For decades, GPS receivers are used in navigation systems. GPS receivers requires minimum of 4 satellite visibility to derive location information and time information. Since the visibility of four satellites could be affected by tall buildings, trees and bridges, its accuracy gets degraded when vehicles move in areas where tunnels or underground passages are present or in urban canyons. To improve the position accuracy of GPS, different systems like Assisted GPS and Differential GPS were introduced but they require network connectivity and more field equipment and infrastructures respectively. Under these circumstances, dead reckoning solution is preferred where present position is calculated from previously determined position and also with the knowledge of position dependent time varying parameters like acceleration, velocity etc. One way of accomplishing dead reckoning is by using inertial navigation system which uses Inertial Measurement Unit (IMU) consisting of accelerometers, gyroscopes and magnetometers. Based on the last known position from GPS, a better approximation regarding the position of the vehicle can be obtained from IMU sensors indicating how far and in what direction the vehicle has travelled. The major disadvantage of using IMU sensor for dead reckoning is that they are subject to cumulative errors which are mainly dependent on the accuracy of the sensors in IMU. The project focuses greatly to optimize the IMU sensor error to achieve precise dead reckoning. The project uses Motion Processing Unit (MPU) which is interfaced with a microcontroller. Firmware development will be done in C language. MPU is calibrated to compensate the cumulated errors. The measured signal is then filtered to remove the noise from the MPU. For this, suitable filter need to be designed and Kalman filter is used here. The signal is then mathematically processed to obtain the position of the vehicle)

INTRODUCTION

Introduction of Global Positioning System (GPS) has paved way to the novel era of practical navigation system. Today, almost all vehicles are equipped with GPS based navigation systems. It is 24 satellite based navigation system and it uses signals from multiple satellite to locate a GPS receiver on earth. The technology was originally used for military purpose and nowadays we cannot think of a vehicle without GPS.

In order to locate GPS receiver in three dimensional spaces, it must lock into the signals from minimum of four different satellites. Achieving and maintaining lock on four or more different satellite signals for a long period of time is difficult because there is chance that these signals can be blocked by tall buildings, dense foliage or terrain that stand between GPS satellite and GPS receiver. For this reason, land-vehicle navigation systems in general cannot continuously position a vehicle using a GPS receiver alone. Several varieties of GPS are introduced to increase the position accuracy of GPS but they are often expensive and have coverage issues. So many land vehicle navigation systems use other navigation aids which are a combination of sensors in conjunction with GPS position fixes to enhance overall system performance. Sensors which are used to position the vehicle are collectively referred to as a dead-reckoning unit. The dead reckoning sensor outputs are also prone to errors and it is different from that of GPS error. The paper focuses on analyzing these errors and thereby develops an error compensation technique in dead reckoning for improving position accuracy of GPS navigation system.

LITERATURE SURVEY

For an accurate positioning of GPS receiver, minimum of 4 satellite visibility is required to derive location information and timing information. Since the visibility of four satellites could be affected by tall buildings, trees and bridges, its accuracy gets degraded when vehicles move in areas where tunnels or underground passages are present or in urban canyons. Accuracy and reliability of GPS can be improved either by using a modification of the currently available technology (eg DGPS, RTK) whilst or by giving additional information (AGPS) to new more accurate technologies [1]. DGPS requires a known location based GPS receiver that records the drift error and post session (data collection phase) supplies these corrections to improve the absolute position of each unit. But its accuracy gets degraded as the separation between DGPS and GPS-Receiver increases. Real time kinematics GPS is similar to DGPS where two mobile systems used together can provide adequate safety and also double the rate of data acquisition. It offers limited coverage due to different terrains. Assisted GPS on the other hand uses a mobile cell phone network. But it is very expensive and rely on mobile network initiate the signals. Under these circumstances, dead reckoning solution is preferred. In dead reckoning [2], present position is calculated from previously determined position and also with the knowledge of position dependent time varying parameters like acceleration, velocity etc. Dead reckoning sensors or otherwise IMU (Inertial Measuring Unit) cannot be used to track a vehicle for a long period of time because it does not measure absolute positioning. So it can be used during GPS outages.

Personal Dead-reckoning (PDR) system was introduced for pedestrian navigation system. The PDR system does not require GPS, beacons, or landmarks; so it can be used in GPS- denied environments, such as inside buildings, tunnels, or dense forests. The PDR system uses a 6-DOF inertial measurement unit (IMU) age, attached to the users boot. The IMU provides real time rate of rotation and acceleration measurements to estimate the location of the user relative to a known starting point. The paper discussed peculiar problems of small IMU, our measures for eliminating these obstacles, and experimental results with the small IMU under different conditions [3].

Nowadays, Micro Electro-Mechanical Systems (MEMS) inertial sensors have found their way in various applications. These low cost easily available sensors require calibrations as their measurements are noisy and imprecise. Various approaches to calibrate an inertial measurement unit (IMU) comprising of a low-cost tri-axial MEMS accelerometer and a gyroscope were introduced. As opposed to existing methods, the method is truly infield as it requires no external equipment and utilizes gravity signal as a stable reference. It only requires the sensor to be placed in proper orientations, along with the application of simple rotations. Thus the system offers easier and quicker calibration comparatively. The results validate the calibration method as a useful low-cost IMU calibration scheme [4].

In the evolution of advanced driver assistance systems, the seamless and accurate positioning of the vehicle has become one of the most important tasks, and dead reckoning plays an important role. Visual odometry which is one of the most attractive approaches for this dead reckoning, cannot be used in urban areas, as its the accuracy gets degraded due to the surrounding moving objects. Moreover, heading estimation error in visual odometry cannot be corrected with satellite information, due to poor satellite signal reception. Solutions to improve the accuracy of the visual odometry in urban environments were introduced. The first key technique is moving object detection using inertial measurement unit (IMU) and pattern recognition, which improves the robustness of visual odometry in the dynamic environments. The second key technique is heading estimation by integrating satellite Doppler shift and IMU, which makes heading correction possible even when there is poor satellite reception. In evaluation experiments in urban areas, the error of dead reckoning using this proposed method is reduced to about one-fourth compared to the conventional approach [5].

More and more applications of location based services lead to the development of positioning technology.

As a part of the Internet of Things ecosystem, low-power Bluetooth technology provides a new direction for positioning. Most existing positioning algorithms are applied to specific situations. Thus, they are difficult to adapt to actually complex environments and different users. To solve this problem, precise Dead Reckoning algorithm based on Bluetooth and Multiple sensors (DRBMs) was proposed. To address positioning accuracy, the system uses Bluetooth propagation model and calculate the steps and step lengths for different users in the process of multisensor track calculation. In addition, it fuses the localization results of Bluetooth propagation model and multiple sensors through the Kalman filter. The experiment results show that the proposed DRBM algorithm can obtain accurate positions. Compared with the traditional Bluetooth positioning methods and other dead reckoning methods, the proposed algorithm greatly improves positioning accuracy [6].
The ideas from these papers paved way to the study of error compensations techniques.

SYSTEM STUDY

Dead Reckoning is cost efficient accurate navigation system where present position is calculated from previous position and with the knowledge of position dependent time varying parameters like acceleration, velocity etc. There are various methods through which we can provide dead reckoning. They are by using Inertial Navigation System, by unit measuring Doppler Effects or by using electronic or optical sensing units.
The system provides dead reckoning by Inertial Navigation System which uses IMU sensors that has accelerometer and gyroscopes. Acceleration will give linear acceleration of vehicle which can be used to calculate velocity and thereby distance travelled. Gyroscopes will give angular velocity of vehicle which can be used to calculate directional changes of vehicle. With this information, microcontroller using the positioning algorithm [7] calculates the position and will be displayed (Fig. 1).

Fig. 1.Block Diagram of System

A. Positioning Algorithm

Acceleration is the rate of change of velocity and velocity is the rate of change of distance. In other words, velocity is the derivative of distance and acceleration is the derivative of velocity. If acceleration is known, distance travelled can be obtained by double integrating acceleration. Integration is known to be area below the curve where it is the sum of very small areas whose width is ideally be zero. Sampling the signal gets the instant values of its magnitude. So small areas can be created between samples whose height is the sampling value and base is the sampling time (Fig. 2).

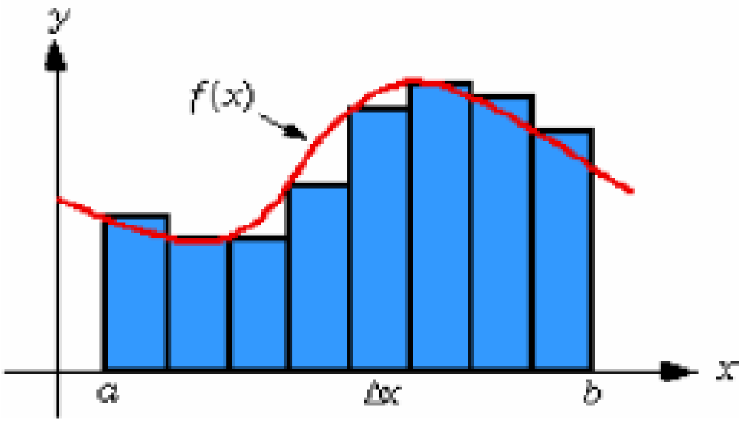

Fig. 2.Sampled Signal for Integration

In real situation, positioning algorithm causes area error which is additionally added while integrating which keeps on accumulating. To reduce this error resulting area can be seen as combination of two smaller areas First one of a rectangle and second one of a triangle. This is known as first order approximation (Fig. 3). Yet data may not be too accurate, because acceleration can be positive or negative. But samples are always taken as positive. So an offset adjustment or reference is needed. This function is defined as calibration routine. So values lower than reference is negative values and greater than reference is positive values.

$$Area_n = Sample_n + (|Sample_n - Sample_{n-1}|)/2)T \quad (1)$$

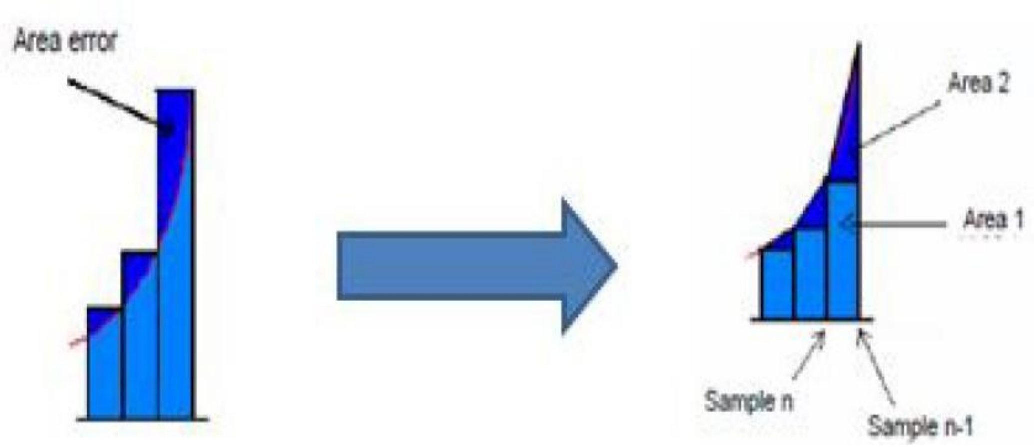

Fig. 3.First Order Approximation

Next one is drift effect where actual position is tend to drift away mainly because of errors in IMU. Following are the types of errors that cause the drift effect.

- Input Range:- Maximum angular rate or acceleration that IMU can meaningfully measure. If the measurements are outside this range it causes drift.
- Bias:- For an input, sensor outputs a measurement offset by a bias. If the actual measurement is 9.80, IMU measures 9.75 with 0.05 biases.
- Scale factor:- It is the relation between input and output. If input is 100% output should also be 100 percent. But actual output is the result of linear effect where output is proportional to input but scales. If input is 10 and has an error of 2% output will be 10.2.
- Random walk (sensor noise):- If a sensor measures a constant signal, random noise in measurement is always present and it is stochastic and eliminated statistically.
- Sensor Non Orthogonality:- IMU consists of 3 axis accelerometer and gyroscope which are mounted orthogonal to each other. If it is not perfectly 90 degree aligned, it causes the error.
- G dependency:- Accelerometer measurements are affected by acceleration due to gravity. If it is not compensated, G dependency occurs in measurements.
- Timing errors:- It is caused due to difference between time the IMU measures and the time that external sources like GPS measures.

B. Error Compensation Technique

Measurements from accelerometer, gyroscope is fed to the filter so that the error in the measurements is compensated and distance with high accuracy is obtained. When the term filter is used, it refers to something that removes, blocks or separates out certain elements. For the purpose of this work, the interest lies in two types of filters:

- Electronic filtering:- It is capable of selectively filter one frequency or a range of frequencies out of a mix of different frequencies in a given circuit.
- Algorithmic filtering:- It is a program or a section of code that is specially design to examine each input or output data request for certain qualifying criteria and then process it accordingly. The

project uses a Kalman filter which is an algorithmic filter.

KALMAN FILTER

Kalman filter are discrete recursive filter that allows the use of mathematical model to estimate the state of the system even in the presence of noisy environment. By using a Kalman filter, noisy measurement data can be combined to obtain an accurate representation of orientation and position.The Kalman filter basically consists of two stages. In the first stage, a mathematical state model predicts the system state. In the next stage this state prediction is compared to measured state values. The difference between the predicted and measured state is moderated based on estimated noise and error in the system and measurements, and a state estimation is output. The output estimation is then used in conjunction with the mathematical state model to predict the future state during the next time update, and the cycle begins again.

Fig. 4 depicts the block diagram of Kalman Filter. Consider the Measurement state equation and output equation.

$$x1 = Ax + Bu \quad (2)$$

$$y = Cx \quad (3)$$

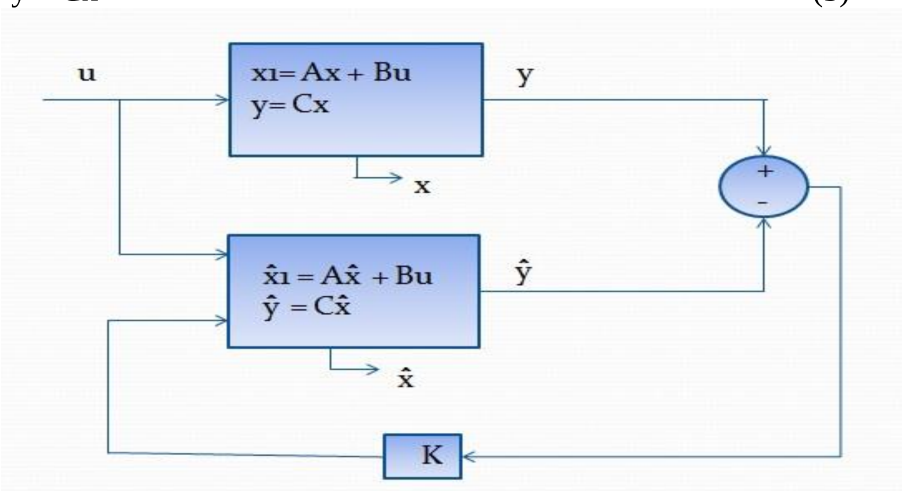

Fig.4.Kalman Filter Block Diagram

and mathematical model equation and its output equation

$$\hat{x}1 = A\hat{x} + Bu \quad (4)$$

$$\hat{y} = C\hat{x} \quad (5)$$

Our aim is to minimise the error to zero.

$$Eobs = x - \hat{x} \quad (6)$$

subtracting Eq 2 and 4 and Eq 3 and 4 will result in

$$\hat{E}obs = (A-KC)Eobs \quad (7)$$

solution to this equation result to

$$Eobs(t) = e\text{^}((A-KC)t)Eobs(0) \quad (8)$$

If A-KC is greater than 0, error tends to zero as t tends to infinity. Time it takes to make the error factor zero depends on Kalman gain which is shown in Fig 5. If Kalman gain is neglected it takes more time for the error to settle to zero.

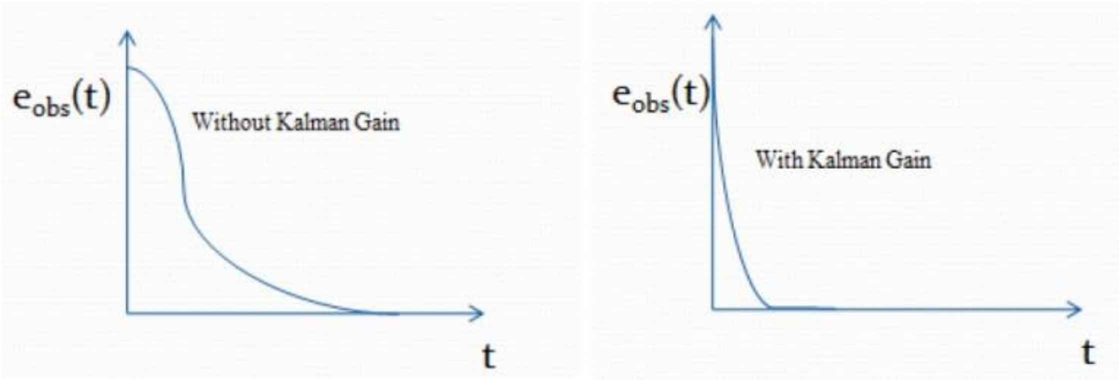

Fig.5.Variation of Error Factor with Respect to Time

A. Kalman Variables

In order to estimate the internal state of a process in presence of noisy observations, one method is to model the process in accordance with Kalman Filter. This means specifying the following matrices:
State matrix X Covariance
matrix P Dynamic Matrix F
Process noise covariance matrix Q
External control matrix B and control unit u
Measurement matrix H
Measurement noise covariance matrix R

The hat over the x means that is the estimate of the state. Unlike just a single x which means the true state, the one trying to estimate. The Kalman Filter model assumes the true state at time k is evolved from the state at (k - 1).

$$X_k = F_k \; X_{k-1} + B_k U_k + w_k \qquad (9)$$

where F_k is the state transition model which is applied to the previous state x_{k-1}, B_k is the control-input model which is applied to the control vector u_k, w_k is the Process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance, Q_k (shown in Fig 6).

$$w_k \sim N(0, Q_k) \qquad (10)$$

At time k an observation (or measurement) z_k of the true state x_k is made according to

$$z_k = H_k x_k + v_k \qquad (11)$$

H_k is the observation model which maps the true state space to the observed space v_k is the observation noise which is assumed to be zero mean Gaussian noise with covariance R_k (shown in Fig. 6).

$$v_k \sim N(0, R_k) \qquad (12)$$

Fig.6. Process noise and Measurement noise

B. Kalman Filter Formulation

The discrete Kalman Filter consists of two stages:

- A prediction stage, where we have the current state of the system and a mapping of the progression of the system as a function of time.
- A correction stage, where the measurements and observations of the variables treated are combined with the actual measured values.

In Predict step, it needs to predict the current state and error covariance matrix at time k. First the filter will try to estimate the current state based on all the previous states and the measurements

$$X_{k|k-1} = FX_{k-1|k-1} + Bu \qquad (13)$$

That is also why it is called a control input, since we use it as an extra input to estimate the state at the current time k called the a priori state. The next thing that try to estimate the a priori error covariance matrix $P_{k|k-1}$ based on the previous error covariance matrix $P_{k-1|k-1}$ which is defined as

$$P_{k|k-1} = FP_{k-1|k-1}F^{T} + Q_k \qquad (14)$$

This matrix is used to estimate how much we trust the current values of the estimated state. The smaller the more we trust the current estimated state. The error covariance will increase since we last updated the estimate of the state, therefore we multiplied the error covariance matrix by the dynamic matrix and the transpose of that F and add the current process noise F^{T} at time k.

The first thing in update step is to compute the difference between the measurement and the a priori state, this is also called the innovation:

$$y_k = z_k - Hx_{k|k-1} \qquad (15)$$

The observation model H is used to map the a priori state $x_{k|k-1}$ into the observed space which is the measurement, therefore the innovation is not a matrix.

Then need to calculate innovation covariance:

$$S_k = HP_{k|k-1}H^{T} + R \qquad (16)$$

It tries to predict how much one should trust the measurement based on the a priori error covariance matrix $P_{k|k-1}$ and the measurement covariance matrix R. The observation model H is used to map the a priori error covariance matrix $P_{k|k-1}$ into observed space. The bigger the value of the measurement noise the larger the value of S, this means that one should not trust the incoming measurement that much. In this case S is not a matrix.

The next step is to calculate the Kalman gain. The Kalman gain is used to to indicate how much one should trust the innovation and is defined as:

$$K_k = P_{k|k-1}HT + [S_k]^{-1} \qquad (17)$$

If innovation is not that much trusty, innovation covariance S will be high. If estimate of the state is trusty, then the error covariance matrix P will be small and the Kalman gain will therefore be small. Transpose of the observation model H is used to map the state of the error covariance matrix P into observed space and compare the error covariance matrix by multiplying with the inverse of the innovation covariance S. Next step is to update the a posteriori estimate of the current state:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k y_k \qquad (18)$$

This is done by adding the a priori state $x_{k|k-1}$ with the Kalman gain multiplied by the innovation y_k.
Last thing is to update the a posteriori error covariance matrix

$$P_{k|k} = (I - K_k H) P_{k|k-1} \quad (19)$$

where is called the identity matrix. It is basically self correcting the error covariance matrix based on how much we corrected the estimate. This make sense as we corrected the state based the a priori error covariance matrix $P_{k|k-1}$, but also the innovation covariance S_k .

RESULT

On board demonstration set up was made which consist of MPU9250 and Arduino. IMU sensor was tested by receiving the default values. In actual case, output of accelerometer in the z-axis should be 1g while placing the sensor parallel to the earth's surface. According to this sensor was calibrated and tested. Calibration is done in such a way that when the sensor is placed at horizontal position parallel to the earth surface, the acceleration values along the X and Y axis should be zero and the Z axis value should be equal to 1g. But before calibration it will not be zero. There will be some acceleration values as offset. To calibrate, took the average of more than 100 samples and write this offset value to the corresponding offset registers of the sensor. After calibrating, the values at the resting positions became to 0 in X & Y axis and 1g in Z axis.
After the designing of system model and Kalman variables, Kalman filter function was programmed .The code was compiled and uploaded successfully. It was tested for small array values. By tuning the error covariance error percentage reduced to 0. But by using motion equation, accuracy was low as it contributes area error. So Kalman filter was again formulated to improve the precision using trapezoidal method. The code was compiled and uploaded successfully and it is tested against large array values. Readings were taken by moving the IMU for 50 cm. Due to error in the sensors measurement was 27cm. By varying the covariance analyzing the error distance measured improved to 40 cm.

1. Linear measurement along 50cm track without filtering

Instead of 50 cm, IMU measures 27cm because of noisy environment. (Fig.7). Kalman filter was used to improve the measurement in noise environment by tuning the varience. By tuning Qpos and Qvel to -0.9 and Rmeasure to 10, distance measured came upto 32cm. Distance of 40cm was obtained by tuning the Qpos and Qvel to -0.5 and Rmeasure to 5.

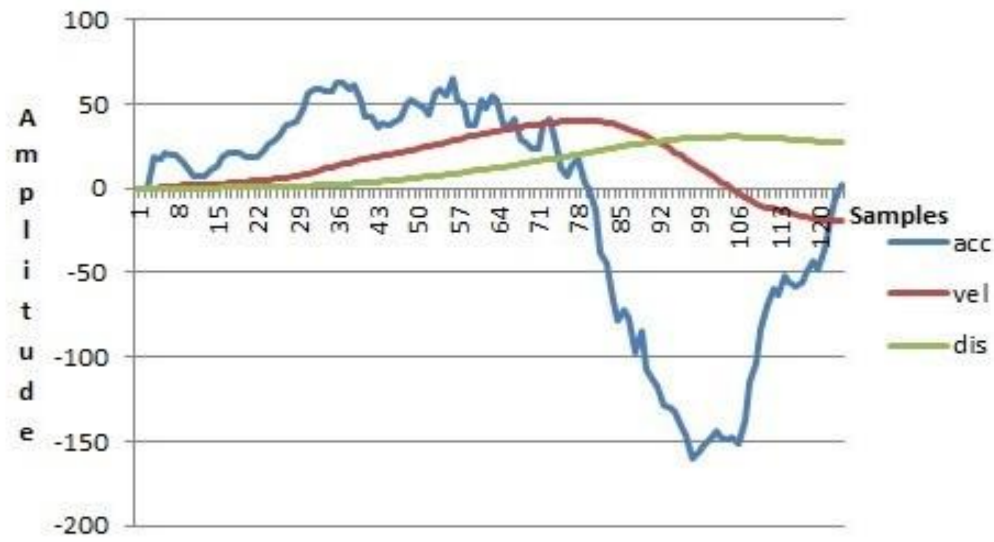

Fig.7: Measurement along 50cm track

2. Linear measurement along 50cm track with filter by varying variance

By tuning Qpos and Qvel to -0.9 and Rmeasure to 10, distance measured came upto 27.38 cm and started to decrease (Fig. 8).

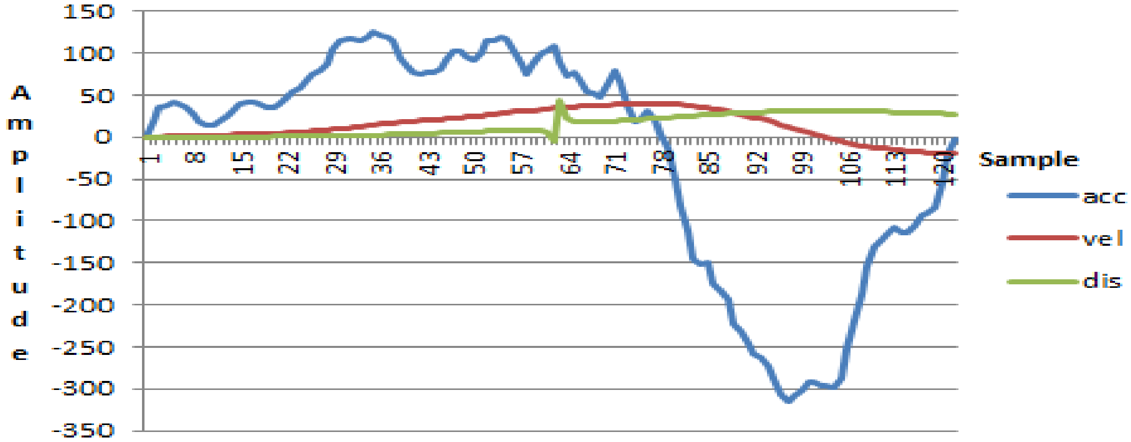

Fig.8: Measurement along 50cm track with process noise covariance -0.2 and measurement noise covariance 5

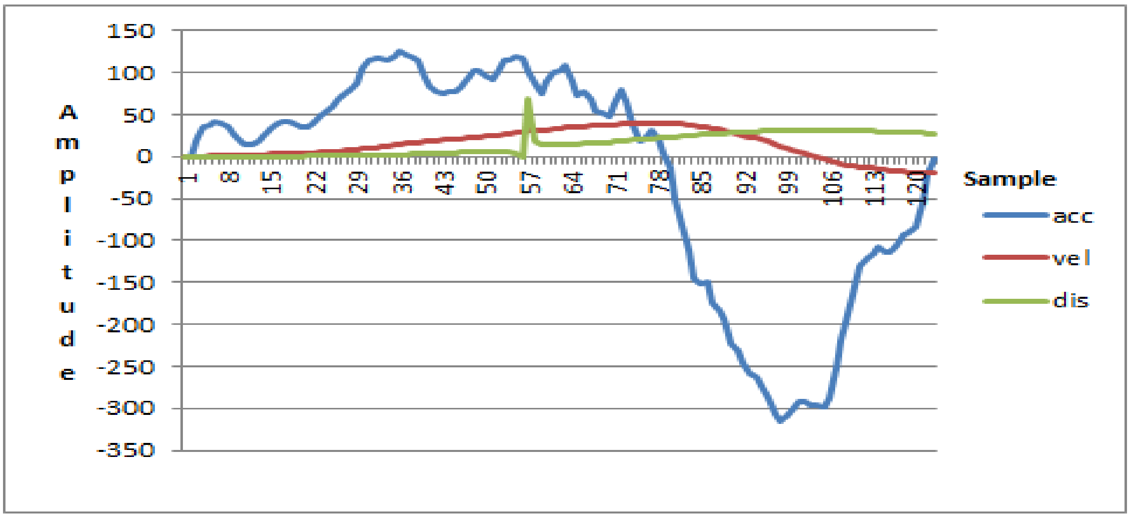

Fig.9: Measurement along 50cm track with process noise covariance -0.5 and measurement noise covariance 10

Distance measured increased to 27.7cm when Qpos=Qvel=-0.5 and Rmeasure=10 (Fig. 9).

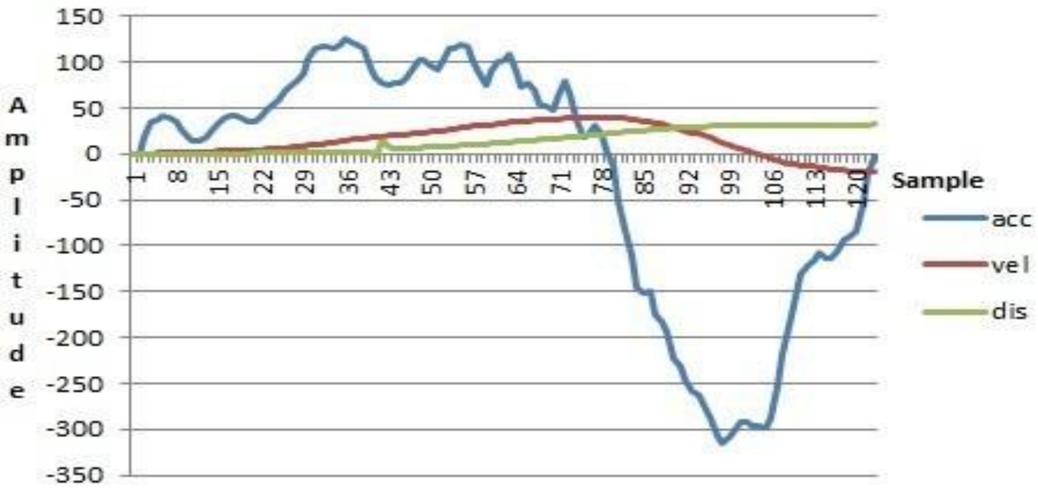

Fig.10: Measurement along 50cm track with process noise covariance -0.5 and measurement noise covariance 10

By tuning Qpos and Qvel to -0.9 and Rmeasure to 10, distance measured came upto 32cm and maintains the value (Fig.10).

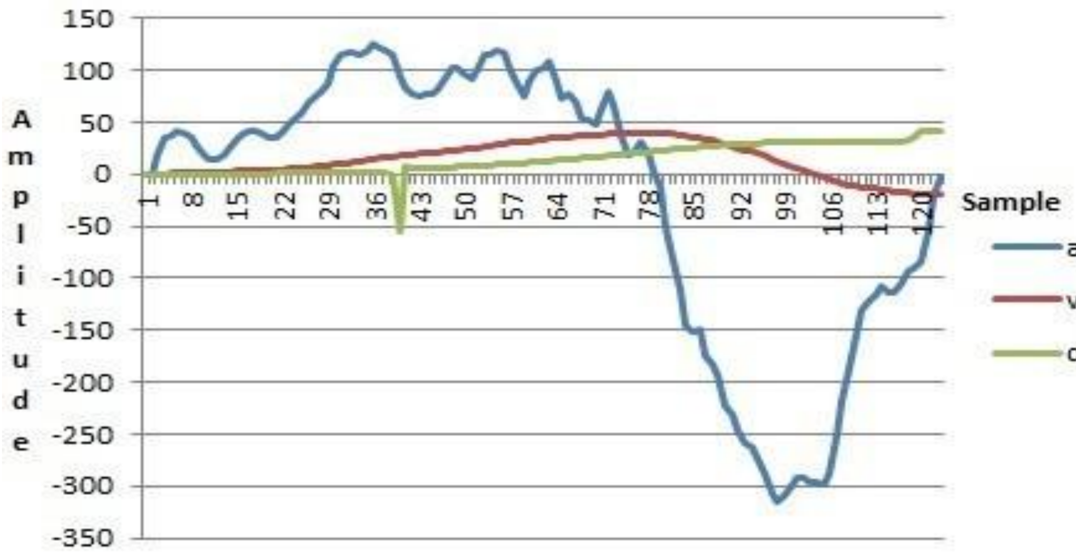

Fig.11: Measurement along 50cm track with process noise covariance -0.5 and measurement noise covariance 5

Distance of 40cm was obtained by tuning the Qpos and Qvel to -0.5 and Rmeasure to 5 (Fig.11).

CONCLUSION

The proposed technique has shown the effective combination of two different sensors (GPS and IMU) each with their own strengths and weaknesses. The low cost IMU used in this work is not capable of running by itself because of drift effect. GPS provides good results, but there is lose of signal due to multipath propagation. The integration of GPS with INS can be integrated by using Kalman filter. In this integration mode the INS error states, together with any navigation state (position, velocity, and attitude) are estimated using GPS measurements. Accuracy of 80-90 % can be obtained by using the filter. To improve the accuracy, more field tests are required to simulate the nature of various noises and there by variance can be tuned accordingly.

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