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A Protocol-Channel-Based Indoor Positioning Performance Study for Bluetooth Low Energy

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ABSTRACT Bluetooth low energy (BLE) technology coupled with fingerprinting provides a simple way to position users with high accuracy in indoor environments. In this paper, we study the effect of BLE protocols and channels on indoor positioning using different distance and similarity measures in a controlled environment. With the aim of reproducing a real positioning system situation, we also study the effect of the user's orientation in the positioning phase and, consequently, provide accuracy and precision results for each orientation. In a 168-m^2 testbed, 12 beacons configured to broadcast with the Eddystone and iBeacon protocols were deployed and 40 distance/similarity measures were considered. According to our results, in a specific orientation there is a group of distance metrics coupled with a protocol-channel combination that produces similar accuracy results. Therefore, choosing the right distance metric in that specific orientation is not as critical as choosing the right protocol and, especially, the right channel. There is a trend whereby the protocol-channel combination that provides the best accuracy is almost unique for each orientation. Depending on the orientation, the accuracies obtained for the abovementioned group of distances are within the range of 1.1–1.5 m and the precisions are 90% within the range of 1.5–2.5 m.

INDEX TERMS Bluetooth low energy, indoor positioning, fingerprinting, distance and similarity measure, protocol, channel.

I. INTRODUCTION

Bluetooth Low Energy (BLE) is nowadays a widely used technology in ubiquitous computing and in many Internet of things (IoT) applications; so much so that, only twelve years later after it was first introduced, the Bluetooth Special Interest Group (BSIG) recently launched the Bluetooth 5 protocol, which offers 4x range, 2x speed and 8x broadcasting message capacity.

BLE technology in combination with fingerprinting is an option that offers many advantages for indoor positioning (IP): BLE is supported by mobile devices; the transmitters (or beacons) are portable, battery-powered, small, lightweight, easily deployable, and have low-energy consumption; and received signal strength (RSS) readings are relatively easy to collect, producing results with high accuracy and precision [1].

Nevertheless, in order to reduce energy consumption, in BLE technology the beacon's transmission power (Tx) is limited; the beacon's range, therefore, is also limited, causing the signal to be susceptible to path loss [2]. As in other radio-frequency technologies, BLE RSS readings suffer from large fluctuations and degradation due to many factors, such as dynamic environments, multipath fading, etc., that make BLE IP a challenge [3].

There are some BLE beacon standards or protocols that depend on how advertising packets work, e.g. Radius Networks' AltBeacon, Google's Eddystone or Apple's iBeacon. A BLE beacon can exchange data with other devices in two modes: advertising mode, that is, sending message packets regularly to other listening devices, and connection mode, that is, transferring data in a one-to-one connection. In advertising mode, messages hop between a fixed sequence of three narrow channels (37, 38, and 39), each of which has different RSS values, to gain redundancy in order to reduce interference with other wireless technologies. Mobile devices do not distinguish between these three BLE channels; combining their RSS values and obtaining an aggregate signal may lead to reduced positioning accuracy [4].

In the fingerprinting method, a position is characterized by the signal pattern detected from each transmitter (BLE beacon in our case). In order to estimate the position of a user in the calibration (or offline) phase, it is necessary to construct a reference fingerprint database for a set of points of known positions. In that database, each reference element, or fingerprint, consists of the coordinates of the reference points, the received signal strength (RSS) of each beacon, the orientation in which these RSS readings have been taken, etc. It is well known that the human body absorbs part of the signal and this effect can be mitigated in the calibration phase by calculating average RSS values per orientation [5]–[7], as has been done in this work. In the positioning (or online) phase, users in an unknown position obtain the RSS values for different beacons (target fingerprints) and compare these RSS values with those stored in the reference database. By means of an algorithm, such as nearest neighbor (NN), k-nearest neighbor (KNN) or weighted k-nearest neighbor (WKNN), users ultimately obtain the coordinates of their position [5], [8].

For deterministic algorithms, the position of the user may be determined using distance/similarity metrics. The process starts comparing the fingerprints stored in the calibration phase with the measurements taken in the positioning phase: the user is located at the coordinates for which the reference fingerprint is at the minimum distance in the signal space of the target fingerprint. Choosing an appropriate distance or similarity measure in IP is also essential, as it may affect data analysis and the interpretation of results.

Therefore, it would be interesting to study the impact on BLE indoor positioning of the protocols, channels, distances and user's orientation in the positioning phase.

In this paper, we present an in-depth study of the performance of BLE protocols and channels in IP—depending on user orientation in the positioning phase—using different distance and similarity measures.

The main contributions of this work are the following:

- We provide an in-depth study of BLE protocols and advertising channel performance, taking into account user orientation in the positioning phase and considering different distance and similarity measures.
- For both the calibration and positioning phases, new databases are generated, filtering the raw RSS databases using maximum, mean and median RSS values, and a posterior analysis is made on which is the best comparison between these new databases.
- To simulate a real situation of a positioning system, data collection was carried out in the positioning phase, and only 4 s of samples were taken with users facing in a specific direction.
- We provide accuracy and precision results depending on the user's orientation in the positioning phase, BLE protocols, channels, number of neighbors, and number of samples in both the calibration and positioning phases.

There are similar studies that analyze distance and similarity measures for Wi-Fi fingerprinting [9], [10] but, as far as we know, there is only one similar study of BLE technology that explores protocol-channel combinations and the effect of the user's orientation in the positioning phase [11].

This paper is organized into six sections. The following section reviews related works. In Section III we will describe the materials and methods used in the experiments. The experiments are described in Section IV and their results are described and analyzed in Section V. Finally, the conclusions and future lines of work are presented in Section VI.

II. RELATED WORK

In relation to the general works on indoor positioning based on BLE, and within the specific category of works based on the fingerprinting method, we may mention that Zhu *et al.* [12] proposed a complete positioning method and a series of optimizations to improve positioning accuracy. Xiao *et al.* [13] proposed a novel denoising autoencoder-based BLE indoor localization method to provide high-performance 3D positioning in large indoor spaces. They conclude that their method performs the best in 2D positioning. Faragher and Harle [14] explored the use of BLE beacons for fingerprint positioning and demonstrated an improvement over Wi-Fi positioning. Fard *et al.* [15] provided a more accurate, cost-efficient approach to the indoor positioning of mobile devices using the iBeacon protocol, concluding that more training data do not always yield higher accuracy. Čabarkapa *et al.* [16] presented a comparative analysis of different BLE indoor positioning solutions. Wen *et al.* [17] stated that compiling a remeasurement RSS database involves a high cost, which is impractical in dynamically changing environments, particularly in highly crowded areas, proposing a dynamic estimation resampling method for certain locations chosen from a set of remeasurement fingerprinting databases. Contreras *et al.* [18] evaluated the viability of BLE for indoor positioning scenarios and developed a framework to analyze, understand and help migrate previous local position systems, based on technologies other than BLE. Lu *et al.* [19] adjusted iBeacon Tx to increase signal differences in indoor environments, reducing RSSI similarity for some reference points; radio frequency signals were filtered using a modified moving average filter to reduce signal variations after reception and pattern matching and the KNN algorithm had been integrated to facilitate positioning. Castillo-Cara *et al.* [20] identified the fact that the use of KNN and support vector machine algorithms may prove effective in developing an indoor location fingerprinting mechanism; they proposed as key parameters the Tx level and the number and placement of BLE4.0 beacons, and the number of neighbors in the performance of the KNN algorithm. He *et al.* [21] investigated the problem of beacon deployment for unambiguous user positioning; they theoretically proved a series of performance bounds on the number of required beacons, and formulated a novel integer linear program that jointly determines the beacon positions along with their power levels and broadcast intervals.

Faragher and Harle [1] were among the first to conduct experimental tests of fine-grained BLE positioning and a detailed study into the key parameters for accurate indoor positioning using the BLE radio signals; the Euclidean distance metric was used to generate a score for each cell in the grid, and then that score was weighted using a Gaussian kernel to generate a probability for that cell. Kajioka *et al.* [22] demonstrated the viability of positioning through the received signal strength of BLE beacons using fingerprinting and squared Euclidean distance for template matching, reaching a precision of 0.96 m 96.6% of the time. Peng *et al.* [23] proposed an iterative WKNN IP method based on BLE RSSI; with respect to other indoor positioning methods such as KNN or WKNN, the proposed method improves mean positioning.

There are also works that make use of the diversity of BLE channels. Zhuang *et al.* [24] used an algorithm combining a polynomial regression model, fingerprinting with BLE channel separation, outlier detection, and Kalman filtering; the Euclidean distance-based WKNN algorithm was used. Ishida *et al.* [25] proposed a BLE separate channel fingerprinting system and developed a separate channel advertising scheme, which enables standards-compliant BLE devices to recognize advertising channels; using the separate advertising scheme demonstrated that separate channel fingerprinting improves localization accuracy by approximately 12 %. Powar *et al.* [4] showed that the different RSS behavior of the three BLE advertising channels has a significant effect on the aggregate signal used by mobile devices, as well as significant implications for positioning; their data analysis shows that a single channel signal is highly preferable to an aggregate signal and that constructing three signal fingerprints results in a greatly improved positioning scheme. Cantón-Paterna *et al.* [3] proposed and implemented a real IP System based on BLE that improves accuracy while reducing power consumption; channel diversity mitigated the effect of fast fading and the effect of interference during RSSI measurements. De Blasio *et al.* [11] provided an analysis of BLE channel-separate fingerprinting using different distance and similarity measures.

In relation to works on studies of distance and similarity metrics, we may mention Deza Deza [26] and Cha [27] as general works, and Prasath *et al.* [28] as a study of the effect of distance and similarity metrics on the performance of k-nearest neighbor classifiers and their possible implications in indoor positioning.

III. MATERIALS AND METHODS

In order to emit BLE signals, twelve transmitters (iBKS105 BLE beacons) were deployed in a controlled environment—described in Section IV—and to collect those signals, an *Asus N56J* laptop with a *Nordic Semiconductor nRF51* BLE dongle were used. The laptop was placed on a table with wheels and at a height similar to that of a standing user carrying a mobile device. The BLE dongle was inserted into a USB port on the right side of the laptop: if the laptop were oriented along a North-South line (screen facing North), the longitudinal axis of the dongle would be oriented along an East-West line (see Fig. 1). Both in the calibration phase and in the testing phase, the laptop screen remained always up and in the presence of a person who oversaw the data collection, and who also partly blocked the signal arriving at the dongle. The software employed were *ble-sniffer win-1.0.1-1111* and *Wireshark 1.10.14*. Both in calibration and positioning phase, the same laptop, dongle and software were used.

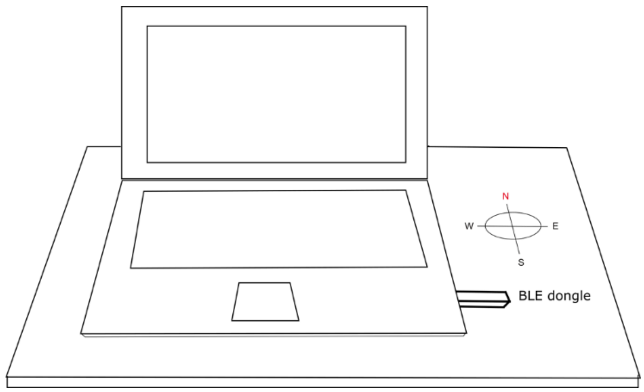

FIGURE 1. Orientation configuration of laptop and BLE dongle.

WKNN, which is an improvement on the classic NN and KNN algorithms, is employed in this paper to compare the fingerprints of both phases. Reference points obtained in the calibration phase, which are close to test points obtained in the positioning phase, should have a higher weight than reference points that are far away. The estimated coordinates (x_e, y_e) of the test points are calculated using the formula:

$$(x_e, y_e) = \sum_{i=1}^{k} (x_i, y_i) \cdot w_i / \sum_{i=1}^{k} w_i, w_i = 1/d_i \tag{1}$$

where (x_i, y_i) are the coordinates of the k reference points and w_i are the weights for each distance d_i.

In this work, we used 38 different distances and similarity metrics, grouped in different families, to address their effect on fingerprinting [26], [27]. We selected the following:

- Minkowski Family L_p: Euclidean, Manhattan, Minkowski L_3, Chebyshev.

- L_1 Family: Sørensen, Canberra, Lorentzian.

- Intersection Family: Wave-Hedges, Motyka, Tanimoto.

- Inner Product Family: Inner Product, Cosine, Jaccard, Kumarhassebrook.

- Fidelity Family: Hellinger, Matusita, Squared-chord.

- χ^2 Family: Squared Euclidean, Pearson χ^2, Neyman χ^2, Squared χ^2, Divergence, Clark, Additive Symmetric χ^2.

- Shannon's Entropy Family: Jeffreys, K-Divergence, Topsøe, Jensen-Shannon, Jenesen-Difference.

- Combinations Family: Taneja, Kumar-Johnson.

- Vicissitude Family: Vicis-Wave Hedges, Vicis-Symmetric χ^2 (Min 1), Vicis-Symmetric χ^2 (Min 2), Vicis-Symmetric Max χ^2, Max-Symmetric χ^2, Min-Symmetric χ^2.

In addition to the above, we will use the Mahalanobis and Pearson correlation distance [26].

IV. EXPERIMENTAL SETUP

Fig. 2 shows the main corridor of our research institution, which was chosen as the testbed. Each of the twelve BLE 4.x beacons deployed were situated on columns at a height of 2.1 m and configured with the Eddystone and iBeacon protocols (see Fig. 3).

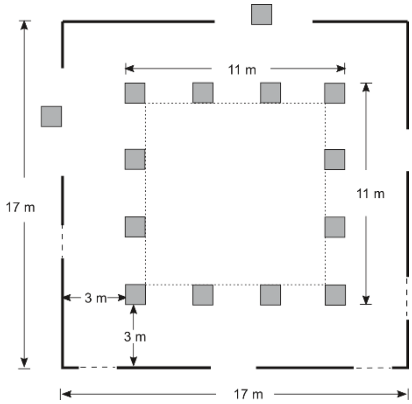

FIGURE 2. **Schematic view of the testbed with dimensions. Columns, wooden doors (dashed lines) and open spaces are shown.**

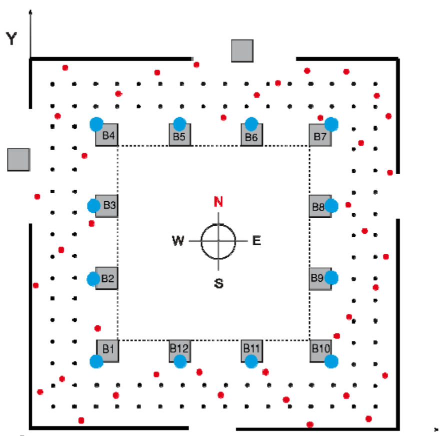

FIGURE 3. **Representation of the axes of the chosen coordinates, along with beacons, and reference and target points. Blue dots represent BLE beacons, black dots reference points and red dots target points.**

A grid of 112 reference points, each measuring 1 m × 1 m, was chosen, resulting in an average beacon deployment of 1 beacon per 14 m^2 and an average of 1.5 fingerprints per m^2. Although the iBeacon specification requires that the advertising interval be 100 ms, we detected that values of 500 ms do not significantly affect the stability of the signal, the iBeacon protocol, or the Eddystone. Thus, the output power and advertising interval were set to 0 dBm and 500 ms, respectively, for both protocols, in order to balance battery life and signal stability and to obtain accurate positioning values. For our positioning purposes, it was only necessary to use the Eddystone-UID frame type.

Once the reference fingerprints had been recorded, several smaller fingerprint databases were constructed. For a particular beacon, protocol and channel, the maximum, mean and median RSS values for each orientation were calculated, and then the maximum, mean and median of those four RSS values were selected, resulting in nine possible databases. We will name these nine reference fingerprint databases RPi_j, where *i*, *j* can refer to maximum (max), mean or median (med) indistinctly, e.g. if we take the maximum RSS values for each orientation and then calculate the mean of those four values, we shall call this database RPmax_mean (see Fig. 4).

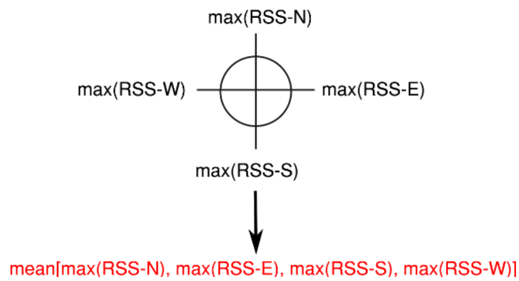

FIGURE 4. **Steps to obtain RPmax_mean fingerprint database.**

In the positioning phase, the same laptop and dongle used in the calibration phase were used to record at 40 target points situated randomly in the grid. Only 8 samples (a sampling time of 4 s approximately) were taken for each orientation, protocol and BLE channel; their coordinates were also taken with the laser pointer. We guaranteed the coherence of the orientation in both phases using a compass.

Three smaller fingerprint databases were constructed from the original. For a particular beacon, protocol and channel, the maximum, mean and median RSS values for each orientation were calculated, and then the maximum, mean and median of those four RSS values of the samples were calculated. We will name these three target fingerprint databases TP*k*, where *k* can refer to maximum (max), mean or median (med). For example, if we take the mean RSS values for each orientation, we shall call this database TPmean.

In both the calibration and positioning phases, measurements were taken with very few people present, and at all measurement points no signal was received from certain beacons during the entire sampling time (for all protocols and channels), e.g. at reference point 1 (the closest point to the origin of the coordinates, O), no signal was received from none of the beacons B6 to B9 (see Fig. 3).

Matching each of the nine reference fingerprint databases and each of the three target fingerprint databases results in twenty-seven possible combinations or comparisons between reference and target fingerprint databases. We will name these comparisons RPi_j-TP_*k*, where *i*, *j*, *k* can refer to maximum, mean or median. For example, if we compare the RPmax_mean and TPmean databases, the comparison will be named RPmax_mean-TPmean.

The purpose of taking orientation into account in the online phase is to simulate the positioning of a user who is specifically facing in one of the four possible directions in real time. These data could be ascertained through a mobile phone compass [11].

V. RESULTS

In this work, positioning accuracy is expressed by the mean error and its precision by the cumulative probability function, CDF, which is expressed in practice in percentile format [8]. For the sake of space, we present in this section only some accuracy and precision results, indicating whether or not they are general results for all possible cases.

As a previous consideration to the results, we present some plots concerning fast fades. Faragher and Harle [1] demonstrated the high susceptibility of BLE to fast fading.

Fig. 5 represents RSS values versus time for the two considered protocols and three channels at a particular reference point and beacon. All six plots clearly show fast fading values: around −25 dBm in a short period of time, particularly for channels 38 and 39 in both protocols. Fast fades can be removed at the creation of all the RSS databases, as in [1], but in this paper, we have employed raw RSS data.

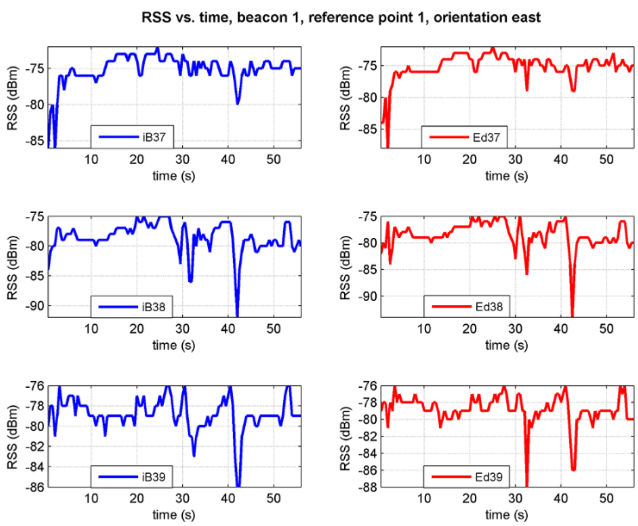

FIGURE 5. RSS from a specific beacon vs. scanning period for iBeacon and Eddystone protocols and 37, 38, 39 advertising channels, at a specific reference point.

A. ACCURACY VS. THE NUMBER OF SAMPLES TAKEN IN THE CALIBRATION PHASE

In this section, we will study the effect on accuracy of varying sampling time in the calibration phase and keeping the number of samples constant and equal to 8 in the positioning phase. Fig. 6 shows accuracy versus the number of sample plots taken in the calibration phase for four orientations and a particular database comparison, distance metric, protocol, channel and k neighbors.

It can be clearly seen in Fig. 6 that for east and south orientations, accuracy increases as the number of samples increases, this not being true for north and west orientations. However, the difference between the worst and best accuracy for north and west are around 10 cm and around 1 cm for

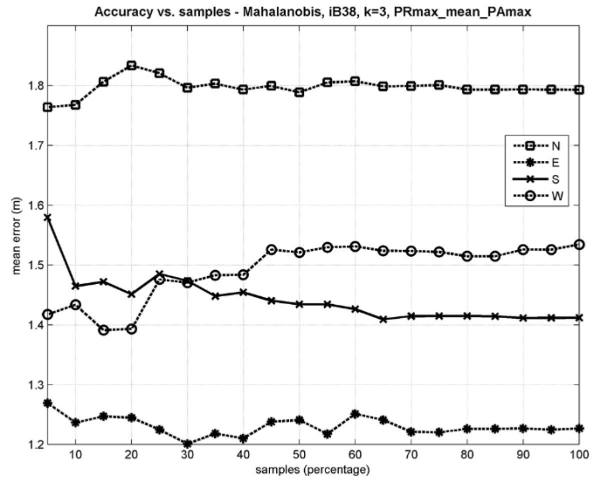

FIGURE 6. Accuracy vs. number of samples for each orientation and for RPmax_mean-TPmax database, Mahalanobis distance, k=3 neighbors, iBeacon protocol, channel 38.

east and south. The same results occur with other database-distance-protocol-channel-k combinations.

The above results indicate that increasing the sampling time does not necessarily increase the accuracy significantly. All results from now on will be considered with respect to 100% of the sampling time in the calibration phase.

It has to be said that, for all orientations, the distance-protocol-channel combination that has the best accuracy is the same regardless of the number of samples. However, for all orientations the number of neighbors that produce the best accuracy depends on the number of samples.

B. ACCURACY VS. THE NUMBER OF SAMPLES TAKEN IN THE POSITIONING PHASE

In this section, we will study the effect on accuracy of varying the number of samples in the positioning phase, keeping the number of samples (100%) in the calibration phase constant. Table 1 shows accuracy versus the number of samples (8 and 16) taken in the positioning phase for all orientations,

TABLE 1. Accuracy vs. number of samples in positioning phase for Euclidean distance.

	8				16			
Prot.-Chann.	N	E	S	W	N	E	S	W
iB37	1.7	1.3	1.4	1.6	1.4	1.2	1.3	1.6
	1.7	1.2	1.3	1.5	1.4	1.1	1.3	1.6
Ed37	1.6	1.2	1.4	1.6	1.6	1.3	1.3	1.5
	1.6	1.2	1.4	1.6	1.5	1.2	1.3	1.5
iB38	1.8	1.3	1.5	1.6	1.6	1.3	1.3	1.5
	1.8	1.3	1.5	1.5	1.7	1.3	1.4	1.5
Ed38	1.8	1.2	1.5	1.6	1.6	1.2	1.4	1.6
	1.8	1.2	1.5	1.5	1.7	1.2	1.4	1.6
iB39	1.6	1.5	1.4	1.5	1.5	1.5	1.3	1.4
	1.6	1.4	1.4	1.5	1.6	1.4	1.3	1.4
Ed39	1.6	1.4	1.3	1.6	1.5	1.5	1.2	1.5
	1.5	1.5	1.4	1.5	1.5	1.4	1.2	1.5

RPmax_mean-TPmax database comparison, Euclidean distance metric, all protocols-channels and $k = 3, 4$ neighbors.

It can be seen that as the number of samples increases from 8 to 16, accuracy values increase between 10 cm and 30 cm depending on the orientation. All results from now on will be considered with respect to 8 samples taken in the positioning phase instead of 16 samples, since the data are more representative of reality.

C. ACCURACY VS. FINGERPRINT DATABASES COMPARISON

The next question that arises with respect to accuracy is which database comparison, between reference and target fingerprint databases, produces the best results.

Taking into account all twenty-seven RPi_j-TPk fingerprint comparisons, we obtained the best accuracy results with RPmax_mean-TPmax for all distance and similarity measures and all protocols and channels. Table 2 shows accuracy values for Euclidean distance considering RPmean_mean-TPmean and RPmax_mean-TPmax comparisons, with $k = 3$ and $k = 4$ neighbors and depending on protocol (iB stands for iBeacon and Ed for Eddyston), channel (37, 38, 39) and orientation (N, E, S, W).

TABLE 2. Accuracy vs. fingerprint comparison results for Euclidean distance.

	RPmean_mean-TPmean				RPmax_mean-TPmax			
Prot.-Chann.	N	E	S	W	N	E	S	W
iB37	1.9	1.5	2.0	1.8	1.7	1.3	1.4	1.6
	1.7	1.5	2.0	1.9	1.7	1.2	1.3	1.5
Ed37	2.2	1.6	1.8	1.9	1.6	1.2	1.4	1.6
	1.8	1.4	1.4	1.8	1.6	1.2	1.4	1.6
iB38	2.1	1.5	2.0	1.9	1.8	1.3	1.5	1.6
	2.2	1.5	2.0	1.9	1.8	1.3	1.5	1.5
Ed38	2.1	1.4	2.0	1.9	1.8	1.2	1.5	1.6
	2.1	1.4	2.0	1.9	1.8	1.2	1.5	1.5
iB39	1.9	1.8	1.9	1.8	1.6	1.5	1.4	1.5
	1.8	1.7	1.9	1.9	1.6	1.4	1.4	1.5
Ed39	1.9	1.8	1.6	2.0	1.6	1.4	1.3	1.6
	1.8	1.7	1.8	2.0	1.5	1.5	1.4	1.5

It can be clearly seen that RPmax_mean-TPmax produces the best accuracy results. The same results occur when checking RPmax_mean-TPmax against the other comparisons for all distance and similarity measures, reaching differences of up to 1.7 m for a certain distance. All results from now on will be considered with respect to the RPmax_mean-TPmax database.

D. ACCURACY VS. NUMBER OF NEIGHBORS, K

The next question is to study the accuracy values vs. number of neighbors, k, for a particular distance and different protocols and channels.

Table 3 shows accuracy values for the RPmax_mean-TPmax database, the first five values of k, iBeacon and Eddystone protocols, channels 37 and 39 respectively, different orientations and Mahalanobis distance.

TABLE 3. Accuracy results vs. k for Mahalanobis distance.

	RPmax_mean-TPmax			
Prot.-Chann.	N	E	S	W
iB37	1.8	1.5	1.5	1.6
	1.7	1.3	1.4	1.4
	1.6	1.2	1.3	1.5
	1.6	1.2	1.3	1.5
	1.7	1.2	1.3	1.5
Ed39	1.7	1.4	1.3	1.6
	1.7	1.4	1.3	1.6
	1.6	1.4	1.3	1.6
	1.6	1.4	1.4	1.6
	1.6	1.4	1.4	1.6

For this particular case, the number of neighbors between $k = 3$ and $k = 5$ produces the best accuracy. Similar results occur for more cases but these are not general results.

Fig. 7 shows accuracy vs. k plot for a particular distance, protocol, channel and orientation.

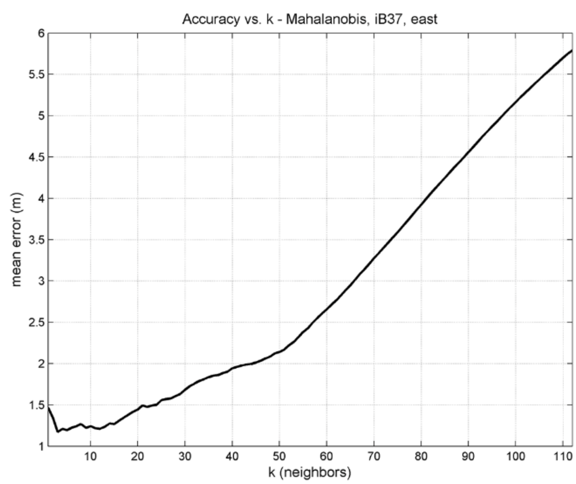

FIGURE 7. Accuracy vs. number of neighbors, k, for Mahalanobis distance, iBeacon-37 and east orientation.

E. ACCURACY VS. ORIENTATION

Table 3 also shows that in the positioning phase, east orientation produces better accuracy than the others. The same results occur with other protocols, channels, orientations and distances. When necessary, some results from now on will be considered with respect to these values of orientation.

F. ACCURACY VS. DISTANCE-SIMILARITY METRICS

If we consider the above parameters, which produce the best results according to the orientation in the positioning phase, is there a particular distance or similarity measure that offers the best accuracy results?

Considering the RPmax_mean-TPmax database, Table 4 shows the five distances that give the highest accuracy results for each orientation. It can be seen that, as we said in Section V Subsection D, except for some cases, values of

$k = 3$, $k = 4$ or $k = 5$ in general produce the best accuracy values.

Some remarks: for all orientations, there are multiple combinations of distances, protocols, channels and values of k that produce the same best accuracy values. In general, for each orientation the best values are obtained with one or two particular protocols, unique channel (except in a few cases) and different values of k combination: Eddystone39 or iBeacon39, $k = 5$, 6 neighbors for north, Eddystone38, $k = 3$, 4 for east, Eddystone39 or iBeacon39 (or iBeacon38) $k = 1$, 3 for south, and finally, iBeacon38, $k = 2$, 3, 4 for west.

We have seen in Table 4 that for each orientation there is a group of distances that produce the best accuracy (only five are shown). Those best distances are associated with a particular protocol and channel. Selecting a distance from this group in Table 4, how would it affect the accuracy if we change protocol and channel? Table 5 shows those results: for each orientation, the best protocol-channel accuracy is shown in the first row, and in the following rows, the remaining protocol-channel combination accuracies are shown (from best to worst).

TABLE 4. Accuracy vs. distance-similarity results.

	North		
Distance	Prot.-Chann.	k	Mean Err.
Clark	Ed39	5	1.5±1.0
Clark	iB39	6	1.5±1.0
VicisSymMin1	Ed39	5	1.5±1.0
Divergence	Ed39	5	1.5±1.0
Hellinger	Ed39	5	1.5±1.0
	East		
Distance	Prot.-Chann.	k	Mean Err.
Pearson Corr.	Ed38	3	1.1±0.7
Pearson Corr.	Ed38	4	1.1±0.7
Squared Eucl.	Ed38	4	1.1±0.7
Neyman	Ed38	4	1.1±0.7
Squared Euclidean	Ed38	3	1.1±0.7
	South		
Distance	Prot.-Chann.	k	Mean Err.
Wave-Hedges	Ed39	3	1.2±0.7
Person Corr.	iB38	1	1.2±0.7
Manhattan	Ed39	3	1.2±0.8
VicisWave-Hedg.	Ed39	3	1.2±0.7
K-Divergence	Ed39	3	1.2±0.8
	West		
Distance	Prot.-Chann.	k	Mean Err.
Pearson Corr.	iB38	2	1.4±0.8
Cosine	iB38	2	1.4±0.9
Pearson Corr.	iB38	3	1.4±0.9
Pearson Corr.	iB38	4	1.4±0.8
Minkowski3	iB38	3	1.4±0.8

From the results shown in Table 5, it is observed that for each orientation, setting a distance and varying the chosen protocol and channel, there can be differences between 10 cm and 30 cm in the accuracy.

The next question that arises naturally is: which distance-protocol-channel-k combination produces the best 'overall' accuracy? In this work, accuracy is expressed by orientation, that is, by a point in a 4-dimensional error-space, so the best overall accuracy would be that with the smallest minimum error module, or minimum distance to the point (0,0,0,0). Table 6 shows the first five combinations (there are six more combinations with the same error module but all involving Pearson Correlation or Mahalanobis distances).

TABLE 5. Accuracy vs. distance-similarity results.

	North		
Distance-Sim.	Prot.-Chann.	k	Mean Err.
Clark	Ed39	5	1.5±1.0
	iB39	5	1.5±1.0
	Ed37	6	1.6±0.9
	iB37	3	1.6±1.1
	iB38	4	1.7±1.3
	Ed38	9	1.7±1.2
	East		
Distance	Prot.-Chann.	k	Mean Err.
Pearson Corr.	Ed38	3	1.1±0.7
	iB38	7	1.2±0.6
	iB37	4	1.2±0.7
	Ed37	6	1.2±0.6
	Ed39	12	1.4±0.7
	iB39	8	1.4±0.8
	South		
Distance	Prot.-Chann.	k	Mean Err.
Wave-Hedges	Ed39	3	1.2±0.7
	iB37	4	1.3±0.9
	iB39	2	1.3±0.8
	Ed37	9	1.3±0.8
	iB38	4	1.4±0.8
	Ed38	3	1.5±0.6
	West		
Distance	Prot.-Chann.	k	Mean Err.
Pearson Corr.	iB38	2	1.4±0.8
	iB37	2	1.4±0.8
	Ed38	4	1.4±0.9
	iB39	2	1.4±0.9
	Ed37	2	1.5±0.9
	Ed39	5	1.5±0.9

TABLE 6. Overall accuracy results.

Distance	Prot.-Chann.	k	Error Module
Pearson Corr.	iB37	2	2.8
Pearson Corr.	iB37	5	2.8
Mahalanobis	iB37	3	2.8
Pearson Corr.	iB37	3	2.8
Mahalanobis	iB37	4	2.8

Thus, taking into account the results of Table 6, it can be said that in general, and not for a specific orientation, Pearson Correlation or Mahalanobis distance, iBeacon protocol, channel 37 and values between $k = 2$, and $k = 5$ show the best overall accuracy.

We followed the same procedure with the target points as with the reference points: the maximum values of all the RSS samples were obtained for each orientation and beacon, and subsequently the mean value from the four orientations was selected. This approach is not real since a mobile device user would never stop to take that many samples facing the four cardinal directions. Nevertheless, it will serve a purpose as a method of comparison for the approach of the previous sections, which we consider closer to reality. We will name this database comparison RPmax_mean-TPmax_mean. Table 7 shows the two distances that give the best accuracy results for north orientation.

TABLE 7. Accuracy vs. distance-similarity results.

	North		
Distance	Prot.-Chann.	k	Mean Err.
MinSymmetric	Ed37	2	0.9
Neyman	Ed37	2	1.0

Comparing the accuracy values of Tables 7 and 4 it can be seen that the former are not that far away and represent a more realistic approach in the online phase than the latter.

G. PRECISION RESULTS

As we have seen in Section V Subsection F, for each orientation there are various combinations of distances, protocols, channels and values of k that produce the same best accuracy values. We will try to differentiate between these combinations with the cumulative distribution function (CDF) [8].

Taking into account table 4, precisions of the five best distance-protocol-k-channel combinations are represented in Fig. 8 to Fig. 11 by orientation (vertical dashed black lines represent the mean error). For north orientation (see Fig. 8), precision values are 90% within 2.1 m (Clark, iBeacon-39, $k = 6$) – 2.2 m (rest of combinations).

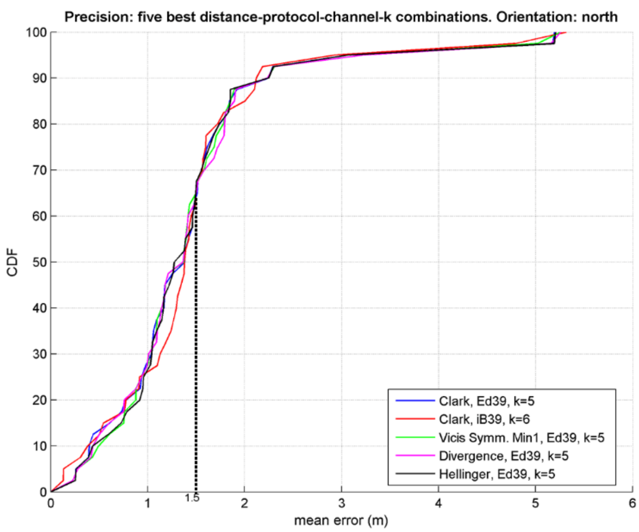

FIGURE 8. Comparison between precisions of the best five distance-protocol-channel-*k* combinations (north orientation).

For east orientation (see Fig. 9), precision values are 90% within 1.5 m (Neyman, Eddystone-38, $k = 4$) – 1.8 m (Pearson Correlation, iBeacon-38, $k = 3$).

For south orientation (see Fig. 10), precision values are 90% within 2.1 m (all combinations except Pearson Correlation) – 2.3 m (Pearson Correlation, iBeacon-38, $k = 1$. Finally, for west orientation (see Fig. 11), precision values are

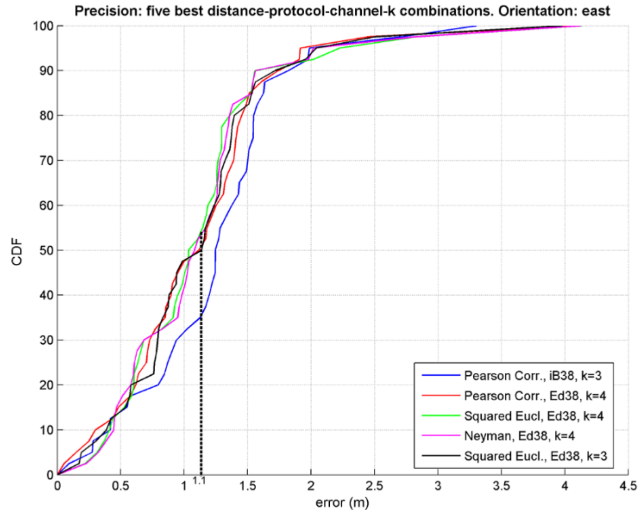

FIGURE 9. Comparison between precisions of the best five distance-protocol-channel-*k* combinations (east orientation).

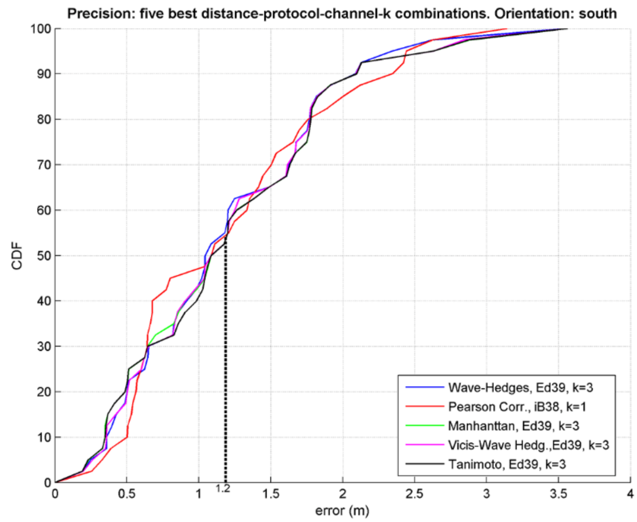

FIGURE 10. Comparison between precisions of the best five distance-protocol-channel-*k* combinations (south orientation).

90% within 2.2 m (Pearson Correlation, iBeacon-38, $k = 4$) – 2.5 m (Cosine, iBeacon-38, $k = 2$).

In Table 4, very similar accuracy values are shown for each orientation. To decide which distance-protocol-channel-k combination to choose, we will select the one with the CDF graph, which reaches high probability values faster: for north orientation, all combinations reach high probability values practically at the same time, with a precision of 100% within 5.2 m; for east orientation, the Pearson Correlation distance (blue plot in Fig. 9) has a precision of 100% within 3.3 m, while the others are within 4.0 m; for south orientation, the Pearson Correlation distance (red plot in Fig. 10) has a precision of 100% within 3.1 m, while the others are within 3.6 m; for west orientation, the Pearson Correlation distance (blue plot in Fig. 11) has a precision of 100% within 3.6 m, while the others are within 3.8 m – 4.5 m.

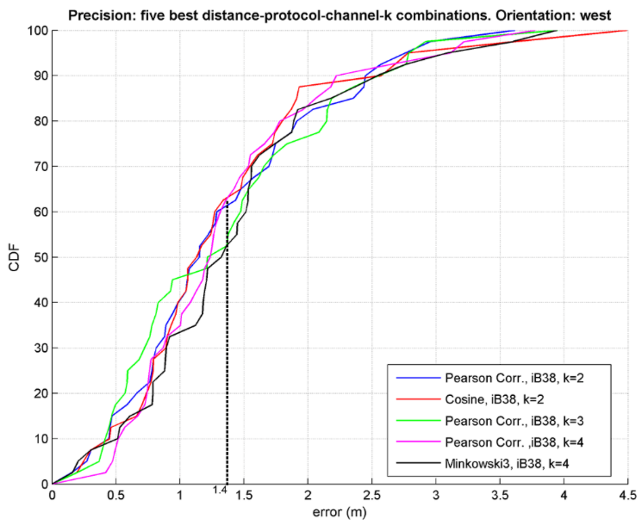

FIGURE 11. **Comparison between precisions of the best five distance-protocol-channel-*k* combinations (west orientation).**

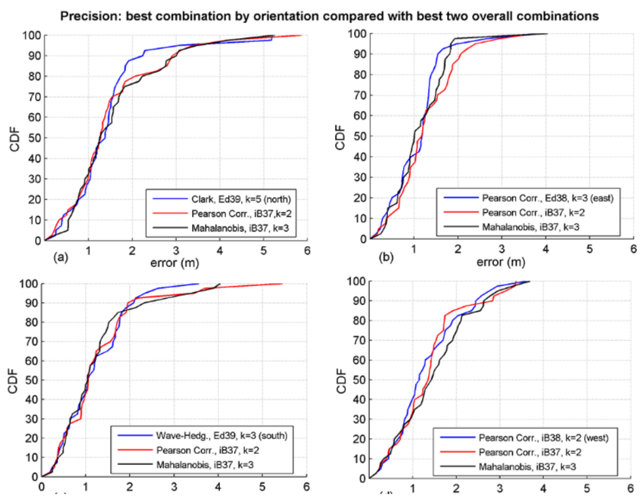

FIGURE 12. **Comparison between precisions: the best two overall combinations, Pearson Correlation and Mahalanobis (with iBeacon 37, *k*=2 and *k*=3 respectively), with one of the best combinations by orientation: (a) north, Clark-iBeacon 38, *k*=5, (b) east, Pearson Correlation-Eddystone 38, *k*=3, (c) south, Wave Hedges-Eddystone 39, *k*=3, (d) Pearson Correlation, iBeacon 38, *k*=2.**

In each of the subfigures of Fig. 12, the precisions of one of the best combinations by orientation are compared with two best overall combinations: those involving Pearson Correlation and Mahalanobis distance, both iBeacon 37 and $k = 2$, $k = 3$ neighbors respectively (see Table 4 and Table 6).

As can be seen, each best combination by orientation (blue plots) performs better than the two overall combinations (red and black plots), especially in high probability values, but as was stated in Section V Subsection F, in general and not for a specific orientation, Pearson Correlation or Mahalanobis distances with iBeacon protocol and channel 37 are also good combination choices.

TABLE 8. **Accuracy and Precision for some BLE IP systems.**

System	Accuracy	Precision
Faragher [1]	N/A	295% within 2.6m (1 beacon per 30 m^2)–4.8m (1 beacon per 100 m^2)
Peng [23]	2.52 m – 4.48 m (office env.)	90% within 4.12m (1 beacon per 21 m^2)
de Blasio [11]	1.47 m–2.15m (harsh env.)	90% within 1.81 m–3.58m (1 beacon per 45.7 m2)
Zhuang [24]	N/A	90% within 2.56m (1 beacon per 9 m^2)–3.88m (1 beacon per 18 m^2)
Xiao [13]	1.09 m	1.0 m and 2.0 m for 52.69% and 92.56% of total instances

VI. CONCLUSIONS AND FUTURE WORKS

In BLE technology, RSS readings suffer from large fluctuations and degradation due to many factors, thereby reducing indoor positioning accuracy and precision values.

With the aim of reproducing a real positioning system we have studied the impact of the orientation in the positioning phase and the impact of protocols, channels, using 40 distance metrics in order to minimize those fluctuations and degradation factors and obtain the greatest possible accuracy and precision. We also studied the impact of sampling time, in both calibration and positioning phases.

According to our results:

- Regardless of the orientation, sampling time in the calibration phase is not critical, with differences of 10 cm in the worst case. The combination of distance-protocol-channel that has the best accuracy is the same regardless of the number of samples, but it is not the same for the number of neighbors, k, in the WKNN algorithm. In the positioning phase, as the number of samples increases from 8 to 16, accuracy values in general increase from 10 cm (east, south, west) to 30 cm (north), but 8 samples represent data closer to reality.
- Filtering the RSS reference fingerprint database with the mean of the maximum values per orientation and filtering the RSS target fingerprint database with the maximum values (considering orientation) produces better accuracy and precision than any other fingerprint database comparison, reaching differences in accuracy of up to 1.7 m for a certain distance.
- There is no clear dependency between accuracy and the number of neighbors, k. The best results are usually obtained with values in the range 3–5, but it is not a general result and depends on the distance-protocol-channel chosen.
- East is the orientation that produces the best accuracy in all situations with differences, when compared to other orientations, that can reach 60 cm. We understand that the main reason behind the existence of an orientation that produces better accuracy results is the testing environment. Although our environment is a square with symmetric points (see Fig. 2), when signals are

propagated, there are certain elements such as wooden doors, concrete columns or open spaces that cause the signals that reach the BLE dongle from the beacons to undergo reflection, absorption, etc., in apparently similar areas. Consequently, different orientations produce different accuracies.

- There is a group of distance metrics (which for some orientations can be large) coupled with a protocol-channel combination that produces similar accuracy results, but when fixing one of these distances and varying the protocol and channel, there are appreciable differences (up to 30 cm) in these values. In addition, those combinations that give the best accuracy results in a specific orientation give worse results (up to 40 cm worse) in other orientations. Therefore, we understand that in a specific orientation choosing the right distance metric is not as important as choosing the right protocol, number of neighbors, and especially, the right channel.
- For the abovementioned group of distances, we have detected a pattern whereby the best accuracy for each orientation is provided by a unique protocol-channel combination: Eddystone or iBeacon 39 for north, Eddystone 38 for east, Eddystone 39 or iBeacon 38 for south and iBeacon 38 for west.
- Depending on the orientation, the accuracies obtained for the abovementioned group of distances are in the range of 1.1 m – 1.5 m and the precisions are 90% within 1.5 m – 2.5 m.
- The best overall distance-protocol-channel-k combination would be the one with the smallest minimum error module. This means that this combination would produce high values of accuracy and precision in multiple cases, regardless of the orientation. The Mahalanobis and Pearson Correlation distance combined with the iBeacon protocol and channel 37 are the best combination in multiples cases (multiple values of k).

Our study was conducted in a controlled environment, transmission power and advertising interval were set as fixed values, with very few people present, but in harsh environments, where the presence and movement of people clearly affect accuracy and precision, it is very likely that the choice of distance measures, protocols and adequate channels will be much more critical than in our test environment. To all this, we must add that the data were collected using a laptop and a dongle, not a mobile device.

In the experiments carried out, we guaranteed the coherence of the orientation in both phases using a compass. In real situations, a user with a mobile device will be placed in a random but known orientation through the compass of the device and therefore that information can be used to select a specific protocol-channel combination and give accuracy results depending on the orientation.

On the other hand, in order to reduce the high cost in time involved in the construction of the database of reference points, we have taken RSS data only in four orientations. In the testing phase the RSS values for a random orientation could be compared with the RSS values of the calibration phase for the closest orientation. Precisely for this reason, we are currently working on the development of a set of tools to automate much of the process necessary for data collection in the calibration phase, which will allow us to have a database of RSS information with more orientations and thus be able to study to what extent the accuracy results improve as we increase the number of orientations used.

It is not a simple task to compare different IP systems. Each system has a range of parameters, which are completely different in each study, such as the number of beacons, their localization and settings, working and ambient conditions of the environment, hardware employed to collect data, etc. In addition to this fact, not all authors express accuracy and precision in the same way, so it becomes evident that it is very difficult to establish a complete comparison between systems. Moreover, the following systems do not study accuracy and precision values with respect to protocols, channels and orientations. Despite this, a comparison between the results of our study and the results obtained by other similar systems is presented below.

To this end, and as future lines of action, we may mention the following: study the implications on indoor positioning of varying the beacons' transmission power and advertising interval; conduct this study in other types of environments, especially harsh environments; change the number and placement of beacons; and check other fingerprinting-based positioning algorithms using pattern recognition techniques and compare their results with the present study.

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