Indoor Location Estimation using a Pair of Wearable Devices

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***Abstract*—People localization is a very valuable information for state-of-the-art theaters, examination halls etc... Input data are obtained from two foot mounted inertial measurements units. A position tracking algorithm based on foot motion and a heading drift correction method is presented for estimating the subject's position. Moreover, a system training phase is adopted for correction of the toe-out angles deviation from the direction of progress. Experimental results validate the effectiveness of this algorithm in heading drift reduction and position tracking accuracy. The positioning errors are determined based on the average of position estimates of the two foots. Using basic motion patterns estimated position errors are below 2.5% of the total distance traveled.**

I. Introduction

Nowadays, indoor pedestrian navigation is being investigated, using radio, sensors, ultrasound and vision technology. In most cases solutions with no infrastructure required are preferable since sensor network technology makes this possible with self-contained systems. Several infrastructure free methodologies for position estimation based on inertial sensors have been developed [1], [2], [3], [4], [5], [6].

Inertial sensors used in such type of applications are low-cost Micro-electromechanical (MEMS) sensors. These self-contained sensor modules normally contain accelerometers, gyroscopes and magnetometers. The challenge of pedestrian position tracking is the presence of random noise in MEMS sensors. To overcome the accelerometer drift errors that are caused by double integration and are growing with a quadratic rate, an appropriate analysis method should be utilized. For applications where the sensors are mounted on the users' feet, as in the present work, Zero Velocity Update (ZUPT) is utilized [7], [8]. The concept of the ZUPT is based on the observation that human foot motion is cyclic in nature, and for a short time the foot is stationary with zero velocity.

In this paper, the objective is to estimate the position of a person (i.e. a student) in a large in-door area (i.e. examination hall) within a set of pre-determined locations or small areas, as shown in Fig. 1. In a scenario where a person has two inertial measurement units (IMUs) sensors mounted on its feet, the goal is to distinctively place each person at a predefined location (i.e. examination desk). The initial position of the person is the reference point or origin point when he enters the in-door area. Therefore, this paper proposes an approach which uses a position tracking algorithm based on foot motion. The algorithm initially uses a training phase and heading correction during normal operation. The final position is the average of the estimated positions, produced by each foot position measurements.

The remainder of this paper is organized as follows. Section II is a detailed description of the position tracking algorithm used which is based on foot motion. Section III presents the heading correction method, while in Section IV the IMUs are presented along with the system training phase and experimental results.

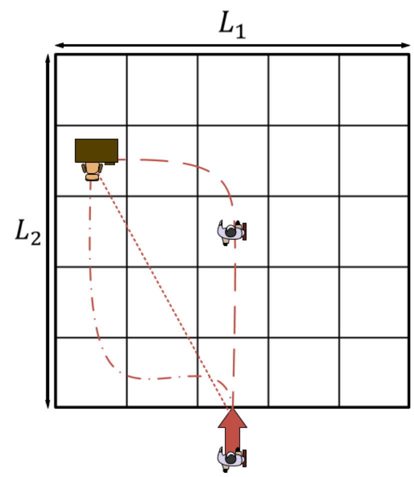

Fig. 1: Person's motion in a large in-door area.

II. Position Tracking Algorithm

A. Explicit Complementary Filter for Orientation Estimation

The main objective of this work is to develop an estimation algorithm for foot orientation based on data from inertial MEMS sensors. To achieve our goal, the attitude estimation problem is expressed as an observer on special orthogonal group SO(3) [9]. The lower portion of Fig. 2 shows an Explicit Complementary Filter (ECF) in quaternion form. Here, ECF has only proportional gain (K_p), as the integral gain of the filter is assumed to be zero. The filter uses the accelerometer and gyroscope measurements, in the Sensor (S) frame of reference with respect to the Earth frame (a^S, ω^S,

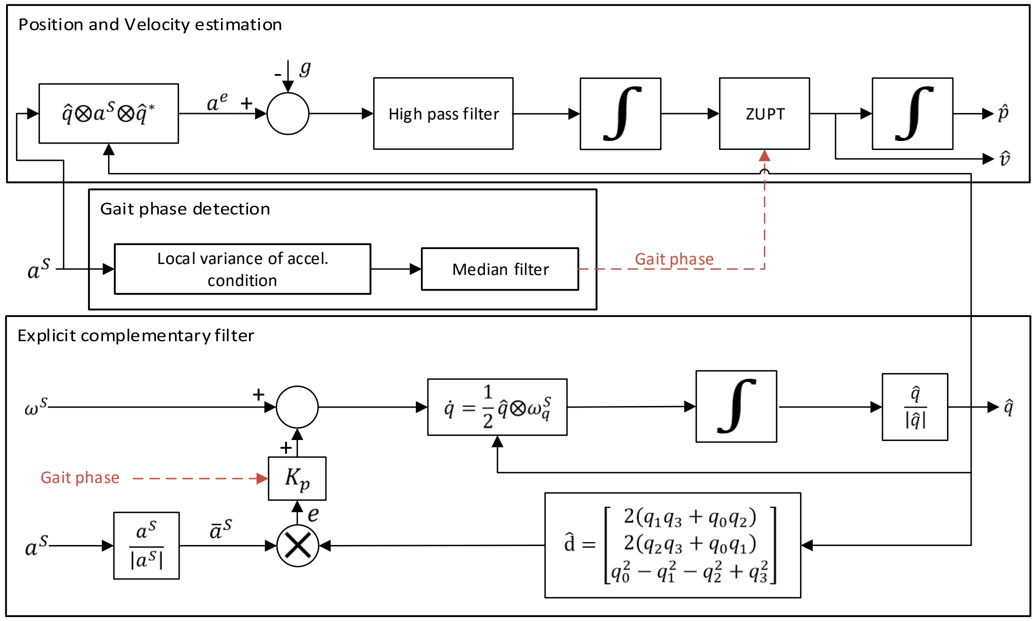

Fig. 2: Block diagram of the position tracking algorithm based on foot motion characteristics [orientation quaternion, position, velocity and phase].

respectively). The output of the ECF is the estimated foot orientation in quaternion form.

Accelerometers and gyroscopes are two independent sources of data that are corrupted by different types of noise. This filter approach is complementary: blends the low-frequency region of the accelerometers, where the attitude is more accurate, with the high-frequency region of the gyroscopes, where the integration of the angular velocity yields to better attitude estimates. The ECF consists of five main steps:

1) Initialization of the filter and data input.
2) Calculation of the direction of gravity.
3) Calculation of the error vector.
4) Fusion approach of error with gyroscope measurements.
5) Calculation of the rate of change of quaternion and integration to obtain the final attitude.

The first step of initialization is to feed the ECF with quaternion, accelerometer and gyroscope measurements. Initially there is no foot rotation. Thus, we use a unit quaternion:

$$q=\begin{bmatrix}1 & 0 & 0 & 0\end{bmatrix}^T \tag{1}$$

In the second step, we estimate the direction of gravity using quaternion:

$$\hat{d}=\begin{bmatrix}2\left(q_1q_3+q_0q_2\right)\\ 2\left(q_2q_3+q_0q_1\right)\\ q_0^2-q_1^2-q_2^2+q_3^2\end{bmatrix} \tag{2}$$

where quaternion is:

$$q=\begin{bmatrix}q_0 & q_1 & q_2 & q_3\end{bmatrix}^T$$

In the third step, we calculate the error vector, which is the cross product between the measured direction of gravity and the estimated $(\hat{d})$:

$$e=\bar{a}^S\times\hat{d} \tag{3}$$

where the measured direction of gravity $(\bar{a}^S)$ is based on accelerometer readings after normalization.

In the fourth step, the error of the filter is applied as a feedback term, which forms a P controller:

$$\bar{\omega}^S=\omega^S+K_pe \tag{4}$$

Finally, in the fifth step, the rate of change of orientation is calculated by the kinematic differential quaternion:

$$\dot{q}=\frac{1}{2}\hat{q}\otimes\omega_q^S \tag{5}$$

where:

$$\omega_q^S=\begin{bmatrix}0 & [\bar{\omega}^S]^T\end{bmatrix}^T$$

The product $\otimes$ is quaternion multiplication and $\hat{q}$ is the most recent quaternion estimate. The estimated quaternion is computed by numerically integrating the quaternion derivative and normalizing the result to remain a unit quaternion.

In order to achieve the most optimal results in foot orientation, we take into consideration the two phases (stance and swing) of the gait phase detection algorithm. For simulation and experimental testing of a position tracking algorithm with adaptive-gain complementary filter, see [6]. Due to the fact that the foot is stationary (on the ground) in the stance phase, measurements provided by accelerometers are sufficient to estimate the foot orientation. Thus, we mostly rely on accelerometer and a relatively large value of K_p is used. During the swing phase, the foot is subjected to large linear accelerations and the orientation estimate becomes less accurate. Thus, we depend only in the integration of angular velocity for estimating foot orientation.

B. Position and Velocity Estimation Algorithm

In order to obtain the position and velocity of the foot, the algorithm is based on the dead reckoning technique. The main idea is to use the accelerometer readings and the estimated quaternion from ECF. These readings are taken with sample interval Δt at discrete sampling times. Details of the designed block are shown in the upper part of Fig. 2 (for brevity k is not shown in the block) and explained below. The accelerations, a_k^S, are transformed from the sensor coordinate frame (S) to the earth coordinate frame (e) using the quaternion rotation operator [10]:

$$a_k^e = \hat{q}_k \otimes a_k^S \otimes \hat{q}_k^* \tag{6}$$

Where $\hat{q}_k$ is the estimated quaternion representing the orientation of the foot and $\hat{q}_k^*$ is the quaternion conjugate.

The acceleration vectors are treated as pure quaternions with the scalar part being equal to zero. After obtaining the acceleration in the earth frame, the value of g (9.81 m/s^2) is subtracted from the vertical component of acceleration to derive the gravity free acceleration value:

$$a_k = a_k^e - [0, 0, g] \tag{7}$$

Theoretically, this acceleration vector can be integrated to obtain velocity in the earth frame. However, due to the presence of measurement noise and drift in the measured acceleration vector and the estimation errors in the estimated quaternion, an immediate integration of acceleration results in unbounded error growth in velocity and position estimation in a relatively short time. As previously stated an approach to reduce error growth in the position and velocity estimation is to apply a velocity correction method called ZUPT. During walking, the foot is briefly stationary in between steps when it is on the ground. In this period ZUPT is used to correct the velocity by knowing the velocity should be zero.

The strategy adopted to deal with this problem is to filter the acceleration readings with a high pass filter for drift reduction prior to integration. This zero phase high pass filter is a Butterworth sixth order with cut-off frequency of 0.4 Hz. The order of filter and the cut-off frequency was adjusted by trial-and-error until a satisfactory result was achieved. Using the gait phase detection algorithm, we can detect when the foot is in the stance phase. Therefore, we can reset the velocity to zero in this phase and we can integrate the acceleration in the swing phase of foot as follows:

$$v_k = v_{k-1} + \frac{a_{k-1} + a_k}{2}\Delta t \tag{8}$$

The numerical integration is done with the trapezoidal rule. This refinement in velocity allows us to integrate once again and obtain the estimated position of the foot:

$$p_k = p_{k-1} + \frac{v_{k-1} + v_k}{2}\Delta t \tag{9}$$

C. Gait Phase Detection Algorithm

The middle part of Fig. 2 shows the gait phase detection algorithm. Step detection is a necessary strategy in order to apply ZUPT for correcting foot velocity. For this purpose, the use of accelerometer data was examined. Detection of gait phase with gyroscopes can be found in [3], [4].

In this paper, the algorithm for step detection is essentially a detector with two states, stance and swing. Logical 1s mark the stance phase and logical 0s mark the swing phase. The local acceleration variance was used to distinguish the foot activity and is calculated as:

$$\sigma^2_{a_k^S} = \frac{1}{2w+1}\sum_{j=k-w}^{k+w}(a_j^S - \bar{a}_j^S)^2 \tag{10}$$

where $\bar{a}_j^S$ is a local mean acceleration value, computed by:

$$\bar{a}_j^S = \frac{1}{2w+1}\sum_{q=k-w}^{k+w} a_q^S \tag{11}$$

and w defines the size of the averaging window ($w = 15$ $samples$). An empirically determined threshold is applied for the detection of the two states:

$$Condition = \begin{cases} 1 & \sigma^2_{a_k^S} < th_{\sigma^2_{a_k^S}}, \\ 0 & \text{otherwise.} \end{cases} \tag{12}$$

In order to make the method robust, we filter the results obtained from the previous condition using a median filter with a neighbouring window of 15 samples. The output of this filter is the resulting phase of gait.

III. Method to Reduce Drift in Heading

Apart from accelerometer drift errors, a heading drift is present during position tracking. Magnetometer measurements which are often used for heading observations are unreliable in indoor environments where there are significant magnetic disturbances. In order to reduce heading error, a new method was proposed by Borestein and Ojeda [11] called Heuristic Drift Elimination (HDE) when navigating in buildings. HDE assumes that in the majority of buildings walls and corridors are straight and other parallel or orthogonal to each other. These orientations of the corridors are mentioned as dominant directions. Following that, another work has been proposed based on these criteria, implemented using extended Kalman filter (EKF) approach with a confidence estimator over the correction of estimated orientation error [12].

To eliminate the error in heading due to gyroscopes bias error, we rely on the work proposed by [13]. This work called Advanced Heuristic Drift Elimination (AHDE) and classifies the type of motion and updates the measurements accordingly. We use the same criteria for detecting the motion of a person in our experiments.

A. Person Motion Detection

The first phase is the detection of motion type. Two types of motions are sensed: non-straight motion and straight motion along the dominant direction. To determine straight motion, every time we use the positions that result from the six previous foot steps and the current one. Specifically, these position points are the positions at the end of the stance period of the gait phase, which in section II was described. Therefore, we perform linear regression, which fits a straight line based on perpendicular offsets throughout the 7 positions. Minimization of the sum of squares of the perpendicular offsets (D) is the value that we use to detect the straight motion. The value of D is the criterion of the way the pedestrian walks. In cases where the person moves along a curved trajectory, D will increase in value, while in cases where the trajectory is a straight line, D will be minimized. Therefore, if $min(D) < th_D$, straight motion is determined, otherwise non-straight motion is considered.

B. Dominant Direction and Angle Estimation

It is important to note here that we utilize a system training phase prior to applying the method of heading drift correction. This phase corrects the toe-out angles of the feet and outputs the best fitted line in the first five steps. The slope (a) of this fitted line is used to calculate the dominant directions and the correction angle. In order to do that we rely on the cardinal directions of a compass to calculate the dominant directions. Specifically, north (N), south (S), east (E) and west (W). These directions can be translated in the X-Y plane, with the help of a fitted line, that is derived from the system training phase, according to:

$$E = \begin{bmatrix} 1 & a \end{bmatrix}, \; W = \begin{bmatrix} -1 & -a \end{bmatrix} \tag{13}$$

$$N = \begin{bmatrix} -1 & \frac{1}{a} \end{bmatrix}, \; S = \begin{bmatrix} 1 & -\frac{1}{a} \end{bmatrix} \tag{14}$$

Regarding the estimation of the correction angle, we measure four angles. These angles are calculated between two vectors, the direction projection vector $\begin{bmatrix} 1 & a \end{bmatrix}$ - a is derived from the fitted line throughout the 7 position points - and the dominant directions. For the purpose of placement in the correct dominant direction we monitor these angles with a predefined threshold, small in value so that the person is placed in one direction of the X-Y plane. It is a strong possibility that the person will not be placed in none of the four zones, when the threshold is small. In this case, no correction is applied since the user's path diverges from the dominant directions and a correction scenario will have negative effect in the estimated trajectory.

C. Position Correction

After completing the estimation of the correction angle, we rotate the whole trajectory path from the foot step that the fitted line was estimated, with angle $\hat{\theta}$ in the X-Y plane as shown in the following equations:

$$x_{corrected} = cos\hat{\theta}x + sin\hat{\theta}y \tag{15}$$

$$y_{corrected} = -sin\hat{\theta}x + cos\hat{\theta}y \tag{16}$$

Due to the fact that this rotation is a rotation of the coordinates system around a predetermined angle, the trajectory path has discontinuities. Specifically, the current corrected trajectory path is orthogonal to the previous correction - where an angle was estimated throughout 7 foot steps of a fitted line - that has be done on this trajectory. Thus, we subtract these discontinuities from the two sides (edges) that adjoin these paths to make the trajectory continuous.

IV. Experimental Results

In order to test the system proposed in this paper two sensor modules were deployed and compared. IMU-1 is a commercial unit, while IMU-2 is a custom design implemented in our lab. The two sensors transmit data via the Bluetooth protocol and the characteristics of each individual MEMS sensor within these two solutions are summarized in Table I.

TABLE I: Characteristics of individual sensors

	IMU-1		IMU-2	
	Accelerometer	**Gyroscope**	**Accelerometer**	**Gyroscope**
Dynamic range	$\pm 16\ g$	$\pm 2000\ dps$	$\pm 16\ g$	$\pm 2000\ dps$
Sampling rate	$100\ Hz$	$100\ Hz$	$100\ Hz$	$100\ Hz$
RMS Noise	$0.027\ m/s^2$	$0.048\ dps$	$0.116\ m/s^2$	$0.100\ dps$

A. System Training

Human walking can be defined as a method of locomotion involving the use of two legs, alternately. Gait describes the manner or style of walking. An important spatial factor which is involved in gait analysis is the angle between the direction of progress and the longitudinal axis of the foot, known as foot angle or toe-out angle. Fig. 3 shows these angles for right and left foot respectively. The angles of sensors X-axis with respect to the direction of progress is also annotated. These foot angles are the system training parameters which are estimated before the foot motion algorithm.

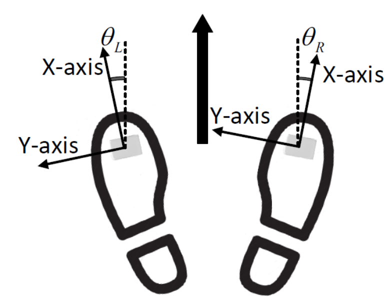

Fig. 3: A person's feet angles along the direction of progress.

In order to correct this rotation of the foot, we propose a training period to be applied before actual measurements. In this stage, we correct these deviations of each foot by rotating all position points by certain degrees of the right and left foot. Calculation of these angles is achieved by performing linear regression and we fit a line based on perpendicular offsets through the first five position steps. These angles are represented by the angle of fitted lines for each foot sensor. Therefore, the user can walk freely with no concern of the toe-out angle. In addition, we re-calculate a fitted line with these new position points to derive the slope of this line. This parameter is used in the heading correction method of the previous section for the calculation of the dominant direction.

B. Experimental Results

The following sub-sections describe experimental results demonstrating the accuracy of position tracking algorithm presented above with the addition of heading correction method using IMU-1. Furthermore, the subject was made to walk on manually surveyed paths marked on the ground, in order to validate the feasibility of tracking 2-D position relative to ground-truth. We conducted these experiments using two sensor modules attached in each foot.

As performance metrics we use the absolute position, the average position, the standard deviation errors and the percentage of the average error relative to the total distance traveled. Specifically, the absolute position error is the euclidean distance error of the X-direction and Y-direction.

1) Straight Path: These experiments include 10 trials in which the subject walked in a straight line of various distances, in order to calculate the error versus distance covered. Table II shows experimental results for 10, 20, 30, 40 meters straight line walks. In addition to this, Fig. 4a shows average position and standard deviation errors of all trials conducted versus distance covered and Fig. 4b shows position percentage errors relative to distance traveled.

2) Curved Path: Ten trials of 3 different curved walks were conducted. Each curved walk have in common a curved path of radius 7 meters and straight lines that increase in distance in a constant manner. Table III shows the position errors of the corrected average of feet.

In addition, Fig. 5 shows the last case of curved trajectory ($D = 53\,m$) with the result of system training phase and heading correction, and the uncorrected trajectory. From this figure becomes clear the effectiveness of heading correction and the necessity of system training phase.

3) Straight Line Walking with IMU-2: Using IMU-2 we conducted another straight walk experiment. Table IV shows the estimated error results of a 40 meters in a straight line.

V. CONCLUSIONS

This paper described an approach of using foot motion pattern and combined sensor estimate for position tracking of a student. In addition, we have described and implemented a system training along with a heading correction method. The estimated errors from the previous experiments validate that this approach was accurate.

Future work will focus in obtaining periodic position updates during the walk, in order to re-calibrate the system in the correct position. These updates can be done by beacons, carefully placed around the examination hall.

TABLE II: Results of straight walking

Trial	**Position Error using Combined Sensor Estimates** Straight walk 10 $[m]$	Straight walk 20 $[m]$	Straight walk 30 $[m]$	Straight walk 40 $[m]$
1	0.15	0.35	0.54	1.00
2	0.16	0.54	0.56	0.97
3	0.16	0.35	0.69	0.72
4	0.31	0.42	0.51	1.03
5	0.18	0.46	0.49	1.01
6	0.21	0.48	0.62	0.90
7	0.16	0.56	0.67	1.11
8	0.23	0.38	0.81	1.07
9	0.29	0.36	0.86	1.07
10	0.22	0.39	0.83	1.22
Average $[m]$	0.20	0.42	0.65	1.01
σ $[cm]$	5.65	7.74	13.7	13.3
Error $[\%]$	2.00	2.10	2.16	2.52

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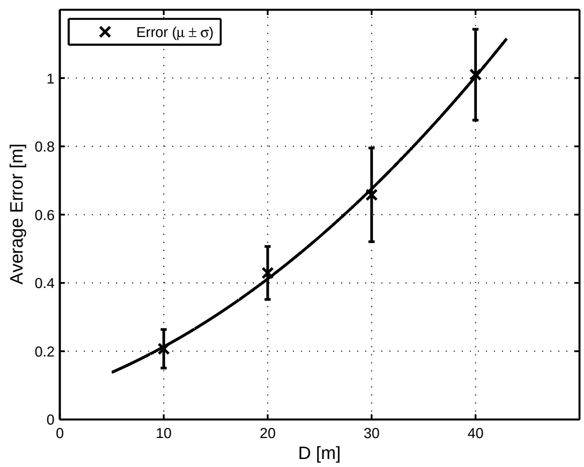
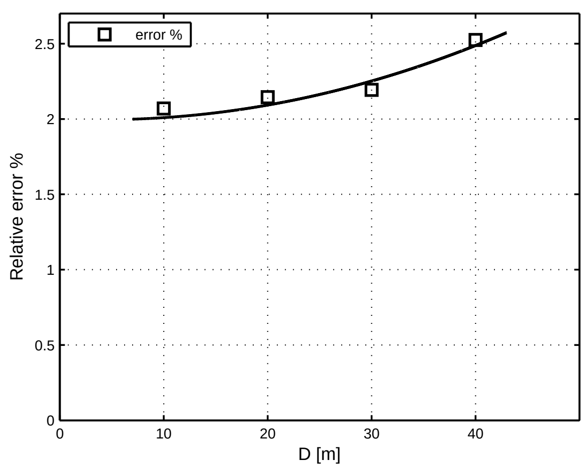
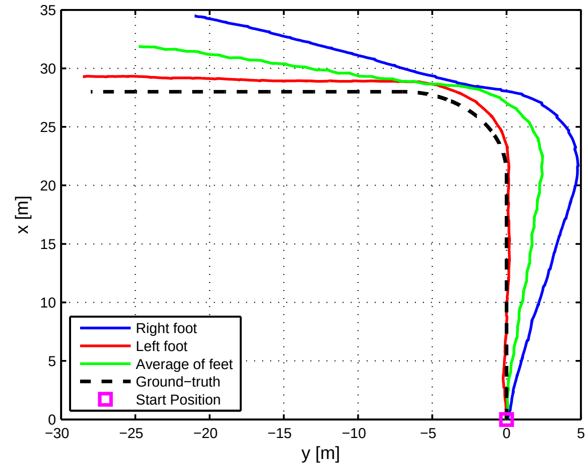


(a) *Position error*

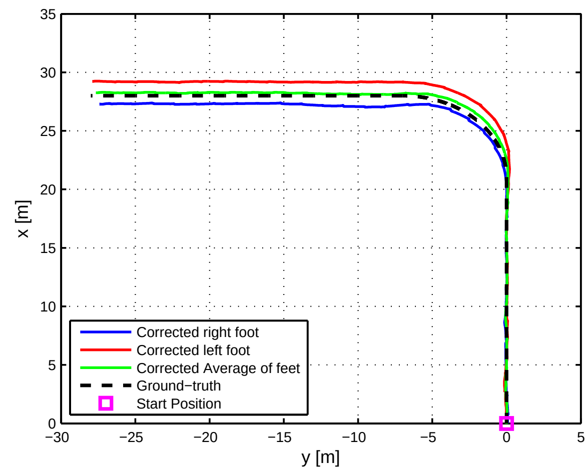


(b) *Relative position error*

Fig. 4: Positioning errors along straight path



(a) *Curved path*



(b) *Corrected curved path*

Fig. 5: Curved paths with distance D = 53 [m]

TABLE III: Summary of results for curved path

	Combined Sensor Estimates Position error $[m]$		
Trial	**Curved path 25** $[m]$	**Curved path 39** $[m]$	**Curved path 53** $[m]$
1	0.29	0.20	0.49
2	0.47	0.55	1.02
3	0.59	0.63	0.97
4	0.49	0.54	0.42
5	0.50	0.16	0.74
6	0.55	0.38	0.62
7	0.40	0.32	1.20
8	0.41	0.30	0.90
9	0.65	0.42	1.01
10	0.34	0.38	0.52
Average $[m]$	0.46	0.38	0.78
σ $[cm]$	11.1	15.23	26.7
Error $[\%]$	1.84	0.97	1.47

TABLE IV: Summary of results for custom design sensor for straight walk

	Sensor Estimate Position error $[m]$
Trial	**Straight walk 40** $[m]$
1	1.34
2	1.49
3	1.36
4	1.25
5	1.48
6	1.31
7	1.42
8	1.82
9	1.54
10	1.80
Average $[m]$	1.48
σ $[cm]$	19.4
Error $[\%]$	3.70