Orientation-Matched Multiple Modeling for RSSI-based Indoor Localization via BLE Sensors

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***Abstract*—Internet of Things (IoT) has penetrated different aspects of our modern life where smart sensors enabled with Bluetooth Low Energy (BLE) are deployed increasingly within our surrounding indoor environments. BLE-based localization is, typically, performed based on Received Signal Strength Indicator (RSSI), which suffers from different drawbacks due to its significant fluctuations. In this paper, we focus on a multiple-model estimation framework for analyzing and addressing effects of orientation of a BLE-enabled device on indoor localization accuracy. The fusion unit of the proposed method would merge orientation estimated by RSSI values and heading estimated by Inertial Measurement Unit (IMU) sensors to gain higher accuracy in orientation classification. In contrary to existing RSSI-based solutions that use a single path-loss model, the proposed framework consists of eight orientation-matched path loss models coupled with a multi-sensor and data-driven classification model that estimates the orientation of a hand-held device with high accuracy of 99%. By estimating the orientation, we could mitigate the effect of orientation on the RSSI values and consequently improve RSSI-based distance estimates. In particular, the proposed data-driven and multiple-model framework is constructed based on over 10 million RSSI values and IMU sensor data collected via an implemented LBS platform.**

***Index Terms*—IMU, Pathloss model, Classification**

I. Introduction

In recent years, the ongoing interest in Internet of Things (IoT) [1]–[3] and the progression made in the Bluetooth technology, Bluetooth Low Energy (BLE) enabled devices have earned vast amount of popularity [4], [5]. The practicality of Bluetooth signals in the indoor localization and positioning purposes [6]–[8], particularly after the introduction of the new specifications of the BLE (BLE v5.0 and v5.1), increased significantly. Basically, Received Signal Strength Indicator (RSSI) is regarded as an important parameter, representing the distance of a user to BLE chip in an indoor environment [9]–[12]. Nevertheless, the low accuracy of the algorithms implemented based on the RSSI signals, mainly stems from the high fluctuations of the RSSI values [13]. Apart from drastic and inevitable RSSI fluctuations, there are other important parameters affecting accuracy of RSSI-based indoor localization. The RSSI received from a smartphone in a fixed distance to the receiver of BLE packet is subject to change when the orientation of the smart phone changes. In other words, the orientation of the transmitter of BLE packets to its receiver is considered as one of the most important parameters influencing the RSSI values. This paper proposes a Multiple Model (MM) based fusion framework [14] that enhances the accuracy of the received signals and compensates the effects of orientation on the RSSI values. The proposed method highlights the importance of using inertial measurement units of smart phone and taking advantage of the phone's built-in sensors in the Location-based Systems (LBS). The fusion of RSSI and Inertial Measurement Units' (IMUs) data [15], [16] would enhance the overall accuracy of localization and mitigates the error caused by orientation of the transmitter to receiver of BLE packet.

In brief, the profound effect of orientation on the RSSI value has remained an unsolved challenge. Consequently, the paper evaluates and models different possible effects associated with orientation of the signal transmitter on the estimated distance in order to enhance the accuracy of indoor localization. In this regard, the paper develops a MM framework to evaluate and eliminate effects of the orientation of the smart phone on BLE beacons. More specifically, RSSI values measured by BLE sensors are analyzed to evaluate the possible effects of orientation on the distance of the user to each BLE sensor. To minimize the effect of prior orientation of the smart phone on the distance estimation based on RSSI values, Pedestrian Dead Reckoning (PDR) techniques are adopted to record the heading (orientation) of the smart phone. To address degrading effects of orientation on RSSI values, the paper performs a

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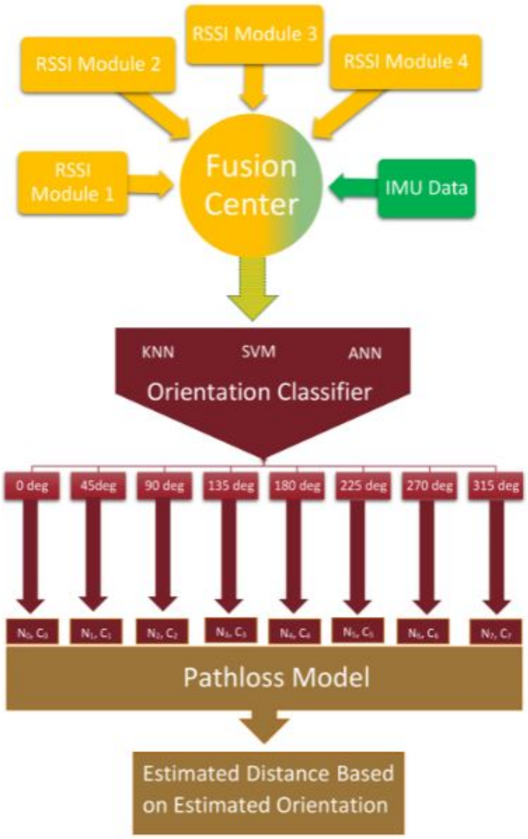

Fig. 1: Block diagram of the proposed MM localization framework.

comprehensive set of data collection based on four different BLE sensors, and constructs a unique data set for orientation modeling consisting of 5 Million RSSI values in 2 distances. At each distance and orientation, the IMU data of the phone is collected to be processed by the heading estimation algorithm. Based on the constructed BLE data set, the proposed MM framework shown in Fig. 1 is constructed where each one of the constituent components is an orientation-matched model resulting in eight orientation models. A multi-sensor and data-driven model is then implemented that estimates the orientation of a hand-held device with high accuracy of 99%.

The reminder of the paper is organized as follows: Section II presents the proposed orientation detection and MM framework. In Section II-A the heading estimation algorithm based on the IMU sensors is explained. Section III presents the dataset and experimental settings and the results. Finally, Section IV concludes the paper.

II. Orientation Detection and RSSI Multiple-Modeling

We consider localizing a single target within the surveillance region monitored with N_b number of BLE-enabled senors. The RSSI value Z_j associated with the j^{th} active BLE sensor, for $(1 \leq j \leq N_b)$, at each iteration is models as follows

$$Z_j = -10\, N \, \log(\frac{D_j}{D_0}) + C_0 + v_j, \tag{1}$$

where $D_j = \sqrt{(X - X_j)^2 + (Y - Y_j)^2}$, and D_0 is the reference distance; C_0 is the average RSSI value at reference distance; (X_j, Y_j) denotes location of the j^{th} BLE sensor, and; N is the path-loss exponent.

Orientation Classification via RSSIs: For finding the orientation of the user's phone, first a set of N_P RSSI values $\mathbb{X}_i = \{\text{RSSI}_i^{(j)}\}_{j=1}^{N_p}$ received by N_b BLE modules are measured in N_o different orientations $(\{\mathbb{X}_i^{(1)}, \ldots, \mathbb{X}_i^{(N_o)}\}$, for $(1 \leq i \leq N_b)$. We have collected about $N_p = 10$ million RSSI values to be analyzed. The scenario that was chosen for collection of this data set is to collect about 5 million RSSI values in 2 distances (1m and 3m). In each distance, we placed the user's phone in $N_o = 8$ different orientations and in each orientation $500,000$ RSSI values were collected. This large amount of data can provide us with invaluable data set to be analyzed, smoothed and used to develop data-driven models.

As stated previously, RSSI values received from BLE beacons are prone to random and drastic fluctuations, which could result in inaccurate distance estimates. To prevent erroneous localization, a recursive Bayesian filter is used where a Kalman Filter (KF) is applied on each $\mathbb{X}_i$ to mitigate the RSSI fluctuations [17]. After smoothing RSSI values, N_o-class classification algorithm including Support Vector Machine (SVM), K-Nearest Neighbors (K-NN), and Neural Networks (NN) are used to classify the RSSI values corresponding to each orientation. For orientation detection, the following two scenarios are considered:

(i) *Stand-alone Orientation Prediction*: In this scenario, RSSI values reported by just one BLE sensor are used as input to the classifier, therefore, we train N_b number of classifiers. In other words, each BLE sensor will provide us with 1-D label vector representing the orientation of the phone to that specific module.

(ii) *Multi-sensor Orientation Prediction*: Orientation prediction is performed in this scenario by using all N_b active BLE beacons. In this case, a classifier is trained based on features of length N_b consisting of smoothed RSSI values obtained from N_b active BLE sensors. In brief, the output of the classifier in this scenario is a vector representing the orientation of the phone to each BLE sensor.

The output of the orientation classification step is an estimate of the device's orientation, which as shown in Fig. 1 will be used to select one of the N_o orientation-matched path-loss models. The latter is described next.

A. IMU Based Heading Estimation

Smart phone's IMU unit consists of 3 axis accelerometer, 3 axis gyroscope, and 3 axis magnetometer. All IMU sensors report data with respect to the 3 orthogonal and pre-defined axis in the smart phone. Due to soft-iron and hard-iron effects, magnetometer is vulnerable to noise and error. In such cases a calibration unit should be adopted on the magnetometer's data such as ellipsoid fit method [18]. This calibration unit can estimate all parameters of the error model and then compensate the errors caused by soft and hard iron interference. Fig. 2

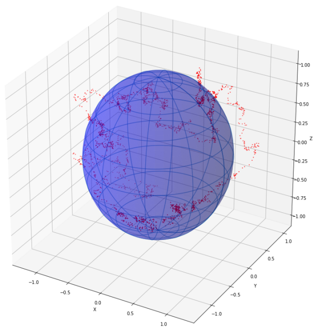

Fig. 2: Magnetometer's calibration.

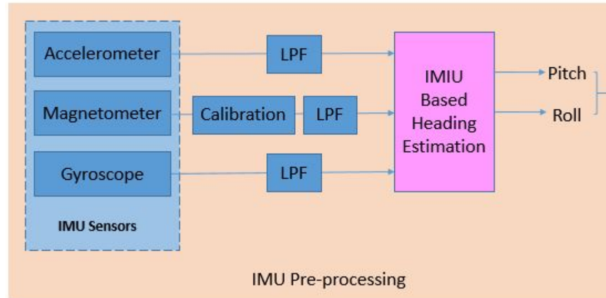

Fig. 3: Heading estimation by IMU.

depicts 3-D magnetometer's data for a real data set after calibration. Basically, in all cases the earth frame acceleration and orientation of the smart phone is desired. In such cases the raw data reported by IMU sensors is not sufficient to report the position or orientation of the smart phone. Therefore, one can process the raw data reported by IMU sensors and then manipulate the data derived from IMU sensors to gain the earth frame heading of the smart phone. Fig. 3 depicts a brief overview of the afore-mentioned IMU heading estimation.

Raw data reported by IMU sensors is prone to noise and fluctuations resulting inaccuracy in the heading estimation. To tackle this problem a low pass filter is designed in PDR approaches to smooth the data before being processed for heading detection. Furthermore, based on the fact that pitch roll and yaw angles are derived from magnetometer's data this unit is considered as an essential and critical step. By merging smoothed accelerometer's data one can calculate pitch and roll, i.e.,

$$\begin{aligned} X_h &= M_x \cos(P) + M_y \sin(P) \sin(R) + M_z \sin(P) \cos(R) \\ Y_h &= M_y \cos(R) + M_z \sin(R) \end{aligned} \tag{2}$$

where $P = \arctan\{A_y / \sqrt{{A_x}^2 + {A_z}^2}\}$ and $R = \arctan\{(-A_x)/A_z\}$ and

$$Yaw^{\text{Rad}} = \arctan -(\frac{Y_h}{X_h}) \tag{3}$$

By manipulating pitch, roll and magnetometer's data one can compute yaw of the device for each sample. By merging accelerometer and magnetometer's data using Eqs. (2), and (3) one can calculate yaw angle. As phone device is in a plenary position, yaw angle is regarded as heading angle of the device.

B. Multiple Modeling Framework

We constructed orientation-matched path-loss-model by learning parameters $\{N_j^{(m)}, C_{0,j}^{(m)}\}$, corresponding to orientation m, for $(1 \leq m \leq N_o)$, and module j, for $(1 \leq j \leq N_b)$ using the mean of the smoothed RSSI values of module j and orientation m at two different distances (D_0, D). After finding the phone's orientation, orientation-matched parameters associated with that specific orientation are replaced in Eq. (1) and distance D to the BLE module is calculated as follows

$$Z_j^{(m)} \quad = \quad -10\, N_j^{(m)} \log(\frac{D}{D_0}) + C_{0,j}^{(m)}. \tag{4}$$

For each sensor and for each particular orientation of the device to the beacon, the parameters of path-loss model are different. Therefore, in Scenario (ii) the distance estimated by each beacon is calculated separately. This would provide us a distance estimation matrix consisting of N values for distance. Weighted average of the distance estimation matrix is considered as the final value for distance estimation. In other words, considering that the classifiers has provided us with $[W_1, \ldots, W_{(N_b)}]$ where W_i denotes the accuracy of orientation classification for a given BLE sensor. Basically the accuracy of each beacon in estimating the corresponding orientation of the smart phone represents the confidence rate of the classifier to accurately estimate the true distance with regard to the orientation of the smartphone. Therefore, the estimated distance for each beacon is weighted based on this confidence rate. By such definition, the higher the accuracy of a beacon in estimating the orientation, the greater the weight of the estimated distance for that specific beacon, i.e.,

$$D = \sum_{i=1}^{N_b} \frac{W_i}{\sum_{j=1}^{j=N_b} W_j} \times d_i, \tag{5}$$

where d_i states the distance estimated by each BLE module and weighted averaging method is used to gain the final estimated distance of the user to BLE modules.

III. Experimental Results

Real Data Collection Setup: As shown in Fig. 4, $N_b = 4$ BLE sensors are fixed in the same distance of $1m$ (for calculating the parameters of the orientation-matched path-loss models and $3m$ (for distance estimation) to the user's phone (IPhone 6). RSSI data is gathered for 8 orientations (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°) of user's phone to BLE modules. Moreover, all sensors are simultaneously gathering the IMU data for each orientation of the phone. The sampling frequency of RSSI values and IMU data is 16 samples per second. In order to prevent the effect of surrounding walls on collected RSSI value, the experiment environment is designed

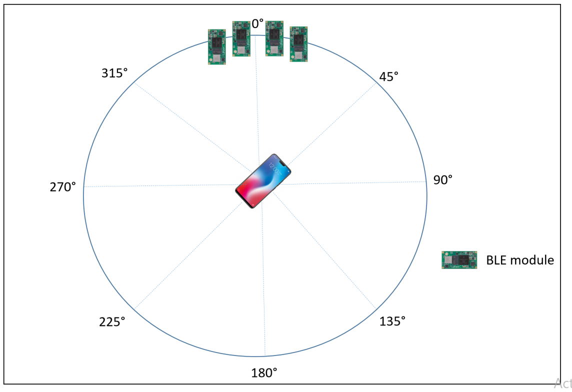

Fig. 4: Real data collection setup.

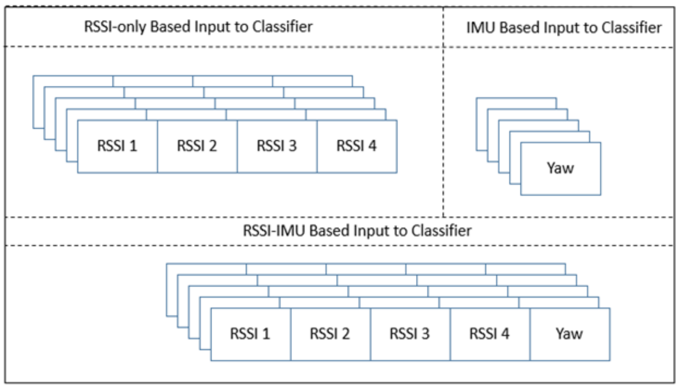

Fig. 5: Schematic illustration of the input data for classification.

sufficiently far from any obstacle or wall in the vicinity of the sensors.

After data collection step, as highlighted in Section II, a KF is applied on raw data to mitigate RSSI fluctuations. Also magnetometer's data is sent to a calibration unit to mitigate the soft and hard iron effect. After magnetometer's calibration step, a low pass filter (100Hz) is applied to reduce the noise and the error in the IMU sensor data. Moreover as was highlighted in Section II-A the yaw angle is also calculated to yield the IMU-based heading of the smartphone. To compare the results from RSSI-only, IMU-only, and RSSI-IMU fusion based orientation classification we implemented the classifiers on the data illustrated in Fig. 5.

A. RSSI-only Classification

Based on the mean of the smoothed RSSI values from $D_0 = 1$m and 3m, the orientation-matched path loss model parameters $\{N_j^{(m)}, C_{0,j}^{(m)}$ for $(j \in \{1,2,3,4\})$, and $1 \leq m \leq 8$ are calculated for each sensor. Firstly, orientation estimation is performed with respect to the RSSI values received from each BLE module separately (Scenario (i)). In another attempt the same orientation classifier method is applied to the RSSI values received from all 4 modules simultaneously (Scenario (ii)). In both scenarios, 80% of all RSSI observations are considered as the training data and remaining 20% RSSI observations are considered as the test data.

Table I illustrates the orientation classification accuracy for each BLE sensor for Scenario (i). The overall accuracy is

TABLE I: Orientation classification accuracy comparison of the proposed algorithm for Scenario (i).

Approach Accuracy(%)			
Classification Method	**ANN**	**SVM**	**K(5)-NN**
BLE 1	**0.73**	0.70	0.65
BLE 2	0.68	0.62	**0.72**
BLE 3	0.66	0.69	**0.70**
BLE 4	0.66	0.69	**0.70**

TABLE II: Orientation classification accuracy comparison of the proposed algorithms.

Approach Accuracy(%)			
Classification Method	RSSI-only*	IMU-only	RSSI-IMU fusion
ANN	70	90	97
SVM	72	93	96
KNN	74	92	99

* The Accuracy of RSSI-only method reported in this table is based on Scenario (ii) that had higher overall accuracy compared to Scenario (i).

not greatly satisfying as the RSSI value has drastic fluctuations causing misclassification of associated orientation. Consequently, based on the predicted orientations the distance of the smart phone to each BLE module is estimated using orientation-matched path-loss model. Compared to the conventional path loss models that estimate the distance with a fixed (N, C_0) the proposed method offers different parameters $(N_j^{(m)}, C_{0,j}^{(m)})$ for different orientations. It is worthy to mention that the same experiment was implemented for different distances between BLE sensors and smart phone and in most cases KNN classifier gained the highest accuracy among all classifiers. The estimated distance for each BLE sensor is then compared to the real distance $(3m)$ and mean error of 1.69m, 1.57m, 1.19m, and 1.45m is recorded for modules 1-4, respectively. Although the RSSI-only approach based on Scenario (i) outperforms the traditional approaches in which one predefined (N, C_0) is considered for path-loss model, the difference is not significant.

To improve the overall accuracy of orientation classification and mitigating the effect of RSSI fluctuations on orientation classification, Scenario (ii) is designed. In Scenario (ii), the weighted mean vector of 4 estimated distance vectors with weights proportional to the orientation prediction accuracy of the associated module $(0.73, 0.70, 0.72$, and $0.64)$ is computed as the final distance vector using Eq. (5). The estimated distance vectors between phone to the 4 BLE modules is formed by mean error of 0.79m, 0.88m, 1.26m, 1.53m and weights $(0.73, 0.70, 0.72$, and $0.64)$, respectively. The first column of Table II depicts the average accuracy of orientation classification in Scenario (ii). Comparing the average accuracy of Scenario (i) and (ii), it is observed that by considering RSSI values received from 4 beacons, one can estimate phone orientation with considerable higher accuracy. This improvement in Scenario (ii) highlights the efficiency of the proposed weighted averaging algorithm.

B. IMU-only Classification

In IMU-only approach, the orientation classification of smartphone is implemented based on the IMU heading rather than RSSI values. As illustrated in Fig. 5, the IMU values are subject of classification. For this purpose, the same classifiers are used to classify the smart phone's heading into 8 different orientations (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°). Then based on each orientation associated to $(N_j^{(m)}, C_{0,j}^{(m)})$ the distance between smart phone and the BLE module is calculated. It is worthy to mention that for orientation classification purpose just the IMU values are fed to the classification unit. Since IMU heading is more robust, it renders lower error in the distance estimation as shown in Table II.

C. RSSI-IMU Fusion Classification

As for the RSSI-IMU fusion method, the vector consisting of the RSSI values and IMU values is subject of classification. Therefore, the classifier has simultaneously the knowledge about IMU sensors and RSSI sensors resulting in higher classification accuracy. In such case, the same as the other two methods (RSSI-only and IMU-only classification) the distance is estimated based on the result of the orientation classification. Table II compares the classification accuracy of the three methods. As is evident from the information provided in the table, the average classification accuracy of the fusion method is much higher. However, in the fusion method the data of all 3 axis IMUs and BLE sensors should be collected simultaneously requiring more complexity in the data gathering phase. Also it is worthy to mention that the high value of classification accuracy in the fusion method resulted in lower distance estimation error of $0.71cm$, which highlights the importance of orientation of the smart phone in localization.

D. Discussions

A major issue is faced during the data collection process, i.e., RSSI values captured from different sensors in the same direction and similar situation act differently. In other words, the received RSSI values in some cases are radically different from others, which was an expected phenomena as sensor modules would not perform similarly. Based on this observed anomaly, we have two main categories of sensors (among the ones tested), where sensors in one category, more or less, perform similarly, while the other sensors act differently (higher average RSSI values at the same distance) but still close to each other. Another interesting observation is that in 135 degree and across different scenarios, there is a large decrease of RSSI values in 1m. It was observed that the RSSI values collected at 1m with 135 degree are much lower than those obtained at 3m, which is an unexpected behavior. The conclusions discussed above are made based on several similar experiments analysis conducted over different distances and different orientations.

IV. Conclusion

In this paper, effects of a phone's orientation are investigated on the distance estimated by RSSI values. Since it is well known that variations occurring due to changes in orientation of a hand-held device is a limiting factor for BLE-based sensors, the inertial measurement unit data is also evaluated. In this regard, the paper proposed an orientation detection and multiple-modeling framework to refine RSSI fluctuations by compensating the orientation effects. It is observed from the results of the proposed data-driven and orientation-free modeling framework that the location estimation is improved considerably when RSSI-IMU fusion model is implemented. The final error in distance estimation with combination of four BLE sensors is 0.72m. Without orientation considerations, the phone orientation can be any of (0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°) with mean error ranging as follows $1.69m$, $2.57m$, $2.19m$, $3.45m$. The error with orientation consideration of 0.72m is, therefore, less than minimum possible mean error without the orientation effect (1.69m).

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