Evaluation of crowdsourcing Wi-Fi radio map creation in a real scenario for AAL applications

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***Abstract*—Indoor location at room level plays a key role for providing useful services for Ambient Assisted Living (AAL) applications. Wi-Fi fingerprinting indoor location methods are extensively used due to the widespread availability of Wi-Fi infrastructures. A main drawback of Wi-Fi fingerprinting methods is the temporal cost involved in creating the radio maps. Crowdsourcing strategies have been presented as a way to minimize the cost of radio map creation. In this work, we present an extensive study of the issues involved when using crowdsourcing strategies for that purpose. Results provided by extensive experiments performed in a real scenario by three users during two weeks are presented. The main conclusions are: i) crowdsourcing data improves accuracy location in most studied cases; ii) accuracy of Wi-Fi fingerprinting methods decay along time; iii) device diversity is an important issue even when using the same device model.**

***Index Terms*—Indoor location, Wi-Fi fingerprinting, Crowdsourcing data.**

I. Introduction

Ambient Assisted Living (AAL) program by the European Union defines AAL as "the use of information and communication technologies (ICT) in a person's daily living and working environment to enable them to stay active longer, remain socially connected and live independently into old age"[1]. Activity recognition and behaviour understanding play a central role in AAL, to support the creation of services to improve the quality of life of people at their own homes [1], and for elderly people in particular [2]. These research fields use data coming from sensors deployed at home, or worn by the user, to gather data used to create human behaviour models. Location at home is an interesting data to be tracked along time, because some issues related with physical and psychological decay can be early detected by using motion patterns at home, for example a decay in walking speed might be a predictor for cognitive impairment [3], [4].

Different technologies, such as sound/ultrasound, RFID, PIR detectors, Bluetooth Low Energy, Wi-Fi, have been used for indoor location [5]. One of the most used indoor location technology is Wi-Fi fingerprinting. Wi-Fi fingerprinting is based on the creation of a radio map by registering, at each point in the mapped environment, the Wi-Fi signals visible at that point. Then, this radio map is used to estimate the position of a user [6]. This technology bases its popularity in the ease of deployment, and in the fact that most wireless devices already have a Wi-Fi chipset attached to them. Low price, already deployed technology, widespread use and ubiquity are among its main advantages. Low accuracy (typically in the range of 1 m.) and uncontrolled changes in environment are among its main disadvantages.

In indoor urban level environments, such as University campuses or Hospitals, crowdsourcing approach has been proposed as a mean of acquiring data for covering such big surfaces [7]. Other interesting environment where to use crowdsourcing data gathering is nursing homes, where residents, doctors and nurses can provide data for mapping the same environment. In

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[1]www.aal-europe.eu

this work we present the results of a crowdsourcing approach for home environments, and we study how joining data gathered by different users can improve the accuracy performance of Wi-Fi based indoor location.

The research questions we want to answer with this work are:

- Do crowdsourced data improve location accuracy in Wi-Fi fingerprinting?
- Which is the accuracy of Wi-Fi fingerprinting for indoor location in a real scenario?
- Do location accuracy degrade along time?
- Which is the feasibility of crowdsourcing data for Wi-Fi fingerprinting?

To answer these questions, the paper is organized as follows: Section II presents the previous work related with Wi-Fi technology used for indoor location. Section III presents background about Wi-Fi fingerprinting methods. Section IV presents the infrastructures and methods used in the experimental phase. Section V presents experimental results. Finally, Section VI presents the main conclusions and lines of future research in the topic.

II. Previous work

The work in [6] can be considered the focus on the interest in Wi-Fi based indoor location. The authors used a two phase method for creating their location system. In the first phase they create a radio map by recording the RSSI signal at some points of interest in the environment, in the second phase they use the nearest neighbour algorithm to estimate the user's location. In our work we use the same two phase location system, but we have tried other machine learning algorithms in addition to nearest neighbours.

A collaborative strategy (crowdsourcing), is used in [7] to bootstrap an indoor location system based on Wi-Fi signal to create a radio map in an University campus. This kind of collaborative data gathering is used due to the big amount of data needed to cover the whole University area. This work reports issues in accuracy when the number of incorrect fingerprints is about 7%, and due to device diversity. To avoid issues related with device diversity, we have used the same model device in all experiments.

Another interesting collaborative work to create radio maps is presented in [8]. A floor map is the only initial information used before creating the radio map. Then data coming from the sensor in a mobile phone, including Wi-Fi signals, are used to estimate the trajectory of the person when compared with possible trajectories on the map and the Wi-Fi readings are reference to such trajectories. A similar approach is used in [9] to create a Wi-Fi radio map. Then, a weighted K-Nearest Neighbour algorithm is used for locating a user.

A method for automatic Access Point (AP) location and propagation model estimation based on crowdsourcing is proposed in [10]. The system automatically updates an AP database based on crowdsourced data provided by a mobile application. This data is also used to estimate the attenuation coefficient in a path loss exponent for a path loss propagation model of the Wi-Fi signal.

In the presented previous works there is not a comprehensive study on how crowdsourcing data improves location accuracy in Wi-Fi locations systems. In addition, KNN, is the only algorithm used when designing the system. Finally, although accuracy decay is reported, no study has been done to confirm this hypothesis.

III. Background

Outdoors location technologies, such as GPS, Glossnass, or the future Galileo system, are useless indoors. The signals used by these technologies are highly attenuated when crossing walls, and its final strength is so low (the signal to noise ratio) that it is useless for indoor location purposes. Researchers have tried to overcome this issue by developing new technologies which work indoors. Some of these new technologies are based on the deployment of new infrastructures, some other take profit of the already developed infrastructures, while others do not need the deployment of any new infrastructure to work (we call these structure-less technologies). In the first group we can find Bluetooth Low Energy (BLE), Ultra Wide Band of ultra-sound indoor location technologies, just to cite a few. In the second group we can find Wi-Fi based indoor location technologies which mostly used the signals coming from the already deployed WAPs. Finally, some technologies use the Earth magnetic field for indoor location purposes. The work in [11] presents an updated review of these technologies.

General AI and Machine Learning (ML) based systems are being developed and used in areas such as context-awareness, agent-based technologies or computer vision, to provide more intelligent, flexible, natural and supportive services for health care. Some examples of how services based on AI and ML techniques can be used in health care services are:

- Human Activity Recognition (HAR): Systems can combine data from multiple sensors to recognize user's activities and identify behavioral patterns. The performance of daily activities can be used as a measure of the cognitive and physical condition of the elderly [12].
- Anomaly Detection: Anomaly detection techniques can expose declining health conditions. Changes and anomalies in the user behavior can be of use in chronic diseases monitoring [13] and early depression detection [14], and can denote elder-specific illnesses such as cognitive decline, Alzheimer, dementia or functional impairment [15]–[17].
- Decision Support: Decision support systems assemble different types of data from multiple patients and help doctors and health care professionals to organize their work, to analyze people personal needs or to survey some common phenomenon [18].

In this work we have used Wi-Fi fingerprinting for indoor location.

A solid Indoor Positioning System (IPS) is a crucial part of the Ambient Assisted Living (AAL) concept, aimed to build intelligent environments in assistance of elderly people.

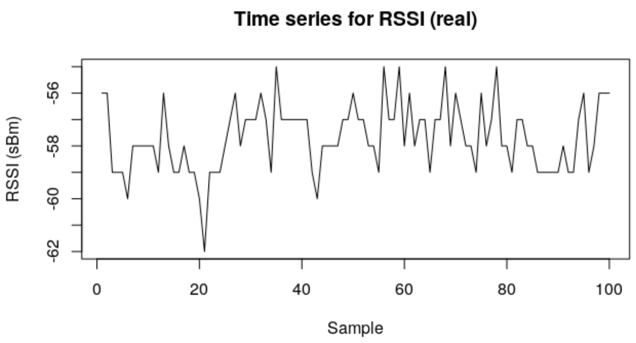

Fig. 1. Temporal behavior of a Wi-Fi signal.

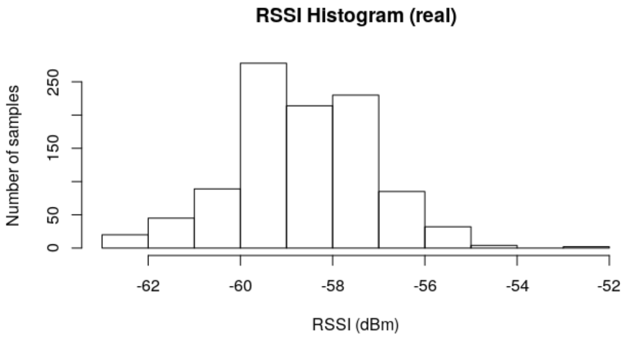

Fig. 2. Histogram of the data shown in Figure 1.

The use of Wi-Fi fingerprinting techniques to determine the location of the user, based on the Received Signal Strength Intensity (RSSI) mapping, avoids the need to deploy a dedicated positioning infrastructure, but comes with its own issues. Heterogeneity of devices and RSSI variability in space and time due to environment changing conditions pose a challenge to positioning systems based on this technique.

Locating a user at room level is enough for most AAL applications. In such cases, location can be seen as a classification task. This is a challenging task due to the temporal random behavior of the Wi-Fi signal. Figure 1 shows an example of the variability of the Wi-Fi signal along time. Machine Learning (ML) algorithms are well suited in this context, they are able to fulfill classification tasks when the data is randomly distributed but some patterns can be found in the data. Figure 2 shows the histogram of the temporal data shown in Figure 1. It can be noted that this histogram is Gauss-shaped, in fact a gaussian density distribution function is used to model Wi-Fi RSSI signals [19], [20]. So, ML can be used for Wi-Fi fingerprinting based on the fact that a gaussian pattern can be found in the temporal distribution of the data.

IV. Materials and Methods

Middlesex University London has a sensorised apartment inside its premises (see Figure 3). This apartment is devoted

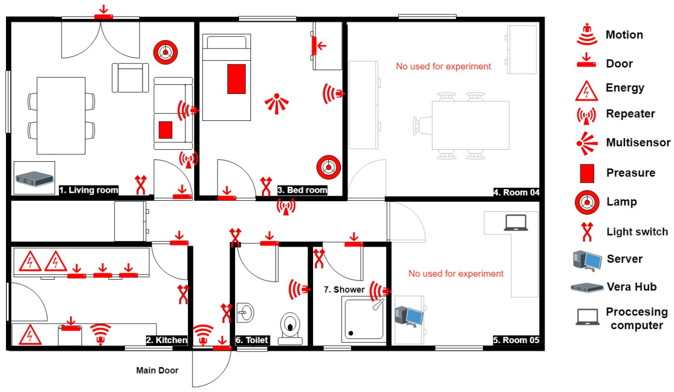

Fig. 3. Floor map of the sensorized apartment at Middlesex University London.

to develop experiments in the AAL realm by the Research Group on Development of Intelligent Environments[2].

The same model device was used in all experiments to minimize the issues reported in [7] due to device diversity. The model of device used for acquiring the Wi-Fi RSSI signals was an Android smart-watch by Sony. These devices are equipped with different sensors and connectors, including Wi-Fi and Bluetooth 4.0 connectors, they run Android wear OS and can be programmed using the Java programming language. Moreover, they include a 420 mA battery which is enough for a full day on regular use. Although most current Android Wear devices are equipped with a Wi-Fi chip, they do not use it to directly connect to the Internet, but by means of the mobile phone they are linked to. Nevertheless, Wi-Fi chips on the smart-watch can be programmed for scanning Wireless Access Points in the surroundings.

An Android Wear application was developed to scan Wi-Fi RSSIs coming from the WAPs in the surroundings. Once the scan finished, the resulting data was sent to the mobile phone linked to the smart-watch which was in charge to send the data to a remote server using Internet connection. This application was used for two different purposes: i) to acquire the data needed to build the Machine Learning classifiers in order to estimate the location of a user based on Wi-Fi fingerprinting location, ii) to monitor a user once such classifiers were built.

A set of experiments were planned to answer all questions presented in the Section I. Three different users have taken part in the experiments. All three users used the same smart-watch device model.

In the first experiment, the three users performed an off-line phase mapping Wi-Fi signals at 5 different rooms (Kitchen, Living room, Bedroom, Office and Dinning room). Three different data sets, one for each user, were acquired. This experiment was performed twice, at the beginning and ending of the experiment separated by two weeks. In the second experiment, the location of one user was tracked during two weeks; the user was provided with a smart watch and was asked to register her location by hand (ground truth) in order to

[2] http://ie.cs.mdx.ac.uk/smart-spaces-lab/

Fig. 4. Mobile APP for registering Wi-Fi RSSI WAPs.

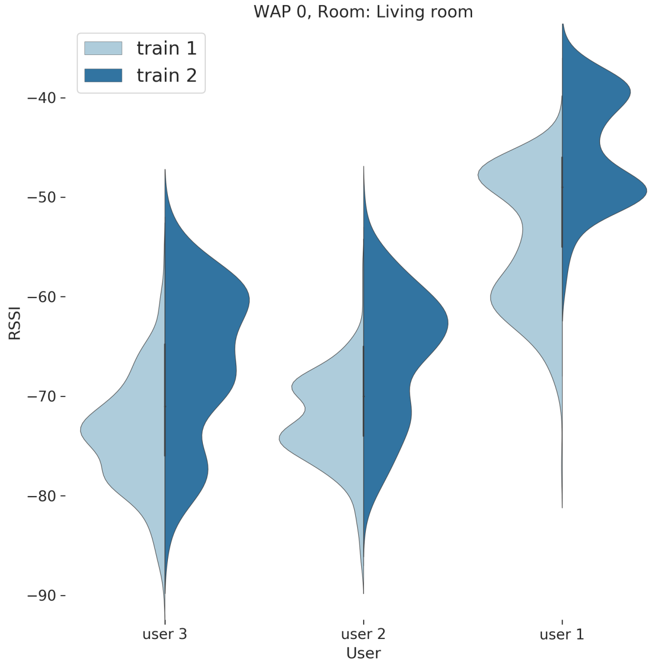

Fig. 5. Comparison between the Wi-Fi RSSI acquired with three smartwatches. Light blue plots are for data acquired in the first off-line phase. Blue plots are for data acquired in the second off-line phase, two weeks later.

compare it with the results obtained by the Wi-Fi fingerprinting method.

Three different ML algorithms were chosen during experimentation: i) K-Nearest Neighbours: this is probably the most used ML algorithm in the indoor location realm, its popularity is due to its simplicity and good results; ii) Bayes Network: this algorithm in based on Bayes' theorem an provides accurate results in scenarios where there are no correlation between the analysed data, this is the case for time correlation between signals coming from different WAPs; iii) Random Forest: it is a decision tree based algorithm which typically provides good results with W-Fi fingerprinting data sets.

Even when using the same device model for experimentation, different devices provide different measures for the same phenomenon. In this case, the set of reported WAPs was not the same for the three users. For comparison purposes, the data sets acquired in the first experiment were filtered in order to remove the data from WAPs which are not present in the three data sets. Finally, the number of commons WAPs was 30, and 4 WAPs were removed because they did not appeared in the all three data sets provided by the three users.

V. Experimental results and discussion

This Section presents the experimental results for the experiments described in the above Section. The Section starts presenting the feasibility of joining data acquired by different users to build most accurate ML classifiers. Then, the results for Wi-Fi indoor location are provided in a real scenario. Afterwards, the issue of accuracy decay along time is analyzed. Finally, main remarks arose after experimentation are summarized.

A. *Indoor location using crowd-sourced data*

In the first performed experiment we tried to answer the question "Do crowd-source data improve locations accuracy in Wi-Fi fingerprinting". For doing that, one of the three data sets was used to build the ML classifiers (training data set) while the other two were used to test the classification accuracy (test data set). Then, two data sets were joined for building the ML classifiers an the third data set was used for testing. This experiment was performed twice. Results for the first experiment are shown in Table I; two weeks later the same experiment was performed, Table II shows the results for the second experiment.

In the first experiment, Bayes Network and Random Forest performs better when two data sets are added to build a classifier, for KNN algorithm there is no clear conclusion, the joined classifier only improves the results in one of three cases. In the second experiment, Bayes Network and Random Forest algorithms perform better in two of three, KNN performs better in one case only. In a general sense, it could be said that to add data coming from more than one user improves the accuracy performance in most of the tested algorithms.

Note also the differences between the location accuracy for different users. Results in columns for *User 1* are always lower than columns for *User 2* and *User 3*. This results maintains for the three classifiers used. Figure 5 shows the histograms of the data acquired by the three users using the same smart watch model. It can be seen that although it was expected that all three data was quite similar, there exists high differences in the data sets between the users. Significantly, the data histogram

TABLE I

ACCURACY COMPARISON USING DATA SET ACQUIRED BY DIFFERENT USERS.

	KNN			Bayes Network			Random Forest		
	User1	User2	User3	User1	User2	User3	User1	User2	User3
User1	-	74.60±0.32	84.87±0.25	-	93.33±0.15	95.87±0.19	-	91.47±0.18	94.80±0.15
User2	60.60±0.40	-	83.73±0.25	79.07±0.28	-	92.20±0.16	83.87±0.23	-	92.47±0.17
User3	70.73±0.34	80.8±0.28	-	87.87±0.20	90.73±0.18	-	84.60±0.22	91.73±0.17	-
User1 + User2	-	-	85.53±0.24	-	-	95.87±0.12	-	-	95.20±0.14
User1 + User3	-	79.00±0.29	-	-	94.80±0.13	-	-	94.13±0.15	-
User2 + User3	61.07±0.39	-	-	88.93±0.19	-	-	87.20±0.21	-	-

TABLE II

ACCURACY COMPARISON USING DATA SET ACQUIRED BY DIFFERENT USERS, AND TWO WEEKS LATER THAN DATA SHOWN IN TABLE I.

	KNN			Bayes Network			Random Forest		
	User1	User2	User3	User1	User2	User3	User1	User2	User3
User1	-	67.20±0.36	77.00±0.30	-	79.87±0.26	88.73±0.19	-	84.13±0.23	87.00±0.21
User2	63.13±0.38	-	74.73±0.32	68.80±0.34	-	85.93±0.22	71.40±0.30	-	84.73±0.21
User3	70.53±0.34	69.07±0.35	-	74.93±0.30	85.13±0.23	-	72.53±0.28	86.20±0.21	-
User1 + User2	-	-	77.13±0.30	-	-	88.13±0.20	-	-	89.87±0.18
User1 + User3	-	68.60±0.35	-	-	85.67±0.21	-	-	85.53±0.20	-
User2 + User3	66.27±0.37	-	-	76.67±0.30	-	-	74.33±0.28	-	-

TABLE III

ACCURACY COMPARISON USING THE ACTIVITY REPORTED BY ONE USER

	KNN	Bayes Network	Random Forest
User 1 + User 2	54.70±0.43	63.03±0.38	62.65±0.36
User 1 + User 3	46.59±0.46	53.86±0.41	61.67±0.36
User 2 + User 3	50.15±0.45	57.58±0.40	58.41±0.37
All users	47.88±0.46	59.47±0.39	62.48±0.36

for *User 1* is quite different from the data reported by the other users in both off-line phases at the beginning and ending of the experiment. But surprisingly this seems not to have a significant impact on the results when two data sets are joined to build a classifier, as it has been analyzed in the above paragraph.

Also note that the accuracy results provided in Table I are better than the results provided in Table II except for the case of User 1 and the KNN algorithm. The differences between the two experiments were the acquired data and the moment they were gathered. This can suggest some "instability" of the data along time. This will be investigated in Section V-C.

B. Indoor location using Wi-Fi fingerprinting in a real scenario

In the real case of tracking a person during two weeks, and having into account the results in the previous section, the classifiers were built joining more than one data set. The estimation provided by the classifier was compared with the information reported by the user. Table III presents the results. Note that the highest accuracy performed (63.03) for the case of a Bayes Network classifier built joining the data from *User 1* and *User 2*.

On average, Random Forest provides the best accuracy results 61.33% with a standard deviation of 2.00%, and KNN provides the lowest results 49.83% with a standard deviation of 3.56%. Bayes Networks is placed between the two previous results with 58.49% accuracy and a standard deviation of 3.82%. It can be seen than a random choice will provide an average accuracy of 20% (five different rooms, pick one randomly).

Note that to join all three data sets for building the classifier does not provide the best results, which seems to be against the assertion made in the previous section. The clue to clarify this contradictory results is that maybe the "quality" of the classifier degrades along time, since this experiment lasted for two weeks.

C. Accuracy decay along time

Tables in I and II show the results for the same experiment, but the second one was performed two weeks later than the first one. All results in Table II are worst than in Table I. Figure 5 shows the differences in the histograms for the signal coming from a WAP at the living room. There are clear differences between the histograms for the first experiment (train 1), and for the second experiment performed two weeks later (train 2). So, which is the impact of this instability along time? Does the accuracy change along time? A new experiment was performed to answer these questions. Classifiers were built with the data sets acquired in the first off-line phase, and the data sets acquired in the second off-line phase were used for testing. Results are shown in Table IV.

When results in Table IV are compared with results in Table I for the same entries, it can be clearly seen that the accuracy in Table IV is lower than in Table I. Remarkably, the same behavior happens for all three users. A possible cause for this decay is that the Wi-Fi signal is not stable along time. Figure 5 shows the RSSI distribution acquired with the three smart-watches. It can be clearly seen that there are differences between the data, not only for the data acquired at the same off-line phase (light blue plots), but also between the data acquired at the two off-line phases. These differences will have a remarkable impact in the accuracy of the ML algorithm used for indoor location, as shown in Table III.

TABLE IV
ACCURACY COMPARISON USING THE FIRST OFF-LINE PHASE AS TRAINING AND THE SECOND OFF-LINE PHASE AS TEST

	off-line phase 2								
	KNN			Bayes Network			Random Forest		
off-line phase 1	User 1	User 2	User3	User 1	User 2	User3	User 1	User 2	User3
User1	56.40±0.42	59.93±0.40	53.07±0.43	66.47±0.35	68.60±0.34	72.40±0.31	63.00±0.31	60.67±0.33	65.67±0.30
User2	47.53±0.46	48.60±0.45	59.07±0.40	72.40±0.32	71.60±0.32	85.20±0.23	73.07±0.27	75.33±0.28	83.13±0.24
User3	69.00±0.35	64.87±0.37	80.87±0.28	79.07±0.28	75.20±0.30	79.13±0.28	73.00±0.27	65.53±0.30	76.60±0.26

D. Feasibility of crowdsourcing for Wi-Fi radio map creation

The last question to answer is about the suitability of crowdsourcing data for indoor location. In the light of the above results, some remarks can be done:

- Even when using the same device model, data acquired by Wi-Fi chipsets in the same environment might be different.
- Although in general joining data coming from several users could improve location accuracy, this is not true in a general sense.
- The accuracy along time decays even in short time periods (weeks), so re-callibration is needed to revert accuracy decay.

As final summary, it can be said that crowdsourcing strategies are valuable for Wi-Fi fingerprinting models even when the accuracy of the model decay along time.

VI. CONCLUSIONS AND FUTURE WORK

In this work exhaustive experimentation was performed to test the feasibility of using crowdsourcing data for indoor location based on Wi-Fi fingerprinting. Experiments were performed in a real scenario and data was acquired during two weeks. In order to avoid issues related with device diversity, the same device model was used by all users.

To assess the location accuracy, the KNN, Bayes Network and Random Forest ML algorithm have been tested. In general, it can be concluded that crowdsourcing data improves the accuracy of the location. On the one hand, the results show the feasibility of crowdsourcing data to create radio maps for indoor location. One the second hand, accuracy decay along time was reported.

A real case of application could be in nursing homes. The need for assistance and health care to the elderly is becoming more and more necessary for social as well as for economic reasons. Due to underlying and often debilitating health conditions that are associated with elderly people, aspects of everyday living can become physically and mentally challenging for them. Technology can be integrated in the health care of senior citizens to provide safe, high-quality lifes, improve their health and happiness, and enable a longer period of independent living. Assistive technical applications should be easy to use, unobtrusive, suitably designed, and adaptable to changing needs and individual preferences.

As future work, we plan to perform new experiments during a longer period of time and with more users in order to understand factors influencing the accuracy decay of Wi-Fi fingerprinting location methods, and to develop strategies to minimize its effect on the location methods accuracy.

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