Improvised Algorithm for Step Detection based on Complementary Filter using LabVIEW

Shanker Ganesh Radhakrishna Prabhu
Faculty of Engineering and Science
University of Greenwich(Medway Campus)
Kent, ME4 4TB, UK.
Contact: s.radhakrishnaprabhu@gre.ac.uk

Shikhar Yadav, Anshul Garg, Aditya Sharma, Purnendu Karmakar
Department of Electronics and Communication Engineering
The LNM Institute of Information Technology
Jaipur, Rajasthan, India. 302031
Contact: {shikharyadav.y12, anshulgarg, adityasharma.y12, purnendu.karmakar}@lnmiit.ac.in

***Abstract*—Development in pedestrian dead reckoning is a significant advancement in localization in indoor environments. The work leading to this paper is aimed at achieving seamless positioning in indoor environments, by improving indoor positioning performance of smart devices. The focus of the work is on developing an accurate step detection algorithm, with high accuracy over a reasonable range of walking speeds. The algorithm is tested using a consumer grade IMU (FreeIMU) and National Instruments myRIO as controller. Pedestrian Dead Reckoning is achieved in three parts: Step Detection, Stride and Heading Estimation, and Map-Aided Navigation. Since there is scope of improvement in accuracy of detection of steps, our work explored algorithms which have potential for improvements in this direction.**

***Keywords*—Indoor Positioning, Inertial Measurement Unit, FreeIMU, LabVIEW, NI myRIO, Pedestrian dead reckoning (PDR), Step Detection, Complementary Filter.**

I. Introduction

The importance of positioning is evident by the wide applicability of Global Positioning Systems (GPS), all over the world. The positioning in indoor environments, however, is not yet successfully implemented on a wide scale. Satellite-based nature of GPS system has limitations in indoor applications, as line of sight cannnot be established with satellites. Therefore, alternate technologies are used to solve the indoor navigation problem. Indoor localization principles can be broadly classified into: inertial navigation (using accelerometers and gyroscopes), mechanical waves (audible and ultrasound) and electromagnetic waves (using the visible, infrared, microwave and radio spectrum). Hence the requirement of satellite communication is not an impedement[1].

The applications of indoor positioning are many in the modern life. A few important ones are discussed below. Tracking the movement of medical personnel within hospitals in emergency situations is a very important application[2]. In law enforcement, fire services and rescue situations[3] etc. this technology has great relevance, for instance, location detection of firemen in a building on fire. Uses in industry include robotic guidance, robot cooperation, automated monitoring etc. In transportation, the provision of navigation can be extended from road guidance to indoor parking areas, by indoor positioning. The driver can be navigated to a parking spot and from there to the pedestrian destination[1]. The visually impaired can be assisted in walking in indoor as well as public transport locations. Cheap smartphone based monitoring and analytics of elderly would significantly help prevent injuries due to falls which are common in old age[4]. Underground construction such as tunneling and mining will also benefit greatly by positioning in the dark environments[1].

This work is a contribution in the direction of indoor localization with the use of smartphones. The motivation of improving smartphone based localization is to leverage the wide availability of smartphones in the present era.

The acceleration and angular position measurements of the person's thigh are easily acquired by the sensors in a smartphone, which can be utilized to capture and trace the information of a persons movements within a building environment.

We utilized a Microelectromechanical systems (MEMS) based Inertial Measurement Unit consisting of gyroscope-accelerometer sensor to replicate the smartphone's motion and orientation in our tests. Algorithms based on acceleration and position of the sensor were explored for improvement in accuracy of step detection.

II. Related work

A. Pedestrian Dead Reckoning Algorithm

The indoor localization can be performed in multiple ways, either accompanying infrastructure utilized is pre-installed in buildings, or positioning is performed independent of infrastructure. Achieving infrastructure independence is possible when the positioning is performed entirely by the acceleration and angular position values of the person's movement[5], and is not relying on hardware installed in buildings, unlike, for instance, WiFi routers required for triangulation positioning.

The current research in the field of indoor localization has a significant focus on pedestrian dead reckoning(PDR). The concept is similar to the way ships were tracked in the sea. The tracking was performed without an external frame of reference on the sea horizon and was purely based on previous position, estimated direction and length of movement. The advantage of PDR approach to navigation is, infrastructure independence can be achieved. In this case, a smartphone alone equipped with required sensors is sufficient to perform this

estimation[6].
Inertial Navigation System (INS) utilizes motion and rotation sensors to apply dead reckoning for calculating the position, orientation, and velocity of a moving object.
The generic sequence of steps to achieve PDR is explained below. This method has a lot of potential in making use of smartphone to acquire raw three dimentional information of movement of a person inside a building, and then correspond it with pre-stored map databases[7] in the smartphone device. This is how navigation is achieved.

1) Step Detection: The cyclic peaks in the foot's motion in general while walking are used for detecting occurance of each step of foot. This is the first step in PDR.

2) Stride Length Estimation: From the data obtained from IMU, velocity and distance are obtained. The position increment is hence estimated at every step, this is known as stride length estimation.

3) Heading and Position Estimation: Along with the length of the step, the knowledge of direction towards which the foot is headed is needed for mapping the movement. So the gyroscope provides this heading.

III. System Model

The acceleration of the foot while walking provides crucial information about the pattern of a person's steps. Hence detection of steps can be achieved using appropriate processing of these real-time acceleration values.

A. Step detection using accelerations

In the algorithm used[8], the processing is performed in four steps.
Step 1: The magnitude of acceleration (a_i) at each step is obtained mathematically.

$$a_i = \sqrt{a_{x_i}^2 + a_{y_i}^2 + a_{z_i}^2}, \tag{1}$$

Step 2: The variance (σ_{a_i}) of this acceleration value is then computed, over an averaging window. This step essentially removes the effect of gravity and only the effect of foot activity remains.

$$\sigma_{a_i}^2 = \frac{1}{2s+1} \sum_{j=i-s}^{i+s} (a_j - \overline{a_j})^2, \tag{2}$$

Here, s is the size of averaging window taken, and we take s as 15 samples. $\overline{a_j}$ represents the local mean of acceleration values. It is calcualted as: $\overline{a_j} = \frac{1}{2s+1} \sum_{q=i-s}^{i+s} a_q$.
Step 3: Two thresholds are applied to this obtained variance, first for detection of swing phase of foot and second for stance phase of foot. The upper threshold is taken as $T1 = 2m/s^2$ and lower threshold $T2 = 0.9m/s^2$.

$$B_{1_i} = \begin{cases} T1 & \sigma_{a_i} > T1 \\ 0 & otherwise \end{cases} \tag{3}$$

$$B_{2_i} = \begin{cases} T2 & \sigma_{a_i} < T2 \\ 0 & otherwise \end{cases} \tag{4}$$

Step 4: Finally, the conditions of detection of step are applied. The conditions are: A) Transitioning from high to low acceleration. ($B_{1_{i-1}} > B_{1_i}$), B) Detection of low acceleration in a $w = 45$ sized window, after the present sample i, i.e.: $max(B_{2_{i:i+s}}) = T2$. These two conditions together signify end of a swing phase and start of a stance phase.

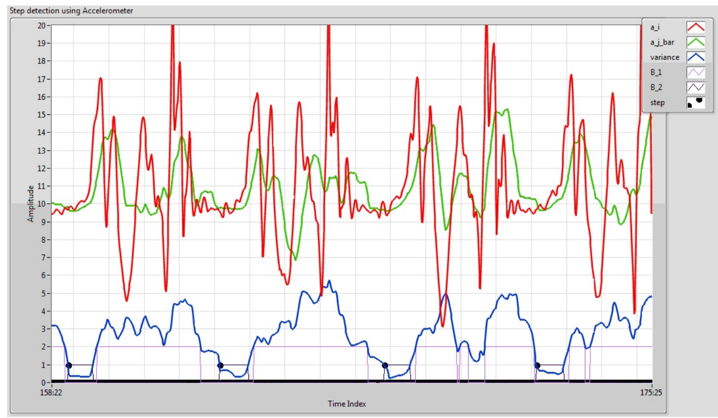

Fig. 1: Implementation of step detection algorithm using accelerations

Fig 1 shows the LabVIEW front panel, with the output curves separately displayed from the four steps explained above.

B. Step Detection using complementary filter: Algorithm combining accelerometer and gyroscope data

Small or sudden disturbances in the foot movement deviate the measurement of acceleration values from the expected periodic measurements. The data taken from accelerometer is therefore reliable on the long term only, hence a "low pass" filter is used.
A gyroscope provides angular position and the error in measurements caused by abrupt disturbances in accelerations is not encountered here. However, since gyroscope obtains angular position by integrating the angular velocity over time, the readings tend to drift, instead of converging to zero when the sensor reaches its original orientation. Therefore, it can be safely stated that the data from gyroscope is reliable only in short term as it begins to drift in long term.
The complementary filter brings together the best features of both methods. The gyroscopes and accelerometers data are weighted appropriately, and added[9]. This way, the non-accumulation of drift in the long term, combines with non-susceptibility to disturbances in short term, resulting in precise angular position values.
The complementary filter gives the value of angular position as follows:

$$angle = 0.98 \times (angle + \omega_z \times dt) + 0.02 \times tan^{-1}\left(\frac{a_{z_i}}{\sqrt{a_{x_i}^2 + a_{y_i}^2}}\right) \tag{5}$$

At every timestep, the data from gyroscope is integrated, and added with the current angle value. Then, the data from accelerometer is processed, as the expression shows, to obtain angular position from acceeration values. The constants (0.98 and 0.02) are the weights, which sum up to 1, and their ratio is how the complementary nature of filter is realized.

IV. Methodology

The logical flow of the entire methodology implemented in this work is explained in this section. It is carried out in two parts. The first part is to initialize configuration registers and access data from data registers of the developing IMU we worked with- FreeIMU. After that, raw values obtained from sensor unit are processed through the two algorithms explained in section 3, the algorithms performes step count, and finally observations are conducted for comparison of their accuracy. Fig 2 shows the foot mounted hardware while the trials were conducted.

Fig. 2: FreeIMU and myRIO hardware attached to the left foot using shoe's laces.

A. Hardware and Platform

1) FreeIMU: The walking-movement during algorithm testing required an Inertial Measurement Unit hence we appropriately chose the hardware as a developing integrated sensor unit- FreeIMU. FreeIMU was an ideal selection as its sensors were comparable with the sensors inbuilt in smart-phones. It consists of MPU6050 which is a combined gyroscope-accelerometer sensor, HMC5883L magnetometer and MS5611-01BA high resolution altimeter.
The MPU-6050 is a unit that comprises of three sub-units which are a gyroscope (3-axis), an accelerometer (3- axis), and a digital motion processor[10].
The Honeywell HMC5883L is a digital interface magneto-resistive sensors designed for magnetic sensing for applications like compassing and magnetometry. It includes a 12-bit ADC that makes it possible to work with heading accuracy of compass of 1 to 2 degrees[11].
The MS5611-01BA is a sensor which functions as altimeter and has both SPI and I2C bus interface. the resolution of it's altitude measurement functionality is 10 cm, and it can also provide precise digital 24 Bit measurements of temperature and pressure[12]. It is the second unit in FreeIMU, the first being MPU-6050 combined with HMC5883L.
The MPU-6050 has an auxiliary I2C bus which communicates with the off-chip magnetometer connected through this bus in FreeIMU. This bus has two operating modes. First is I2C master mode, where MPU-6050 acts as master to the external sensors connected with it. Second is pass-through mode, where MPU-6050 directly connects the primary and auxiliary I2C buses together, allowing the system processor to directly communicate with the external sensor. To access the magnetometer connected through the auxiliary bus of gyroscope and accelerometer unit, pass-through access via MPU-6050 was used.

2) MyRIO: National Instruments myRIO is a controller build on the company's Reconfigurable Input Output(RIO) architecture. It utilizes ARM A9 with Xilinx Zynx FPGA at its core[13]. We used the MyRIO to interface the FreeIMU with our programming platform.

3) LabVIEW: NI LabVIEW[14] is used for data acquisition and algorithm testing. We chose LabVIEW due to it's ease of interfacing with the embedded hardware used.

B. Programming Block

The first step was to successfully acquire and validate raw data obtained from the each sensors of the Inertial Measurement Unit.

1) IMU sensors addressed: Data from the sensors are accessed though a LabVIEW virtual interface(VI)[15] and necessary mathematical manipulations are performed to extract meaningful output. The data obtained is recorded and displayed on the front panel of the VI.
The individual blocks of the VI are executed sequentially. Registers of the components of the FreeIMU are initialized before the main loop is executed. Then within the main loop, data is fetched from registers that store sensor measurements. The individual blocks of the VI are separately explained below. Initially the relevant registers are initialized for proper accessing of MPU-6050's data, as well as to enable pass through mode for the auxiliary bus. Then, the 14 bytes data from sensor measurement registers is read, necessary mathematical manipulation is worked out, and then it is bundled for display on front panel.
The MPU-6050 has an auxiliary I2C bus. To access the

magnetometer which is connected through the auxiliary bus of gyroscope and accelerometer unit, the pass-through mode was activated, in which the MPU-6050 directly connects the primary and auxiliary I2C buses together, allowing the system processor to directly communicate with any external sensors. Then similar to MPU 6050, configuration registers of the magnetometer are initialized to set the data output rate, measurement configuration etc. Then the data from data output registers is read, and displayed accordingly.

2) Algorithms implemented: The values obtained in units of Least Significant Bit (LSB) fetched from registers of the sensors were converted into SI units. Then the first algorithm based purely on accelerations was developed. The functionality of the logical block, for application of magnitude, variance, and thresholds was developed. Step detection logic was then developed from the two conditions of algorithm described in section 3.
After the pure acceleration based algorithm, the complementary filter based algorithm, as explained above in section 3, was developed. It inputs the linear acceleration and angular rate values, and outputs the angle. Appropriate thresholds are applied and the step counter is incremented at the observed peaks. The output of front panel during one test is shown in fig 3. Optimum thresholds levels were found out by narrowing down to the best value in successive observations.

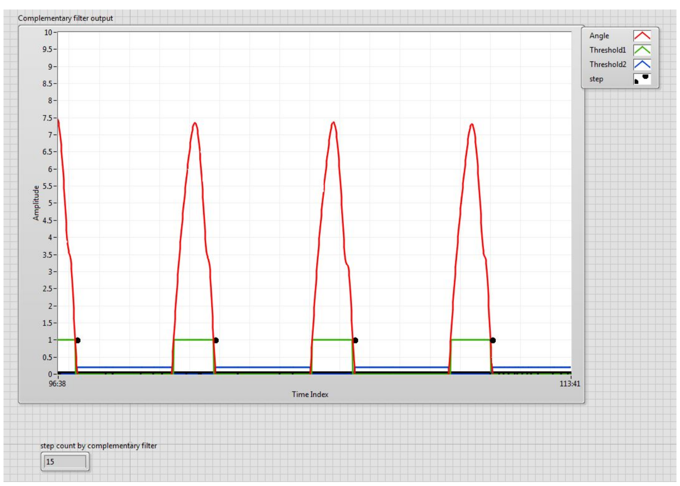

Fig. 3: Implementation of step detection algorithm using complementary filter

C. Optimising constants

Further, we followed the process of narrowing down to the most optimum value of the constants in our algorithm, from observations.

1) Optimising constants of accelerations based step detection: Firstly the optimum value of lower threshold B2 was arrived at, by maintaining the upper threshold B1 at a constant value, and measuring the accuracy of steps counted by the algorithm. The value of B2 was varied from 0.5m/s^2 to 1.5m/s^2. Observationally, it was concluded that B2 as 0.9 m/s^2 resulted in highest accuracy. These observations are presented in fig 4.

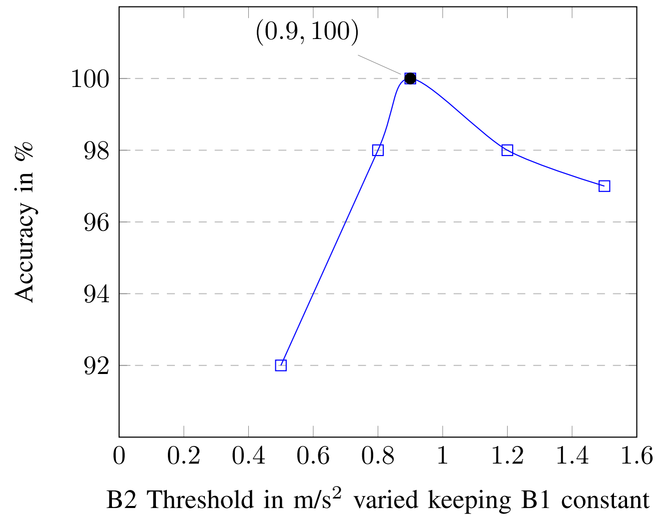

Fig. 4: Plot of Accuracy vs B2 Threshold for arriving at optimum value of B2 experimentally.

Then, with B2 kept constant at the most optimum value of 0.9 m/s^2, we varied B1 from 1.5 m/s^2 to 2.5 m/s^2, and measured the accuracy of counted steps. Highest accuracy was observed with B1 at 2m/s^2. The graph in fig 5. depicts these observations.

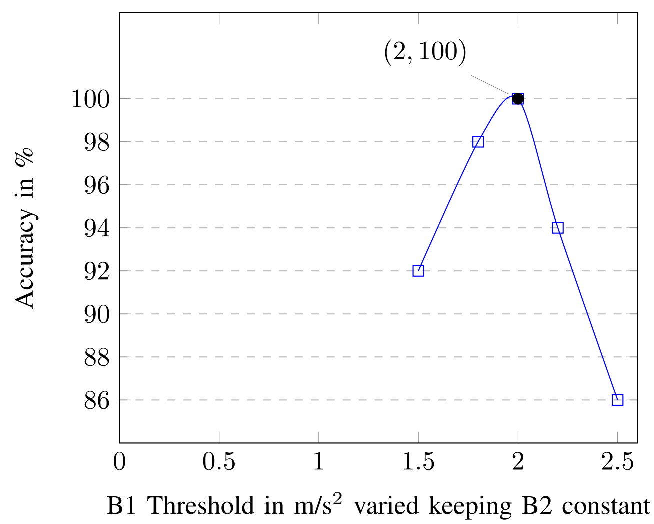

Fig. 5: Plot of Accuracy vs B1 Threshold for arriving at optimum value of B1 experimentally.

Further, two main observations from the results are as follows. First, the closer the difference of B1 and B2 is to 1 m/s^2, the higher the accuracy of algorithm in detecting steps. If the difference was either increased or decreased, the accuracy was reduced by a margin (2% to 8%). Secondly, when the lower threshold B2 was reduced to values below 0.5 m/s^2, the algorithm stopped detecting stance phases, and resulted in wrong step count.

2) Optimising constants of complementary filter based algorithm: The weighted coefficient in eqn (5) was varied from 0.9 to 1, and corresponding values accuracy of counted steps were plotted. From the plot in fig 6, it can be easily concluded that the complementary filter failed to to remain a complementary filter, if the value was equal to 1. Further, the accuracy at coefficient = 0.98 was the highest.

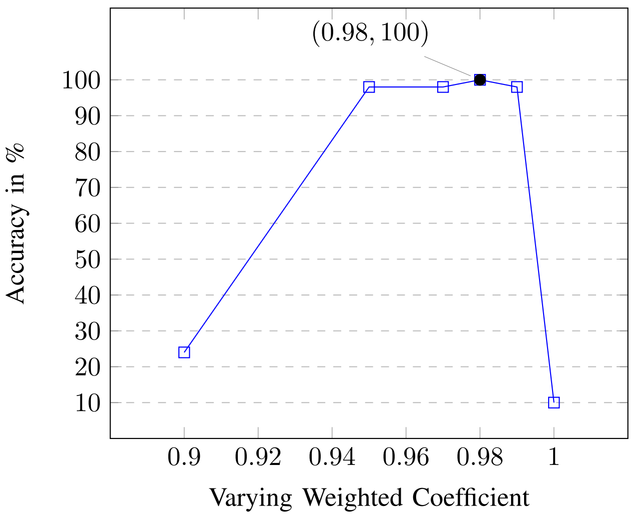

Fig. 6: Plot of Accuracy vs Weighted Coefficient(WC) for arriving at optimum value of WC experimentally.

The complementary filter based algorithm worked best when the upper threshold was maintained within a range of 1 radian to 3 radian, and the lower threshold between 0.2 to 0.5 radian.

V. Results and Contribution

The results inferred from our observations of the step count by both algorithms are mentioned below. The limitations of the conventional algorithm which utilizes only the values of acceleration and the benefits of complementary filter based algorithm are explained in this section.

A. Limitations of accelerometer

By successive testing it was observed, for high walking speeds(>5 Km/Hr), most of the steps were skipped by the algorithm.
Non periodic distortions in the motion-cycle disturbed the accurate count of step detection. Even small abrupt force on the sensor disturbed measurement completely.

B. Improvised complementary filter algorithm

In our tests, the complementary filter based algorithm utilizing both gyroscope and accelerometer performed slightly better in terms of step detection than the accelerometer only algorithm as evident from table 1.

Speed of walking in km/hr	Actual no. of steps	Counted by acceleration based algorithm[8]	Accuracy	Counted by complementary filter based algorithm	Accuracy
3.7	100	100	100%	99	99 %
3.8	100	97	97%	100	100 %
3.9	100	101	99%	100	100 %

TABLE I: Comparison of results of two algorithms

VI. Conclusion

The most optimum values of thresholds in the acceleration based algorithm were experimentally found out, by varying one of the threshold, keeping other constant, and plotting accuracy as a function of threshold. The best value of B1 was found to be 0.9 m/s^2 and B2 was found to be 2 m/s^2. The weighted coeficient in the complementary filter based step detection algorithm was also varied and corresponding accuracy was plotted, to arrive at the best value, which is 0.98 based on our tests. Finally the performances of both algorithms in accurately counting steps were compared. The comparison showed, for better accuracy, as well as for larger range of walking speeds, complementary filter based step detection algorithm faired well.

A. Scope of further work

In this work, only accelerometer and gyroscope sensors out of the four sensors built in the FreeIMU were used. In future work, the magnetometer and altimeter would be used as well. The possibility of testing on smartphone would then be explored.
It is hoped that the superior performance of the algorithm we worked upon and tested, would motivate future researchers to explore it in further works, and possibly utilize it in localization applications. Since the detection of steps by complementary filter based algorithm fulfills the requirement of pedestrian dead reckoning based indoor navigation system, there is scope to expand this work and carry it forward to test entire map aided navigation systems using this technique. The advantage of acceleration and gyroscope based systems is, these sensors are inbuilt in the smartphones already widely available. An integrated combination of outdoor system which tracks position of vehicle with GPS and indoor system which tracks position of person entirely with the sensors in smartphone may become a reality in the near future, achieving full indoor-outdoor positioning completely through the smartphones widely available in the present day.

Acknowledgment

The authors would like to thank the Department of Mechanical-Mechatronics Engineering of The LNMIIT, Jaipur for the generous grant of permission to utilize National Instruments Laboratory for carrying out of our research work. This development work wouldn't have been possible without the support of the administration and faculty at various stages.

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