No More Hiding! WALDO: Easily Locating with a Wi-Fi Opportunistic Approach

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Abstract: The popularization of mobile devices and increasing the number of sensors and embedded resources boosted a large amount of research in the area of context-aware. Among the most relevant contextual information is the location. In outdoor environments, the GPS technology is already widespread and used. However, the people tend to spend most of their time indoors, such as universities, hospitals, malls, and supermarkets, where the GPS location is compromised. Several approaches using mainly radio frequency technologies have been proposed to solve the problem of indoor location. So far, no widely accepted solution solves the problem of location indoors. In this way, this work to use an opportunistic approach, making use of the Wi-Fi infrastructure available in the environment, to provide the location of mobile stations. Based on this objective, the WALDO architecture was developed that unites the characteristics of different approaches of the works that have been produced in recent years, taking into account the techniques that present better results at each stage, in conjunction with a zone-based approach and ranking, on phase online of the fingerprint technique, which makes ignoring RSS readings that present noises.

1 INTRODUCTION

Nowadays, it is quite common to find mobile devices with several sensors, which collect information from the environment in which the device is inserted, aiming to offer greater convenience and improve the user experience, presenting information and useful services, such as showing the user the nearby restaurants or suggest the best route to reach the desired destination. In this sense, location information is a fundamental parameter. A large part of these technologies are targeted for indoor use, such as visitor orientation at malls (Oosterlinck et al., 2017), airports (Ahmed et al., 2016), real-time monitoring of patient location in hospitals (Kanan and Elhassan, 2016), identification of crowd concentration (Fukuzaki et al., 2015), among others.

Although GPS (Global Positioning System) technology is quite widespread for outdoor environments (Yang et al., 2013), due to signal interference, it often does not provide satisfactory accuracy indoors (Paul and Wan, 2009) (Rai et al., 2012). To mitigate this demand is necessary to use a source of information more suitable for this type of environment. In this sense, several technologies have been used as a source of information to perform the mapping of the environment. Mostly technologies that emit radio frequency signals, such as Wi-Fi (Wireless Fidelity), Bluetooth (Oosterlinck et al., 2017), RFID (Radio Frequency Identification) (Ahmed et al., 2016) and NFC (Near Field Communication). Due to the popularization and enabling opportunistic approaches, the Wi-Fi technology in IPS (Indoor Positioning System) implementations are among the most widely used technologies (Rai et al., 2012). Among the approaches used are the fingerprint technique and estimates using geometric calculations (Yang and Shao, 2015). The fingerprinting technique depends on a prior mapping of the environment, whereas geometric estimates use the distances between the object to be located and three or more landmarks with a known location.

The popularization of Wi-Fi networks has made more and more people stay connected through their mobile devices (Ge and Qu, 2016), opening up opportunities for other ways to exploit this technology. In recent years, several works have used Wi-Fi technologies to obtain the location of devices in environment indoors. In addition to allowing the use of existing

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and widespread infrastructure, another motivator lies in the energy savings of mobile devices. The use of other sensors or interfaces, such as the accelerometer, gyroscope, Bluetooth and magnetometer, for the sole purpose of providing device location, result in extra energy expenses (Lane et al., 2013).

For systems that provide localization in indoor environments, there is a relationship between accuracy in location, complexity, cost, and scalability estimates for implementation in real environments (Mainetti et al., 2014). Many papers in the literature(Yang and Shao, 2015)(Lymberopoulos et al., 2015)(Chen et al., 2014)(Rai et al., 2012)(Kannan et al., 2013) discuss these points separately, or even address just a few of these. This paper presents a low-cost, scalable, indoor location approach that uses the Wi-Fi infrastructure available to obtain the location of commercial smartphones.

Among the main contributions presented in the present work is the use of an opportunistic approach. Another contribution is the use of a zone scheme and ranking in the location phase of the fingerprint technique, which ignores some RSS (Received Signal Strength) readings that present noise. For this to be possible, during the location phase, the mapped area is zoned, which has a set of sampling points with their respective fingerprint signatures. Areas with the most extended distances between online measurement and sampling points are calculated and excluded. Since only the two zones with the highest probability of the device are left, a ranking scheme is performed, to prioritize the readings with less noise.

The rest of the paper is organized as follows: Section 2 presents the motivation and related works in the literature. Section 3 explains WALDO architecture and the methodology used, explaining the implementation of the modules that make up the architecture. Section 4 describes the tests and results. Finally, conclusion and future work are given in Section 5.

2 MOTIVATION AND RELATED WORK

The use of the fingerprint technique, coupled with the use of mobile devices (such as smartphones and tablets) with Wi-Fi technology, has presented promising results in the development of indoors positioning systems. In this approach, the smartphone to be found must have an active Wi-Fi interface. Among the challenges encountered in this approach are the inherent limitations of mobile devices, such as low processing power, limited memory, battery usage, and the diversity of distinct hardware found in mobile devices (Kannan et al., 2013). Also, radio frequency signals suffer much interference from obstacles present in closed environments, making the use of this parameter for the unambiguous characterization of the environment, become a great challenge. In order to better characterize each section of the mapped environment, Chen et al. (Chen et al., 2014) proposes an algorithm that relates not only the power of the received signal (RSS) but also the proximity order of the APs according to their power. The authors hope that in this way, the fingerprint of each room in the environment will be better defined, making it easier to locate even when the devices have different hardware characteristics. Using a different approach, Rai et al. (Rai et al., 2012) make use of some of the sensors present in smartphones (accelerometer, compass, gyroscope, etc) together with data obtained from Wi-Fi and a user-informed map containing the characteristics of the environment, and barriers (walls and other obstacles).

Another challenge for the use of fingerprint-based approaches lies in the mapping of the environment, which demands time and work. Since the fingerprint based on a particular feature of the environment, such as radio frequency, magnetic field or background sound is used, this information must be captured and stored (training stage). Therefore, the time demanded the offline step is related to the size of the area to be mapped, as well as the precision that one wishes to obtain. In order to reduce this time, without compromising accuracy, a series of tests with short and long duration readings were carried out in the work of Yang et al., and it was verified that the value that most frequently appears in the measurement (a few minutes) is the same as long-term measurements (a few hours). Thus, there is no need for large amounts of capture time per site. Also, the mean values of the readings of each position were compared with the most frequent value, and a significant difference between the two measurements was found.

The WALDO architecture presents an approach that detects RSS noise-free readings during the online stage, eliminating them from the localization estimation process and thus presenting better estimates. Also, are used techniques that have already been addressed and tested in the literature separately.

3 WALDO ARCHITECTURE

WALDO uses the fingerprint technique to perform mapping and location devices, which in turn uses the Received Signal Strength (RSS) data of different WLANs whose signal covers the area to be mapped.

The fingerprinting technique is divided mainly into two distinct stages: training phase (offline) and location phase (online). In general, this technique consists of comparing the set of RSS readings obtained during the training phase and the location phase RSS readings set.

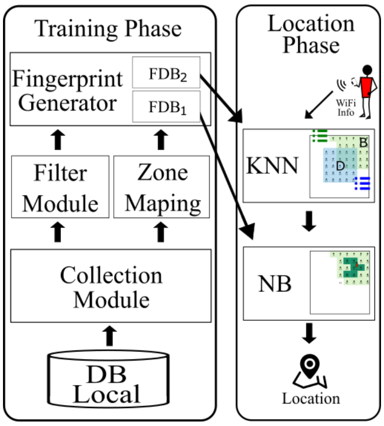

Figure 1: WALDO Architecture.

Figure 1 gives an overview of the WALDO architecture. As can be seen, the training phase and the location phase have subdivisions which will be explained in the following sections.

3.1 Methodology

The expected result of WALDO consists of determining the location of a smartphone, within a previously mapped area, using information from a set of nearby Wi-Fi networks. Figure 2 presents an information flow that describes the methods and procedures performed in the process. As can be observed, analyzing from the left, during the training phase the area and it's RPs (1a) are defined. In the next step (1b) the radio map is obtained, which is composed of the readings performed in each of the RPs. The radio map information is used to generate FDB_1 and FDB_2, used for comparison purposes in the tracing process. The location phase starts (2a) with the reading performed by the smartphone, in the place where it should be located. This step consists of calculating the sum of the RP distances of each zone and the values read at the time of the estimate of the location. The two zones that have the sums of smaller distances will be used in the next step. In the next step (2b), two classifications are generated containing the RP list of the two remaining zones. This RP list considers only RPs that establish neighborhoods with the leading RP (the nearest neighbors) of the ranking. Finally, the zone with the highest probability of being the correct one is identified and the Naive Bayes algorithm (NB) is applied at the remaining points.

3.2 Collection Module

The process of the data capture consists of storing in the database the RSS readings, associated with the respective identifiers of the APs, performed by the smartphone in each RP of the mapped area. To start the capture is necessary to have the information about the dimensions of the area to be mapped, as well as the location of the RPs used.

During the data collection, were considered four main characteristics. They are the number of readings per RP, reading time, device orientation at the time of reading and the number of RPs. The amount of RPs and distance of spacing used in the scenario, take into account information observed in the literature, which indicates average distances of errors over one meter, in an approach using Wi-Fi fingerprint. Also, the variation of RSS readings in close RPs, presents subtle differences, making the distinction between very close RPs difficult. Once decided the number of RPs, it is necessary to define the number of readings performed by RP as well as the time of measurements demanded. In the present work, the approach used where the readings are performed pointing the device to four different directions, using the walls of the room as references for each direction. In this case, at least four different readings are taken, pointing in each direction. Based on works cited in the literature, such as the (Yang et al., 2013), it is known that, although the oscillations demand a certain amount of measurements per point, the values that appear with more frequencies in short duration measurements will be the same values that will appear more frequently in long-duration measurements. Therefore, making the most frequently measured value the best choice for each RP fingerprint.

3.3 Filter Module

The variability in RSS measurement performed by a Wi-Fi mobile device is a consequence of radio frequency communication characteristics and interference caused by indoor obstacles. Since RSS and the identification of APs (MAC addresses and locations in the mapped environment) are the main parameters used in the estimation of positioning, the selection of the data to be labeled and used in the calculations will directly impact the quality of the positioning estimates. In this context, the filter module selects the data that will be used as parameters in the location phase. Firstly, we tried to disregard data that had

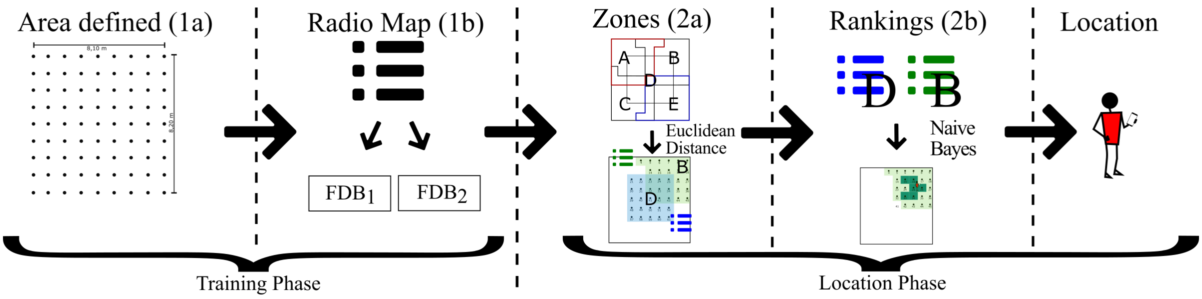

Figure 2: Information Flux.

characteristics that were inappropriate for the application. In this sense, were identified (using interquartile range) and excluded the outliers, generated by noise and other phenomena such as multipath. In addition to the outliers, data that did not appear in all RPs was also removed. This is because the AP is distant physically or has the signal obstructed by an obstacle. In this way, some areas of the mapped environment are not covered by the signal, while others, get fickle readings with low power. The second question is related to the distance between the mapped location and the device. If the long distance between the AP and the mobile station has caused poor signal coverage, and this signal is not available in all regions of the mapped environment, the chances of obstacles occurring between the transmitter and the receiver will increase.

In approaches that use probabilistic calculations, the larger the database, the better the results tend to be. On the other hand, when the comparison is performed with distance calculations (such as Euclidean distance), it is more appropriate to use a less extensive FDB, containing the measures that best characterize each RP. In the present work, the two approaches were used, in different stages. In this sense, two FDBs were generated, where one presents all the readings (after filtering) and the other presents only the RSS readings that best characterize the RP (most constant RSS values).

3.4 Fingerprint Generator

The fingerprint generator module is responsible for obtaining the two (FDB_1 and FDB_2) database corresponding to the training phase. The first fingerprint database (FDB_1) is formed by all remaining data after the deletion of the outliers. The variation of the signal, caused by the interference of the environment, causes the intensity of the received signal of the same AP in the same point is variable. Thus, it is known that the higher the signal strength, the less interference will be. In this sense, in order to prioritize the data that suffered less interference, the records were organized in order (decreasing) of signal power. The reading that presents the highest RSS value for an AP and a specific point is put first in the sequence of the records. This organization is performed for each AP of each point. Also, APs are also organized in descending order of power. In addition to the organization and arrangement of data in an orderly manner, the FDB_1 will be used to perform the comparison approach by probabilistic means.

FDB_1 is used to create FDB_2. In the FDB_2, each RP will only have one RSS value per AP, that is, only the RSS that most often appeared in each AP. In this sense, the number of values present in the FDB_2 will depend on the amount of RPs, and the amount of APs used. The two factors are self-explanatory. The higher the number of RPs and APs, the greater the data set associated with them. During the creation stage of the FDB, were captured the data of all the upcoming APs. Several APs can be observed in the readings at each point, however, it is worth noting that in the location phase some APs that were found during the creation of FDB will not appear, as well as some APs observed in the training phase will not appear in the location phase. Only values observed in the two steps will be used.

3.5 Zone Module

The use of zones has the objective of improving the location estimates, prioritizing the values measured in the location phase with a lower incidence of noise. For this, the mapped area is divided into a certain amount of zones, as can be observed in Figure 3.

The division of the area into zones takes into account the characteristics of the mapped area as the dimensions of the area and the total amount of RPs (TRP). The scenario presented in Figure 3 was divided into 5 zones (Tz), identified by upper case letters. The equation 1 give the number of RPs for each zone. The division begins with the choice of five strategic points on the map. From these points each zone is segmented. In the example, the area of each zone (Az) corresponds to 24 RPs plus the chosen

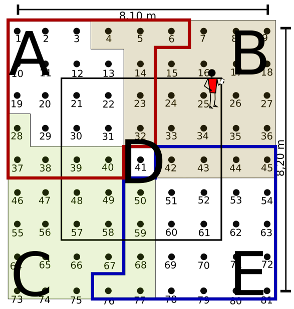

Figure 3: The total area of the computer lab divided into five zones.

point, totaling 25 RPs per zone. In this scenario, the four extreme RPs (1, 9, 73 and 81) besides the central RP (41) were chosen as starting points of each zone.

$$Az = \lfloor (TRP/Tz) \rfloor + [\lfloor (TRP/Tz)/2 \rfloor] \qquad (1)$$

3.6 Location Phase

Once the environment is mapped, the next step is the location of the smartphone. The location of the device is performed by comparing the data obtained at the time of screening (online step) and the present data from the system database. The process of location estimation starts when it is in the mapped environment, with the active Wi-Fi interface. Given the characteristics of the Wi-Fi technology, described by the IEEE 802.11 standard (Potortì et al., 2016)(Group et al., 1999), in order to obtain the device data (MAC address and RSS), it is not necessary that it be connected to the Wi-Fi network. This information is broadcast on the mobile device in order to find the available APs within reach. This information can be obtained at both ends of the communication, that is, in both the mobile station and the AP. In the present work, the validation tests and implementation of architecture were created with the help of two applications. These are designed to obtain the data from all APs close and send them to a server. Thus, in the implementation, the RSS data obtained from the mobile station were used. Therefore, there are no change requirements in the existing network infrastructure.

3.6.1 k-NN Module

Upon receiving the data, the manager application, running on a remote server, performs the necessary procedures to obtain the approximate location of the mobile station. First, it checks which APs read from the database FDB_2, and discarded the readings from unknown APs. The first comparison uses the Euclidean distance equation, where are comparing the location parameters with each of the RPs. The closer to zero is the value resulting from the comparisons, the more similar the values are.

From the Euclidean distance calculation, it is possible to verify the locations with less probability of the smartphone being. In this sense, an approach based on the kNN (k-Nearest Neighbors) algorithm, which uses a measure of similarity (or dissimilarity) between neighboring points, was used to classify datasets (Ge and Qu, 2016). In this approach, the measure of similarity used is the Euclidean distance, and the neighbors are the data of the RPs present in the FDB_2, whose Euclidean distance is the smallest. When obtaining the similarity value for each RP, they are added between each zone separately, in order to obtain the sum of the distances of each zone. By identifying the two zones with the smallest sums of Euclidean distances, we discard the zones whose calculations have indicated to be the least likely (farthest) of the smartphone to be located.

With two zones remaining, the next action consists of identifying and eliminating the zone with the least probability of the device being, so that only one remains to be analyzed. The next action taken takes into account RSS variability characteristics. It is known that within the set of parameters obtained, some of them reflect the characteristics of the environment where the device is, while others, due to interference suffered at the time of reading, are with parameters that do not characterize that point. From this information, it is observed the need to identify which data was read with interference and which suffered less variation. In this sense, a ranking of results is generated for each remaining zone, in ascending order, from the most similar to the least similar. From this step, the comparison between the zones is no longer made by the sum of all the results, and starts to be done by comparing the positions of each ranking, prioritizing the most similar values with those present in the FDB_2, and keeping the least similar (which have undergone significant variations) for tiebreaking ends.

The table 1 presents an example of ranking, with the most probable points of each zone. To reach these points are taken into account two Euclidean distances. The first is the distance between RSS values calculated in the first location phase. The second is the physical distance between the RPs. This distance does not take into account radio frequency information, but rather the distance of all points of the zone, concerning the leader point of the ranking. In other words, it seeks to find the neighboring points of the leader RP. With this information, the first 13 points closest to the leader of each zone are selected, which in the test scenario correspond to half the total number of points in the zone. Of the 13 selected points, 12 are located within the zone. Of the remaining 12, only 6 are points near the first point of the ranking. These 6 points are those presented by the table 1.

Table 1: Ranking table for zones B and D.

AP Zona B / Zona D	PA B/D	Distância B/D
fe:d1:b8 / be:b4:ab	24 / 41	0 / 0
f7:8f:26 / f7:8f:26	27 / 20	0 / 1
8e:d0:a0 / be:b4:ab	33 / 31	0 / 2
be:b4:ab / 87:22:01	35 / 51	1 / 1
87:22:01 / fe:d1:b8	24 / 49	1 / 2
be:b4:06 / -	21 / -	2 / -

The comparison between the remaining zones, to determine which zone is most likely, follows the following conditions:

- First (most common) case: the values of the table 1, the distance from the leading point of zone B will be compared with the distance of the leading point of zone D. When verifying that they are equal, the second point of zone B will be compared with the second point of zone D. At this point, it is verified that the distance value of zone B is smaller. Then the set of points in Zone B is elected the most probable set;
- Second: when one of the two zones compared presents all values of distance equal to zero, the zone will be chosen as most probable;
- Third, because the two rankings have different sizes, in some cases, during the comparison the values of one of the rankings will be exhausted, while the other will still have values to test. In these situations, where the tie in the comparisons persisted, the zone identified with the highest probability during the comparison between the five possible, will be the zone chosen.

With the set of RPs reduced, it is necessary to identify which of the remaining RPs is most likely to be the location of the device. For this applied Naive Bayes classifier algorithm.

3.6.2 NB Module

When using Naive Bayes classifier algorithm, the odds obtained through the measures for each of the APs are independent of each other since the RSS measures read by the smartphone about each AP are also independent. In the current scenario, with a reduced set of RPs to be analyzed, the use of Naive Bayes becomes an interesting approach. In this sense, the data stored in the training phase corresponds to the training dataset, while the data received from the client station, in the location phase, is the data to be classified. In order to NB classifier present better results, in this step is to use the FDB_2, which has a more extensive data set.

Continuing the example of the smartphone location, six points remain. Starting with the RP number 15, the parameters to be passed to the Naive Bayes are: the identifier of the RP, one of the APs sent by the mobile station and its respective RSS measure. The result returned is the probability that the AP and RSS belong to the set of values of RP 15. This process is repeated in RP 15 as there are distinct APs provided by online reading. If the mobile station sent a set of five APs in the reading, the five APs and RSS would be compared with the RP 15. The same process carried out in RP 15 is done in the other RPs. To conclude, the sets of probabilities are summed and verified which RPs have the most significant sum.

4 TESTING AND RESULTS

Among the methods used to evaluate IPSs are the precision, accuracy, scalability, robustness, cost and complexity tests (Hossain and Soh, 2015). As noted in the literature, short distance technologies usually provide better accuracy than others because they suffer less interference and ensure device position more accurately. Thus, the tests used for the validation of a tool, are dependent on the approach that was used. A Wi-Fi-based IPS does not offer as good an accuracy as an IPS that uses NFC TAGs, for example. On the other hand, the need to install TAGs, besides requiring the use of mobile devices compatible with technology, make the NFC-based approach more expensive and less scalable. In that sense, while a technique gains in accuracy, it loses in scalability and cost.

Considering the characteristics of WALDO, the tests carried out have the objective of evaluating the precision and accuracy of the location estimates. The precision is determined by some method of distance measurement, such as Euclidean distance, accuracy is obtained based on a set of precision test results. Due to the amount of Wi-Fi available for use in most urban areas, the challenge of scalability, as well as for the complexity of the implementation, is related to mapping the area, which demands time. Because it is an opportunistic approach that uses the existing infrastructure, the cost of implementation is reduced.

To validate the architecture, in addition to the dataset used in the architecture development, we used the KIOS Wi-Fi RSS dataset, more specifically the database called Desire, made available by (Laoudias et al., 2013). KIOS consists of a collection of RSS samples, a mobile device with Wi-Fi support. Data were collected in a typical 560 square meter office space consisting of a conference room, laboratories, and corridors. Within this area, data were selected at 105 different sampling points.

Using the dataset obtained in the computer lab, a test was performed in each RP, aiming to obtain a perception of the results throughout the room area. In this sense, 81 location estimates were made. The readings were made from a smartphone and sent to a server with the implementation of the WALDO architecture, which performed the calculations.

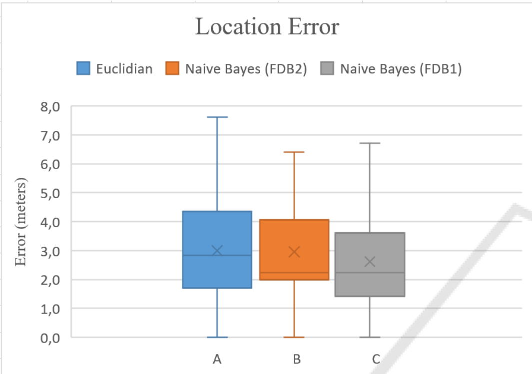

Figure 4: Location errors using the dataset of the computer lab.

In the graph of Figure 4 the results of steps A, B and C are presented respectively. Of all the points tested, the location estimate with the greatest discrepancy between the estimated location and the actual location presented just under 8 meters away. Despite this, most of the results shown in C (using WALDO), present results with errors of little more than 2 meters. In the histogram presented by Figure 5, the data from step C are shown, evidencing the frequency with which each estimate was made. Among the tests that presented estimates with a precision of 0 to 4 meters, most of these show estimates with a little more than 2 meters of error.

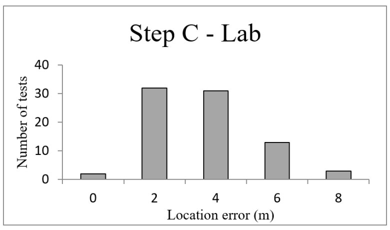

Figure 5: Histogram: location estimation errors using WALDO architecture with the computer lab datase.

The same tests were performed by the KIOS dataset and the results are presented in Figure 6. In total, 792 tests were performed in several RPs of the mapped environment. Observing the results of the estimates made through WALDO (step C), it can be observed that most of the tests present results with errors between 2 and 5 meters, with a median of approximately 3 meters. In addition, some outliers can be observed, with errors over 10 meters.

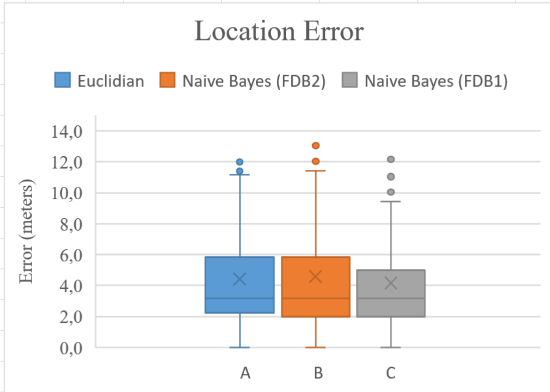

Figure 6: Location errors using the KIOS dataset.

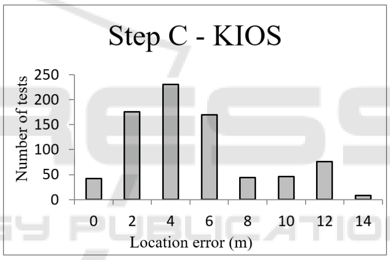

Figure 7: Histogram: location estimation errors using WALDO architecture with the KIOS dataset.

5 CONCLUSION AND FUTURE WORK

In the present work, an opportunistic system was presented that uses the available WLAN infrastructure to provide the indoor location. Since there is no need to install additional sensors, the costs for implementing the WALDO architecture are greatly reduced. In addition, Wi-Fi technology is widely used by smartphone users, so it is easy to access.

Because of the high variability of the strength of the Wi-Fi signal, due to the interference and noise common indoors, the estimation of positioning calculations can often suffer great influences. With the approach used in WALDO, by dividing the mapped environment into zones and using the rankings scheme, it was possible to prioritize the readings (trace stage) with less noise, causing outliers to receive less weight or to be disregarded in the calculations.

With the increasing growth of ubiquitous and pervasive technologies directed to internal environments, it is evident the need of the applications to know the location of the mobile devices to better adapt to situations, offering better services. Identifying that a user is in a certain environment, because it is porting a smartphone, creates several new possibilities for applications. The WALDO provides parameters to identify the location of mobile devices, with low location errors, making it suitable for many types of applications. The precision tests were performed using two distinct datasets, aiming to obtain non-biased results. Although this is an opportunistic approach, using variable signal technology, the test results were satisfactory.

As future work, tests will be performed regarding the influence caused by the use of heterogeneous devices during the estimation of positioning. In addition, it is intended to implement a system that obtains the RSS and MAC information through the APs, in a passive tracking approach. In this way, it is possible to estimate the location of both sides of the communication, seeking to improve the precision in the estimates. In addition, the use of other information sources along with Wi-Fi will be tested.

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