This full text paper was peer-reviewed at the direction of IEEE Instrumentation and Measurement Society prior to the acceptance and publication.

Indoor distance estimated from Bluetooth Low Energy signal strength: comparison of regression models

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***Abstract*—Bluetooth Low Energy (BLE) is a wireless technology for exchanging data, over short distances, designed for the Internet-of-Things era. As widely supported by wearable devices, BLE has the potential to become an alternative for indoor-localization and proximity sensing. The aim of this work was to perform a thorough characterization of the RSSI-distance relationship under controlled conditions using two BLE devices. Four calibration models underwent to a comparative evaluation analysis. The best results were obtained using a polynomial model with a mean distance percentage error equal to 25.7% (0.4 m) in the range 0-3 m. An overall improvement of 14.3% (0.24 m) in the distance estimate compared to the exponential model commonly adopted in the literature was reported.**

***Index Terms*—Indoor-localization; distance estimation; wearable devices; Bluetooth Low Energy; RSSI;**

I. Introduction

The knowledge of the position of an individual during daily-life activities is essential in several applications, such as pedestrian navigation, fall localization, guidance with handheld devices [1]. Global Positioning System is a very effective technology for outdoor localization [2], however it cannot be used for indoor-applications due to weak penetration into buildings. Since a large part of our day is spent indoor, alternative solutions must be pursued. Localization using wireless network technologies, such as WiFi, Radio Frequency Identification, Ultra Wide Band and Magneto-Inertial Measurement Unit (MIMU), has been widely investigated [3-4]. Very recently, Bluetooth technology has been further optimized to minimize the power consumption and cost (Bluetooth Low Energy; BLE) [5-6]. Its maximum range can be up to 100 m depending on the class of the antenna used. For these reasons, BLE has become the "de facto" radio standard for the Internet of Things and it is now embedded in the majority of the wearable devices (mobile phones, tablets, etc). An important feature of BLE technology is that the Received Signal Strength Indicator (RSSI), defined as the ratio between power of the transmitter and that of the receiver, is available to the users (IEEE 802.11 standard). Since the RSSI decreases as the distance between transmitter and receiver increases, some researchers explored the use of BLE RSSI for distance estimation [7-11]. The majority of the studies have modelled the RSSI-distance relationship through an exponential model [7-9]. The model calibration is generally based on two calibration points which are used to determine the propagation coefficient of the specific indoor environment and the RSSI offset [8]. However, the BLE signal can be highly unstable and its strength is influenced by a number of experimental factors [12]. These circumstances may limit the overall accuracy level of the distance estimates obtained from "general purpose" BLE wearable devices. In this respect, a thorough characterization of the RSSI-distance relationship under controlled conditions is a fundamental prerequisite for any localization applications using BLE devices.

The aim of this study is to address the following specific research questions:

1) What is the best model to represent the relationship between RSSI and distance within a given range?
2) What is the influence of calibration data set size on the estimated distance accuracy?
3) Does the orientation between receiver and transmitter influence the RSSI-distance relationship?

II. Materials and Methods

A. Distance estimation based on RSSI measurement

The relationship between the RSSI and the distance d is generally described by an exponential model [8]:

$$RSSI_{dBm} = -10 \cdot n \cdot log_{10}(d) + A \quad (1)$$

where n is a real number between 2 and 4, which depends on the specific environmental conditions; A is the RSSI value reads at an arbitrary selected distance.

By isolating d from (1):

$$d = 10^{\frac{-RSSI+A}{10n}} \quad (2)$$

The latter exponential model (*EXP10*) was compared with the following regressive models:

- Exponential (*EXPE*):

$$d = a \cdot exp^{b \cdot RSSI} \quad (3)$$

- Power (*POW*):

$$d = a \cdot RSSI^b + c \tag{4}$$

- Polynomial (*POL*):

$$d = a \cdot RSSI^2 + b \cdot RSSI + c \tag{5}$$

B. Hardware architecture

The system used is composed of two MIMUs and a computer tablet. The devices are connected via BLE as shown in Fig. 1. The two MIMUs have been programmed to work as a receiver (Master) and a transmitter (Slave) simultaneously. When a device is working as receiver, it can start a connection and read the RSSI from the transmitter. The computer tablet is only used as a support to acquire, store and visualize real-time data from the MIMUs.

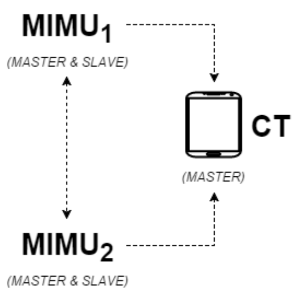
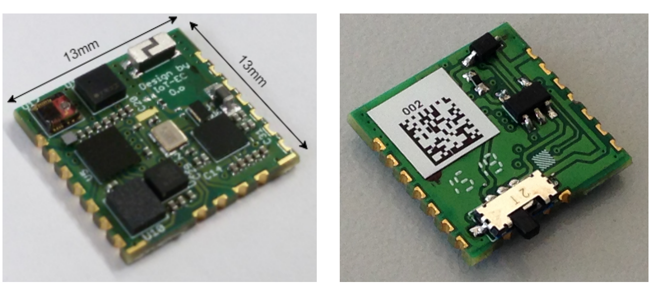


Fig. 1. System connection overview

The hardware architecture consists of two different devices:

- The main component is a small (13×13 mm^2) and low-power MIMU. The device includes a triaxial accelerometer, a triaxial gyroscope, a triaxial magnetometer, a complete Bluetooth Low Energy radio with a class 2 chip antenna (coverage range up to 10 m) [13-14], an ARM Cortex-M4-based microcontroller and the power supply stage for a Li-poly battery (Fig. 2).



(a) Top layer (b) Bottom layer

Fig. 2. MIMU PCB

- The second component is a computer tablet Samsung Galaxy Tab 3 Lite equipped with a BLE module (Android KitKat v.4.4.4 operating system). An Android App was developed to acquire data from the MIMUs in real-time. The RSSI acquisition rate was set to 10 Hz. An example of RSSI data read from the MIMU$_1$ at a distance of 0.5 m is reported in Fig. 3.

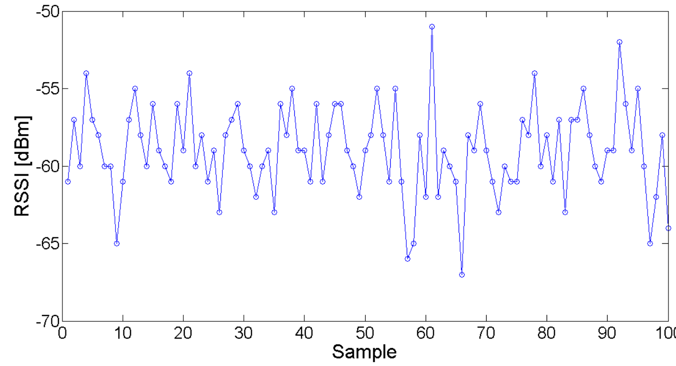


Fig. 3. RSSI 10 s acquisition data example

C. Experimental setup

The MIMU$_1$ was positioned with the z axis of the antenna pointing vertically and was kept stationary, while the MIMU$_2$ was moved to different positions with the x axis vertical and the z axis pointing to the MIMU$_1$. According to the antenna datasheet [13], the relative orientation change during the acquisition should have no effect. The experimental data consisted in 10 s static acquisitions (100 RSSI samples) at four different distances (0.5 m, 1 m, 2 m, 3 m) and at different angles (from 0° to 180°, angular increment 15°) (Fig. 4). A total of 52 (4×13) positions were explored. For each position, the mean value over the 100 RSSI samples was calculated (experimental data point). Since MIMU$_1$ and MIMU$_2$ have been programmed to work simultaneously as receiver and transmitter, a separate and independent experimental data set was recorded by each MIMU during the abovementioned experimental acquisition protocol.

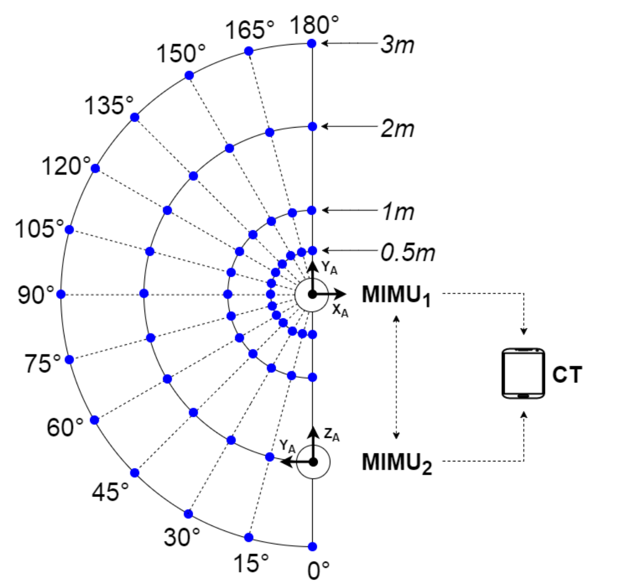


Fig. 4. Experimental indoor scenario

D. Model parameters calibration

The determination of the model parameters requires a number of experimental data points equal or higher than the number of parameters. Among the calibration models selected for comparative analysis, the simplest ones are *EXP10* and *EXPE*, which are described by only two parameters. The values of n and A are generally determined using the RSSI values recorded at 1 m and 3 m [8]:

$$n = -\frac{RSSI_{3m} - RSSI_{1m}}{10 \cdot log_{10}(3-1)} \tag{6}$$

$$A = RSSI_{1m} \tag{7}$$

Please note that the latter equations are derived for *EXP10* but equivalent solutions can easily obtained for *EXPE*. However, when more than two experimental data points are available, this redundancy can be exploited to improve the calibration procedure. To investigate the effect of the number of data points, on the distance estimation using two BLE devices, we performed the calibration of the models parameters using three calibration data sets of different size. The first data set (DS_{28}) included the data recorded in 4×7 positions (angular increment 30°), the second data set (DS_{16}) the data recorded in 4×4 positions (angular increment 60°) and the third one (DS_{12}) the data recorded in 4×3 positions (angular increment 90°). Curve fitting were performed on the mean RSSI values, recorded by each MIMU while working as receiver, using the Matlab function *cftool* (v.R2013a, MathWorks).

E. Data analysis

The performance of the four regressive models (*EXP10*, *EXPE*, *POW* and *POL*), were tested using a validation data set. This was composed by the experimental data points recorded in the 4×6 positions which have not been used for the calibration (from 15° to 165°, angular increment 30°). For each position i, three inter-MIMUs estimated distances ($\hat{d}_i^{MIMU_1}$, $\hat{d}_i^{MIMU_2}$, $\hat{d}_i^{MIMU_{1,2}}$) were computed. In detail, $\hat{d}_i^{MIMU_1}$ and $\hat{d}_i^{MIMU_2}$ are the estimates provided by $MIMU_1$ and $MIMU_2$ while working as receiver, and $\hat{d}_i^{MIMU_{1,2}}$ is the average value between the latter values. For each estimated distance, the error $e_i = \hat{d}_i - d_i$ was computed. The overall model accuracy was evaluated in terms of mean absolute error (*MAE*) and its percentage value ($MAE_{\%}$):

$$MAE = \frac{1}{24}\sum_{i=1}^{24} |e_i| \tag{8}$$

$$MAE_{\%} = \frac{1}{24}\sum_{i=1}^{24} \left|\frac{e_i}{d_i}\right| \cdot 100 \tag{9}$$

with d_i = 0.5 m, 1 m, 2 m, 3m.

In the ideal case, two BLE devices working simultaneously as receiver and transmitter should read the same RSSI values. To take into account the non-ideal behavior of the sensors, due to the imperfections of the electronics, the RSSI difference between the two BLE devices was evaluated:

$$\Delta_i = \left| RSSI_{MIMU_1,i} - RSSI_{MIMU_2,i} \right| \tag{10}$$

where $RSSI_{MIMU_1,i}$ and $RSSI_{MIMU_2,i}$ are the mean of the value over the 100 RSSI samples at position i acquired by $MIMU_1$ and $MIMU_2$, respectively.

III. Results

A. RSSI-distance relationship

As an example, the relationship between the RSSI data recorded by the $MIMU_1$ and the tested distances is reported in Fig. 5. The RSSI values varied from -61.1 dBm and -43.0 dBm for 0.5 m, -64.6 dBm and -55.0 dBm for 1 m , -69.1 dBm and -61.5 dBm for 2 m, -71.0 dBm and -65.7 dBm for 3 m (the outlier at 150° was discharged). The red ellipses indicate the overlapping observed in the RSSI values between two consecutive tested distances. A similar trend was observed for the $MIMU_2$.

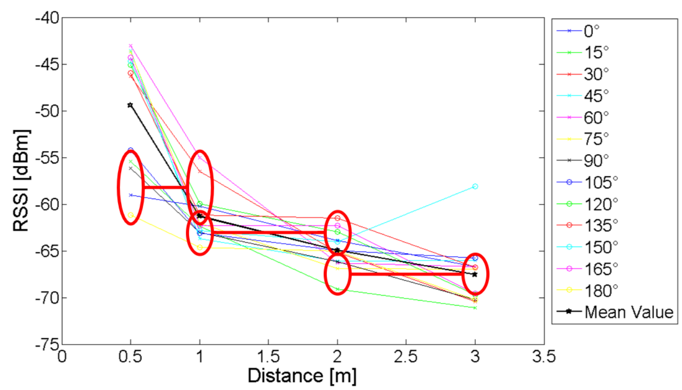


Fig. 5. RSSI-distance relationship obtained for the $MIMU_1$ working as receiver

An alternative graphical representation of the RSSI values recorded by the $MIMU_1$ is depicted in Fig. 6. The RSSI mean values were -49.4 dBm for 0.5 m, -61.3 dBm for 1 m, -64.9 dBm for 2 m and -67.5 dBm for 3 m. A similar trend was observed for the $MIMU_2$.

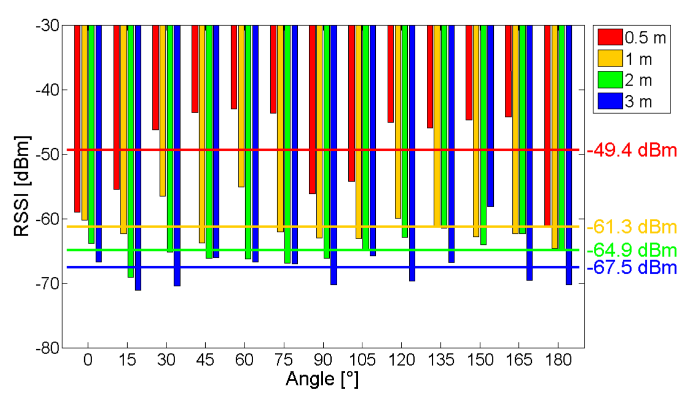


Fig. 6. RSSI-angle relationship obtained for the $MIMU_1$ working as receiver

The RSSI differences between the two BLE devices is reported in TABLE I.

TABLE I
COMPARISON BETWEEN $MIMU_1$ AND $MIMU_2$ RSSI RECORDED DATA

Distance $[m]$	Δ $[dBm]$
0.5	2.0
1	1.4
2	1.2
3	1.0

B. Regressive model

For sake of comparison with previous studies [7-9, 15-16], the results obtained for *EXP10* model using two calibration points, are reported in TABLE II.

TABLE II
EXP10 MODEL RESULTS, FOR $MIMU_1$, $MIMU_2$ AND $MIMU_{1,2}$, WITH TWO CALIBRATION POINTS

	$MIMU_1$		$MIMU_2$		$MIMU_{1,2}$	
Distance $[m]$	*MAE* $[m]$	$MAE_{\%}$ $[\%]$	*MAE* $[m]$	$MAE_{\%}$ $[\%]$	*MAE* $[m]$	$MAE_{\%}$ $[\%]$
0.5	0.25	50	0.33	65.5	0.27	54.7
1	0.16	16.4	0.28	28.0	0.20	20.1
2	0.77	38.7	0.86	43.0	0.81	40.8
3	1.39	46.2	1.18	39.3	1.28	42.7
Mean	0.64	37.8	0.66	43.9	0.64	39.6

In general, by assuming that the variance of the RSSI readings is identical for both MIMUs, the estimated distance error is minimized by considering, for each position, the average of the distance estimates provided by $MIMU_1$ and $MIMU_2$ ($MIMU_{1,2}$). Therefore, only the estimated errors $\hat{d}^{MIMU_{1,2}}$ has been reported for the different models and calibration data sets (DS_{28}, DS_{16} and DS_{12}) (TABLE III, IV, V). The results obtained for *EXP10* were not shown because they were identical to those obtained with the *EXPE* model. The best performance was obtained with the *POL* model. The average improvements with respect to the *EXPE* and *POW* models were equal to 0.04 m and 0.06 m, respectively. No clear trends were observed between the magnitude of the errors and the number of calibration points used. Overall, the magnitude of the errors increased with the distance for all models.

IV. DISCUSSION

The aim of the present study was to provide a characterization of the RSSI-distance relationship between two BLE devices in an indoor environment in the absence of obstacles. Looking at Fig. 5, it is evident that the RSSI values greatly varied changing the relative angle between sensors for a constant distance thus causing overlapping between the RSSI values observed between two consecutive distances. Interestingly, by reorganizing the RSSI values according to the angle values

TABLE III
POL MODEL DISTANCE ESTIMATED ERRORS, FOR VALIDATION DATA SET, USING 28, 16 AND 12 CALIBRATION POINTS

	Polynomial Model (*POL*)					
	DS_{28}		DS_{16}		DS_{12}	
Distance $[m]$	MAE $[m]$	$MAE_{\%}$ $[\%]$	MAE $[m]$	$MAE_{\%}$ $[\%]$	MAE $[m]$	$MAE_{\%}$ $[\%]$
0.5	0.11	21.5	0.06	12.8	0.12	24.4
1	0.64	64.0	0.57	57.2	0.33	33.4
2	0.34	17.0	0.40	20.2	0.45	22.6
3	0.54	17.9	0.57	18.9	0.67	22.3
Mean	0.41	30.1	0.40	27.3	0.39	25.7

TABLE IV
EXPE MODEL DISTANCE ESTIMATED ERRORS, FOR VALIDATION DATA SET, USING 28, 16 AND 12 CALIBRATION POINTS

	Exponential Model (*EXPE*)					
	DS_{28}		DS_{16}		DS_{12}	
Distance $[m]$	MAE $[m]$	$MAE_{\%}$ $[\%]$	MAE $[m]$	$MAE_{\%}$ $[\%]$	MAE $[m]$	$MAE_{\%}$ $[\%]$
0.5	0.20	39.9	0.22	43.7	0.27	54.7
1	0.64	63.9	0.57	57.5	0.32	32.5
2	0.33	16.6	0.38	19.1	0.45	22.7
3	0.56	18.5	0.61	20.2	0.75	24.9
Mean	0.43	34.7	0.45	35.1	0.45	33.7

TABLE V
POW MODEL DISTANCE ESTIMATED ERRORS, FOR VALIDATION DATA SET, USING 28, 16 AND 12 CALIBRATION POINTS

	Power Model (*POW*)					
	DS_{28}		DS_{16}		DS_{12}	
Distance $[m]$	MAE $[m]$	$MAE_{\%}$ $[\%]$	MAE $[m]$	$MAE_{\%}$ $[\%]$	MAE $[m]$	$MAE_{\%}$ $[\%]$
0.5	0.12	24.5	0.17	34.1	0.65	129.7
1	0.61	61.0	0.58	57.7	0.34	34.4
2	0.35	17.3	0.38	19.2	0.44	22.1
3	0.58	19.3	0.60	20.1	0.68	22.6
Mean	0.41	30.5	0.43	32.8	0.53	52.2

(Fig. 6), the RSSI consistently decreased by increasing the distance (the only exception was observed for 45° and 3 m; 150° and 3 m and 165° and 2 m). This is probably due to the effects of the antennas directionality although, according to the BLE antenna datasheet, the antennas should be omnidirectional for the XY and ZY planes [13].

Due to unavoidable differences in the BLE antennas mounted in different devices (TABLE I), the RSSI values measured for a given distance varied between the two BLE devices. To compensate possible under/over estimation errors, the "optimal guess" was obtained by averaging the distance values provided by each device while working as receiver. This "countermeasure approach" improved the distance estimation, obtained with the best calibration model (*POL* model), up to 40% (mean improvement over distances, angles and calibration data points equal to 4.6%). This simple method can be applied to any device by programming the firmware.

The worst results were obtained for *EXP10* using two calibration points (MAE = 0.64 m; $MAE_{\%}$ = 40%). The best performing calibration model was, irrespective of the calibration data set used, the *POL* model (TABLE III). On average, the mean absolute error was about 0.4 m, which correspond to percentage errors between 25.7% and 30.1% depending on the number of data points used for the calibration (from 12 to 28). As expected, because *EXPE* and *EXP10* differ only for the base of the exponential function, identical results were obtained. The performance of the different methods showed minor variations for the different calibration data sets used (28, 16, 12 points). In this respect, 12 calibration points seems to assure a good accuracy while reducing the calibration time. A further decrease of the number of data points caused an increase of the errors. The errors reported in this study were obtained by averaging 100 distance estimates (10 s at 10 Hz). However, we verified that by decimating the number of data points from 100 to 10, an average worsening of the POL model performance of 1.8% (maximum percentage error equal to 3.8% (0.11 m) at 3 m) was obtained. Furthermore, we programmed the firmware for a RSSI acquisition rate equal to 10 Hz, but, if required, this can be easily set up to 20 Hz.

V. Conclusion

The findings of this study confirm that miniaturized system, based on BLE technology, can be proficiently used to provide inter-distance estimates in a 6×3 m^2 room with an average percentage error equal to 25.7% (0.4 m). These performances were obtained using a polynomial model under controlled conditions (absence of obstacles between transmitter and receiver, no other BLE devices in the environment). For those localization applications requiring an higher accuracy, a further improvement could be obtained by increasing the number of BLE devices following a “fingerprinting” or trilateration approaches [17-19]. These approaches exploit the information provided by a redundant number of nodes to optimize the final position estimate. It is quite evident that the performance of the latter optimization methods would benefit from a reduction of the errors affecting the estimate of each inter-nodes distance. Furthermore, sensor fusion algorithms based on the use of magneto-inertial measurement may benefit by the additional information provided by BLE unit to improve the position estimate [20]. This approach has great potential for monitoring human behavior in indoor environment and it opens interesting applications in various fields, such as fall detection, depression monitoring and rescuers navigation.

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