Low cost infrastructure free form of indoor positioning

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Abstract— This paper is concerned with smartphone based inertial sensors for locating pedestrians. Two set of experiments were conducted over seven subjects. One set of the subjects walked along a straight path at a perceived normal and speedy pace, and the other set of subjects traversed a simple map consisting of two L shaped paths. In the experiments, a smartphone – HTC 2710e was handheld, with screen facing upwards was used to record the acceleration, magnetometer and gyroscope samples at 20Hz. The accelerometer samples are then analyzed to detect and count the footsteps, while gyroscope and magnetometer samples are used to estimate the heading. The results of our experiment show that the average error in foot step detection rate is less than 3% in normal walking and 5% in speedy walking using Fast Fourier Transform (FFT) based approach. While the most nearly correct estimated displacement is via Weiner approach with average percentage error of 5.74% in normal walking and 8.07% in speedy walking. The average percentage error in heading is less than $11^\circ$ in turnings in both the L shaped paths.

Keywords—Pedestrian dead reckoning (PDR), indoor positioning system, smartphone, foot step detection, stride length, heading

I. INTRODUCTION

Generally, the indoor positioning solutions have focused on using Received Signal Strength Indicator (RSSI) signal or inertial sensors such as accelerometers and gyroscopes for locating the pedestrians in indoor environments [1]. The RSSI-based approach is based on estimating the signal strength of the received electromagnetic wave carrying the signal or received power. Although, the RSSI-based approach is appealing for its accuracy, it requires additional infrastructure for its implementation and frequent signal calibration. This adds to an overall cost of the system [2].

Inertial sensors compute the position of the pedestrian by employing dead reckoning (DR) algorithms. DR is an estimation of the current position by using a pre-determined start point and then updating the position estimate through the knowledge of acceleration, speed and direction over time [3]. Pedestrian dead reckoning (PDR) systems based on fixed inertial measuring unit (IMU) systems have been in existence for several years. In fixed position IMU-based PDR, sensor block is either attached to the shoe or fitted around the belt [4]. Recently, smartphones have been used as PDR systems. However, the orientation of a smartphone is typically non static so, one has to be careful about how the signal pattern may change with different orientations of the smartphone. The main idea of PDR mechanization is to use accelerometer signals to detect footsteps, estimate step length and propagate position using measured heading. Heading can be computed using a magnetometer or gyroscope [3].

In this paper, we develop the indoor positioning system based on PDR algorithms using various inertial sensors in smartphone – accelerometer, gyroscope and magnetometer. The initial heading has been estimated using magnetometer. Since, the magnetometer suffers from environmental perturbations. Therefore, subsequent headings have been estimated using gyroscope. Moreover, it has also been observed in [5] that the gyroscopes are more stable in indoor environments. An experiment has been performed to validate the headings estimated by the gyroscope in two L shaped paths. Several foot step detection methods and step length estimation models are reviewed, and compared by testing over several subjects via walking in a straight path of length 14.9m, 17.8m and 32.7m. The key contributions of this paper are:

- Comparison of the foot step detection algorithms – peak detection, zero crossing and Fast Fourier Transform (FFT) based.
- Comparison of the stride length models – Weiner approach, Scarlet approach and Kim approach.
- Estimating of the heading error, generated by the gyroscope sensor in two L shaped paths.

The structure of the paper is as follows: Section II describes the principles of PDR. It also details our smartphone based PDR system. This is then followed by our experimental setup, results and discussion in Section III. Finally, we present our conclusion and future work in Section IV.

II. BACKGROUND

Pedestrian dead reckoning is a relative navigation technique through which the new location of a pedestrian is estimated with the help of the start location, the distance travelled and direction of motion [6], according to (1) and (2)

$$X(t+1) = X(t) + S \cos \theta$$  \hspace{1cm} (1)
Where $X(t)$, and $Y(t)$ represent the pedestrian’s location at time index $t$, $X(t+1)$ and $Y(t+1)$ represent the pedestrian’s location at time index $t+1$, $S$ is the displacement in one foot step, and $\theta$ represents the direction of motion. Typically, the step length $S$ is estimated with the help of accelerometers and the direction $\theta$ is estimated with help of magnetometers or gyrosopes. In order to efficiently apply the DR technique we need

- An accurate detection of the pedestrian’s displacement
- Precise estimation of the heading direction.

In general, there are two methods used to find the displacement by using accelerometer sensor signal [4]. These are as follows

- Integration method
- Signal processing method

A lot of earlier research [7, 8] is based on finding the displacement by double integration of the signal from the accelerometer. However, due to the presence of noise in the accelerometer output, error accumulates rapidly with time. Another source of error is the presence of a component of acceleration due to the gravity of the earth when the phone has an arbitrary orientation. These factors lead to positioning errors in displacement to grow super linearly over time. It has been observed in [9] that this error can grow 100 meters after 1 minute of operation and 1000m after 2 minutes of operation.

To overcome this error accumulation, Zero Velocity Update (ZUPT) method [8] is usually applied. The ZUPT sets the velocity to zero when the pedestrian’s foot is detected to be stationary. In this way, it corrects the linear velocities obtained after integrating the accelerometer values subsequently minimizing the drifts to propagate further. The best scenario to use the ZUPT algorithm with high precision is when sensor unit is attached onto foot to detect a step.

The second method to find the linear displacement is the signal processing method [10, 11]. In this method, accelerometer signal is analyzed for detecting footsteps. A specific pattern is repeated at each foot step. A linear displacement is calculated during each foot step by using stride length estimation methods. Since, smartphone orientation is non-static and can vary with time, so, integration method is not suitable.

Fig. 1 shows the block diagram of the algorithm flow of our smartphone based PDR positioning system. The accelerometer samples were initially filtered using a low pass filter according to (3), and then subsequently were forwarded to the activity classification module. The pedestrian state was recognized whether it is walking or static. Based on the state recognized; if it is walking, the footsteps were detected followed by the estimation of the stride length at each detected foot step. Finally, the heading was determined using magnetometer and gyroscope data.

$$\hat{y}(t) = \alpha \hat{y}(t-1) + (1 - \alpha) \hat{x}(t)$$  \hspace{1cm} (3)

Here $\hat{y}(t)$ is the filtered accelerometer signal at time $t$, $\hat{x}(t)$ is the raw accelerometer signal at time $t$ and $\alpha$ is a constant

A. Activity Classification

The pedestrian’s walking and static states are recognized from the filtered accelerometer signal by observing several characteristics in the frequency domain like FFT amplitude and FFT energy via sliding window of 20 samples, with no overlap. Each sliding window covers a time interval of 1s. The window of 1s is used to sufficiently capture cycles of the pedestrian activities – walking and static. Moreover, the size of the 20 sample window enables a balanced time and frequency domain resolution [12]. Out of various frequency domain quantities – FFT amplitude is the most promising to identify between the start and stop of walking as shown in Fig. 3. The figure depicts pedestrian to be at rest for the first 2 seconds (see Fig. 3(A) and Fig. 3(B)) and walking for the remaining 2 seconds (see Fig. 3(C) and Fig. 3(D)). Empirically, we have set two FFT amplitude thresholds $T1$ (approx. 0.6) and $T2$ (approx. 0.2). $T1$ is called dynamic threshold and is used to identify the walking state and $T2$ is the static threshold. It is used to recognize the rest state. If FFT amplitude is greater than $T1$, dynamic state is identified, else if FFT amplitude is less than $T1$ then it is checked for static threshold and if FFT amplitude is less than $T2$ too, rest state is identified otherwise previous state is retained as explained in Fig. 2. The red line in Fig. 3 depicts the static threshold ($T2$) and green line depicts the dynamic threshold ($T1$).

B. Foot step detection

Accelerometer has been commonly used for foot step detection. The measured acceleration values represent a combination of the applied acceleration on the smartphone due to motion and the force of earth’s gravity [13]. Considering the fact, that a smartphone can be at any position on the pedestrian’s body, with time-varying orientation change, we use the magnitude of 3-axis accelerometer readings instead of
its vertical and horizontal components. The earth’s gravity is filtered out by subtracting the mean value of the accelerometer samples collected over a long idle log. In general, there are three types of foot step detection methods which can be used to analyze acceleration signal [14]: peak detection, zero-crossing detection and flat zone detection. Also, some researchers have utilized the rhythmic nature of footsteps to detect and estimate the foot step frequency [15]. We present here three of the state-of-the-art foot step detection techniques: the peak detection method, zero crossing method and FFT.

1) Peak detection

The peak detection algorithm is based on filtering the magnitude of acceleration signal followed by applying a threshold on the acceleration signal over a sliding window [16, 17]. Its current implementation depends on high accuracy foot mounted accelerometers, which differ significantly from phone-embedded sensors. We quantify its performance when applied to phone sensors in Section III. The algorithm counts a valid footstep when local maximum peak (maxima) and local minimum peak (minima) are detected in sequence. The value of local maxima should be higher than that of the most recent valid local minima by at-least a threshold value \( \Delta_{th} \) (approx. 0.5m/s²). Also, the value of the valid local minima should be lower than that of the most recent valid local maxima by at-least a threshold value \( \Delta_{th} \) (approx. 0.5 m/s²) as shown in Fig. 4. Red dots represent valid maxima which is a peak acceleration exceeding upper threshold. Black dots represent valid minima which is peak acceleration lower than lower threshold. The detection threshold \( \Delta_{th} \) is determined through experiments.

2) Zero crossing

Another method for foot step detection based on acceleration values is the zero crossing method discussed in [18]. This method first computes the magnitude of the acceleration signal. The foot step boundaries are defined by either positive or negative going zero crossing of a filtered version of the acceleration signal as shown in Fig. 5. Black dot points the occurrence of a valid step in Fig. 5. One condition that needs to be fulfilled is that the number of samples between two zero crossings should be within certain thresholds. If they are greater than maximum threshold or less than minimum threshold, foot step is not counted. Empirically, we have determined maximum threshold to be approximately 700ms and minimum threshold to be approximately 300ms. This method has been applied to foot-mounted sensors and we quantify its performance when applied to phone sensors in Section III.
3) Fast fourier transform (FFT)

The FFT based approach employs the periodicity of the signal to estimate the footsteps [15]. Since, walking is indeed a periodical activity at its core that can also be observed from the pattern of the acceleration signal in Fig. 4 and Fig. 5. In order to further validate this postulate, a FFT \( X(k) \) was taken over the whole filtered acceleration signal \( \hat{x}(t) \) according to (4)

\[
X(k) = \sum_{i=0}^{N-1} \hat{x}(t)e^{-j2\pi ki/N}, k = 0,1,...,N-1
\]

Where \( N \) is the window length over which the FFT is calculated. The output is presented in Fig. 6. A sharp peak can be observed at a frequency of 1.79 Hz while the actual recorded footstep frequency was of 1.45 Hz. Since, in our experiments we chose the sampling rate of 20Hz which results in a maximum step frequency detectable to be 10 Hz. This is sufficiently high to detect a pedestrian who is running as the highest ever recorded step frequency for a runner is 4.3Hz [19]. The length of window on which FFT is applied is a critical parameter. It determines the resolution in time and frequency domain [12]. If window length is too long, the resolution in time domain is too small, i.e. different step frequencies at different times cannot be separated. For instance, if the FFT is applied on a 10 second window, it will result in only one step frequency however the step frequency of the pedestrian could have changed dramatically during these 10 seconds. If the window is too short, the resolution in frequency domain is too high, i.e. close walking frequencies cannot be separated [15]. This results in a lack of accuracy in the step frequency measurement. Therefore, we chose a window size of 1 second (20 samples) high enough to recognize normal walking footsteps.

C. Stride length estimation

Once the footsteps are detected, the step size is still needed in order to compute the relative position of the pedestrian. One way to estimate the step size is to assume that all steps have equal lengths as proposed by Groves [13]. This assumption can be true for some cases, but not always because the step size is not a constant value but related to walking speed and acceleration magnitude [11]. In a typical human walking behavior, it has been observed that as step frequency increases, the peak acceleration difference increases, the time period between footsteps decreases and stride becomes larger [14].

There are different methods for stride length calculation, but in most of them the sensor unit was attached to foot [20, 21]. This work calculates the stride length by placing the smartphone based sensor unit near to the chest (see Fig. 8). The following stride length (SL) calculation approaches are compared in this document to get a better estimate of the stride length.

1. Weinberg approach: It is based on the principle that a vertical bounce in an individual’s foot step is directly correlated to that persons stride length. This bounce is calculated from the difference of the peaks at each foot step [22]. \( SL \) is calculated using the filtered accelerometer signal by following equation.

\[
SL = k\sqrt{\bar{x}_{\text{max}} - \bar{x}_{\text{min}}}
\]

Where \( k \) is constant and it is determined experimentally. For our experiments we choose \( k \) to be 0.55, since it best fitted to our data. The peak acceleration values \( \bar{x}_{\text{max}} \) and \( \bar{x}_{\text{min}} \) are calculated separately for each footstep.

2. Scarlet approach: This approach calculates the stride length by deriving a correlation between the value of maximum, minimum, and average acceleration of a step, as shown in (6). It tries to solve the accuracy problem caused by the variation of spring in the steps of different people, or in the steps of one person using different paces from one measurement to another [23].

\[
SL = k\frac{\sum_{i=1}^{N}|x_i|}{N} - \bar{x}_{\text{min}}
\]

Where \( k \) is a constant and it is determined experimentally. For our experiments we choose \( k \) to be 0.56, since it best fitted to our data and \( N \) is the window size.

3. Kim approach: This approach calculates the stride length by placing fixed markers at known locations (60cm and 80cm) [11]. The acceleration values are measured when the pedestrian walks through these marked locations. An experimental equation is derived for a step as shown in (7).\( k \) is modified for our case due to different placement of the sensor. In our experiments, we choose \( k \) to be 0.76 since it best fitted to our data and \( N \) is the window size.

\[
SL = k\sqrt{\frac{\sum_{i=1}^{N}|x_i|}{N}}
\]

D. Heading estimation

After estimating the stride length of a step, the last part of our positioning algorithm (see Fig. 1) is to estimate the pedestrian’s heading. Heading can be obtained from either the magnetometer or gyroscope [24]. The magnetometer measures
Earth’s magnetic field. It can be used to estimate the pedestrian’s initial absolute heading. The gyroscope provides the angular velocity around the three axes of a smartphone. It can be used to estimate the change in the pedestrian’s heading. The characteristics of two sensors are summarized in Table 1.

In summary, the magnetometer has a long-term accuracy. Therefore, they are better to estimate the absolute initial heading, while gyroscope for relative heading estimation. Also, it has been observed that the gyroscopes are more stable in indoor environments than the magnetometers [5]. Therefore, this research work utilizes the magnetometer for its initial heading estimation and gyroscope for subsequent heading estimation.

III. EXPERIMENTAL SCENARIO

In order to evaluate the reliability of our positioning algorithm the actual walking test was done. We chose seven test subjects consisting of three females and four males in aged 20 - 40 years old. The height of the test subjects ranged from 1.55m to 1.75m. We used inertial sensors - accelerometer, gyroscope and magnetometer embedded in HTC Sensation 2710e, supported with Android Gingerbread operating system. The inertial sensor values were logged at sampling rate of 20Hz. But, because of the limitation of the Android kernel the sampling events were generated at varied time instants. Therefore, the accelerometer and gyroscope signal was resampled at 20Hz to uniformly distribute the samples. Fig. 7 shows the raw and filtered accelerometer signal variations over a time period of 40 seconds when a pedestrian holding a smartphone was walking in a straight aisle as shown in Fig. 8. It was assumed that there was no obstacle in front of the pedestrian. Moreover, the smartphone was assumed to be kept flat and stationary on the palm with screen facing upwards during the whole walk. The accelerometer signal was filtered according to (3).

A. Results & Discussion

In this section we present our results. The results have been grouped into two subcategories:

- Straight line experiment
- Square turning experiment

1) Straight line experiment

To evaluate the performance of foot step detection and stride length determination algorithms, we performed two set of experiments with seven subjects walking along a straight aisle of length 32.7m. In the first set of experiment the subjects were asked to walk at a normal pace. In the second set of experiments the subjects were asked to walk the same distance at varying pace, normal at half the distance (14.9m), then pause and then remaining at a higher pace. The pedestrian steps varied from 40 to 55 steps in the first set of experiment. While the pedestrian steps varied from 17 to 24 steps in the first half and 12 to 27 steps in the second half on the second set of experiment. The percentage of foot step detection error is evaluated by (8)

\[
\text{Step detection error} = \frac{S_{\text{actual}} - S_{\text{estimated}}}{S_{\text{actual}}} \times 100
\]

Where \( S_{\text{actual}} \) is the actual number of footsteps taken and \( S_{\text{estimated}} \) is the number of footsteps estimated by the foot step detection algorithms. The step detection error for all test subjects during first and second set of experiment is shown in Fig. 9 (A & B). The arrowed bars (red, blue and green) in Fig. 9(B) represent footsteps detected over length of 14.9m and the circle bars (red, blue and green) represent the footsteps detected over a length of 17.8m. Average error of the results for all the test subjects during first and second set of experiment is shown in Table II and III.

The results indicate FFT based algorithms outperform the other foot step detection techniques during the two sets of
TABLE II. COMPARISON OF ERROR CHARACTERISTICS FOR FOOTSTEP DETECTION ALGORITHMS FOR THE FIRST SET OF EXPERIMENT

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Length</th>
<th>Average error (%)</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFT</td>
<td>32.7m</td>
<td>2.7</td>
<td>1.7</td>
</tr>
<tr>
<td>Zero crossing</td>
<td>32.7m</td>
<td>5.1</td>
<td>2.3</td>
</tr>
<tr>
<td>Peak detection</td>
<td>32.7m</td>
<td>7.12</td>
<td>2.5</td>
</tr>
</tbody>
</table>

TABLE III. COMPARISON OF ERROR CHARACTERISTICS FOR FOOTSTEP DETECTION ALGORITHMS FOR THE SECOND SET OF EXPERIMENT

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Length</th>
<th>Average error (%)</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFT</td>
<td>14.9m</td>
<td>3.6</td>
<td>4.5</td>
</tr>
<tr>
<td></td>
<td>17.8m</td>
<td>4.9</td>
<td>4.0</td>
</tr>
<tr>
<td>Zero crossing</td>
<td>14.9m</td>
<td>3.72</td>
<td>5.0</td>
</tr>
<tr>
<td></td>
<td>17.8m</td>
<td>5.4</td>
<td>5.6</td>
</tr>
<tr>
<td>Peak detection</td>
<td>14.9m</td>
<td>3.97</td>
<td>5.3</td>
</tr>
<tr>
<td></td>
<td>17.8m</td>
<td>7.45</td>
<td>4.2</td>
</tr>
</tbody>
</table>

Fig. 9. Comparison of foot step detection algorithms for (A) first set of experiment (B) second set of experiment

experiment. This behavior is expected, since the peak detection algorithm considers a valid foot step when the acceleration peak crosses a minimum threshold. Because of which several footsteps are missed and also falsely detected. In contrast, zero crossing algorithms reject false foot step detection via time based thresholding. While FFT based approach employ the nature of the pedestrian’s gait and the periodicity of placing the footsteps on ground to count the footsteps as a result this approach rejects the false foot step detection and avoids missing steps. Comparing the first half walk’s performance to second half walk’s performance in second set of experiment; all techniques perform better in the first half walk when a pedestrian was walking normally. This is due to the fact that when a pedestrian moves briskly he shakes his body more as a result more step misdetection occurs and subsequently the accuracy of the algorithm is reduced.

After foot step detection, the stride length is determined to estimate the actual distance travelled. The total distance travelled is calculated by summing up the estimated step length of every detected foot step. We use the dynamic methods, as described in section II via (5), (6) and (7), to estimate the stride length. Comparison of total distance travelled using these methods are summarized in Table IV and V. It has been observed that Weinberg approach can estimate travelled distance better than others. This is indicated by smallest average percentage estimation error and the smallest standard deviation. In comparison, the stride length models perform relatively poor in the second set of experiment. Again, this behavior is expected. It can be explained with the same reasoning as before (see section III) that is due to the fact when the pedestrian walks briskly his footsteps are often missed and falsely detected. As a result, the accuracy of the foot step detection algorithms decreases down and because of which the performance of the stride length models also decreases.

2) Square turning experiment

For heading determination test, we again performed two set of experiments with seven subjects walking along two L shaped paths – path 1 and path 2 as shown in Fig. 10. The green dot in Fig. 10 represents the starting point of the walk and red dots represent the stopping point of the walk in two L paths. In the first set of experiments, the subjects were asked to walk along the path 1 of length 12.1m. The first straight path walk was of length 8m then a 90 degree turn and then the rest path was of length 4.1m. In the second set of experiments, the subjects were asked to walk the path 2 of length 15.4m. The first straight path walk was of length 11.3m then a 90 degree turn and then the rest path was of length 4.1m. In both the cases the subjects started at the same point and it was assumed that there was no obstacle in the path.

Fig. 11 (A & B) shows the actual and estimated trajectory of the pedestrian of height 1.79m walking along the two L paths. The estimated trajectory does not have the same exact trajectory but it is close to the actual walking path. The average percentage error in heading at turning corners is evaluated by

\[
\text{Heading error} = \frac{|\theta_{\text{actual}} - \theta_{\text{estimated}}|}{\theta_{\text{actual}}} \times 100
\]
### TABLE IV. COMPARISON OF ERROR CHARACTERISTICS FOR THE STRIDE LENGTH MODELS FOR FIRST SET OF EXPERIMENT

<table>
<thead>
<tr>
<th>Approach</th>
<th>Average error (%)</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weinberg</td>
<td>5.74</td>
<td>5.1</td>
</tr>
<tr>
<td>Scarlet</td>
<td>7.1</td>
<td>7.0</td>
</tr>
<tr>
<td>Kim</td>
<td>6.27</td>
<td>6.2</td>
</tr>
</tbody>
</table>

### TABLE V. COMPARISON OF ERROR CHARACTERISTICS FOR THE STRIDE LENGTH MODELS FOR SECOND SET OF EXPERIMENT

<table>
<thead>
<tr>
<th>Approach</th>
<th>Average error (%)</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weinberg</td>
<td>8.07</td>
<td>4.78</td>
</tr>
<tr>
<td>Scarlet</td>
<td>8.87</td>
<td>6.25</td>
</tr>
<tr>
<td>Kim</td>
<td>9.23</td>
<td>5.88</td>
</tr>
</tbody>
</table>

Where $\theta_{\text{actual}}$ is the true heading during turning at corners. It is equal to $90^\circ$. $\theta_{\text{estimated}}$ is the estimated heading during turning at corners. Table VI summarizes the results. As can be seen, the average percentage error in heading is less than 110 in corners in both the cases. This is sufficient to trace the sharp changes in the heading when a pedestrian reaches the end of corridor and makes a left or right turn. Comparing the path 1 with path 2, the average percentage error is less in path 2. This behavior is expected since the path of the pedestrian is more constrained during turning in the path 2, which can be observed from Fig. 10. Therefore, the pedestrian takes a sharp turning in the path 2 when approaches the turning point J (see Fig. 10).

### IV. CONCLUSION & FUTURE WORK

We have described, implemented and compared some of the most relevant algorithms in the state of the art for pedestrian dead reckoning. While knowing an initial point the trajectory of the pedestrian is estimated which is close to the actual trajectory. In addition, a comparison of foot step detection algorithms, stride length estimation algorithms and change in heading at corners is done. In this work a simple scenario of straight line motion and two L shaped paths are tested. It is observed that average percentage heading error is less than 110 in corners in both the L paths. This is sufficient to trace the sharp changes in the heading when a pedestrian reaches the end of corridor and makes a left or right turn. We restricted this study to the smartphone placed stationary and flat in the hand. But, this scenario is not always true. Therefore, our future work will be extended in evaluating the positioning accuracy while placing the smartphone in different modes. Another important limitation of our employed PDR algorithm is that, it does not provide absolute vertical position information. Although the algorithm is able to detect the sharp changes in turning, it is not able to deduce an absolute height estimate which is an essential parameter for detecting the floor level [25]. Therefore auxiliary sensors such as a barometer are necessary to obtain accurate height information. Moreover, special peculiarities in human walking such as lateral or retral steps, as well as the influence of particular ground structures on the dynamics of gait still have to be studied. Also, additional map features or geometries like building walls are not considered so far by the map matching algorithm and will certainly make the process of position estimation more reliable.

### REFERENCES


