LIGHTWEIGHT INDOOR POSITIONING IN A REAL ENVIRONMENT BASED ON WIFI FINGERPRINTING TECHNIQUE AND M-WKNN ALGORITHM

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Abstract - *The aim of this work is to study a lightweight system for predicting indoor location in an ordinary dwelling using the fingerprinting technique and the M-WKNN (Modified Weighted K-Nearest Neighbors) algorithm based on listening to the power levels of Wi-Fi terminals. To this end, an error reduction procedure has been developed and implemented in the M-WKNN algorithm. The residual calculation technique and sample weighting are used for this error reduction. In order to assess the performance of the proposed approach, a comparison is made with two traditional algorithms, KNN and WKNN. The results reported in this work evaluate the performance of the M-WKNN algorithm at 92% with respect to the input data*

Key Words: indoor localisation, fingerprinting technique, power levels, M-WKNN algorithm, residual method.

1. INTRODUCTION

Geolocation is essential today for many of the applications embedded in electronic devices. In fact, the technological boom that the world has been experiencing for the last two decades or so means that we need to have a perfect command and understanding of the space around us. Geolocation has two main applications, depending on the environment: outdoor geolocation and indoor geolocation. Today, because of the ever-improving results of satellite systems [1-2] used or dedicated to positioning, the scientific community is focusing mainly on the indoor environment, especially as some studies show that the human being spend most of the time in enclosed spaces [3-4] (indoor environment). The Global Positioning System and other satellite systems can no longer provide the same reliability here as they do outdoors. Firstly, it is difficult for waves to propagate and penetrate the indoor environment, and secondly, the multipath phenomenon that characterises this system in particular clouds the results and distorts them. Another factor is the reference frame, which can be physical, relative, absolute or symbolic [5-6]. To overcome these disadvantages, a number of indoor methods have been proposed, particularly those involving fingerprinting.

To date, however, there is no standard method for either indoor or outdoor positioning [7-9]. In order to find the position of an RF device, different measurements can be used such as Received Signal Strength (RSS), Time Of Arrival (TOA), Time Difference Of Arrival (TDOA), Frequency Difference Of Arrival (FDOA), Angle Of Arrival (AOA), Power Difference Of Arrival (PDOA), Frequency Difference of Arrival (FDOA) and Differential Doppler Rate (DDR). Depending on the degree of criticality of the information provided by the position of the object to be geolocated, the choice of one technique or another is open. In recent years, the aim has no longer been simply to geolocate an object or provide it with a means of navigation, but to find the best compromise between the complexity of implementing the hardware and software, the cost of the process and the results obtained, given that the results depend on all these parameters.

Several works studying different algorithms for indoor positioning have been done. Zhou et al. [10] proposed an RSS transform–based weighted k-nearest neighbor (WKNN) indoor positioning algorithm to improve the positioning accuracy and real-time performance of Wi-Fi fingerprint–based indoor positioning. From the results, the proposed approach achieved a localization error of 1.52 m. Hu et al. [11], studied a self-adaptive WKNN algorithm with a dynamic K for indoor positioning based on Wi-Fi. In [12], the research leverages the use of a deep neural network-based ensemble classifier to perform indoor localization with heterogeneous devices. Among many indoor position calculation algorithms, those using machine learning are most studied such as deep learning and neural networks (DNN and MLNN) [12-14]. Works carried out in indoor positioning system [14-16] generally deals with near-perfect environments, free of human traffic (empty corridors, houses with no furniture). With such perfect process, the results can easily be duplicated. However, these results are far from reflecting the reality of locating or tracking an object. The presence of an object in the path of the wave amplifies the multipath phenomenon, reduces the power picked up and increases the propagation time [8]. The presence of a human body randomly distorts the signal by reducing its energy [17].

This work is a contribution to the search for the best compromise in smartphone positioning in a real indoor domestic environment. The first objective is to propose a lightweight and most effective method, and the second is to present the phenomena that reduce the efficiency of the used algorithm, working in real indoor location conditions. This work is based on an existing technique; the improvement comes from modifying of the data sampling procedure. Derived from the KNN algorithm for fingerprinting [12-13], the W-MKNN [14] have been choose in this work, which is itself derived from the WKNN algorithm [15-16]. Aware of the fact that multipath is present and causes the results obtained to drift, we set up an effective error reduction procedure using sample weighting, selective sorting using the residual method [8], and the use of radio distance. The body effect is neglected because its consideration would have added complexity and therefore cost. Experiments carried out in a domestic indoor environment are compared with the KNN and WKNN algorithms. Later, some factors that considerably influenced the result of the algorithm (temperature and propagation inside materials) are highlighted. The Wi-Fi 802.11b standard signal was used.

The aim of this work is to simplify the positioning process and minimise the hardware used, while guaranteeing good results for domestic use of the positioning system. Experimental conditions for both the online and offline phases were identical (calculation of the residual, weighting of the samples, human presence during the surveys).

2. MATERIALS AND METHODS

2.1 The Indoor experimental environment

The first step in setting up an indoor positioning system is to identify and analyze the appropriate environment in which the system is to be deployed. This environment may be a household, as in the case of this work, a hospital, a supermarket, a covered stadium or an airport. The studying environment is a breeze-block house of 20 m long and 11 m wide, excluding the veranda. The four APs (Access Points) are fixed throughout the data collection for the database. Fig -1 shows the experimental environment.

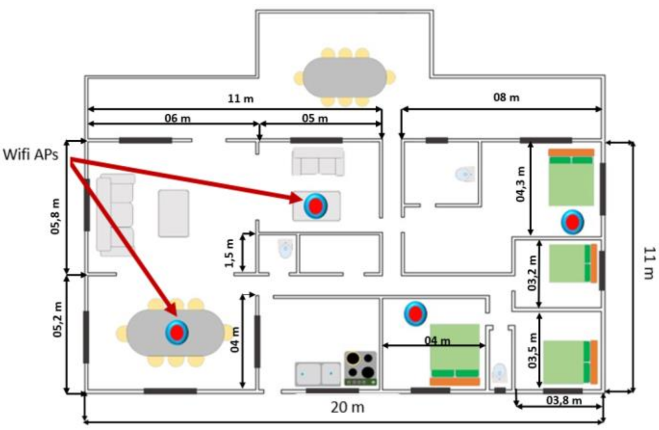

Fig -1 : Indoor domestic experimental environment

The collection of footprints for the database was carried out using a mesh, with points 1.2 m apart along the two axes of the horizontal plane. Measurements were taken at a height of 1 m from the ground. The various Wi-Fi APs are placed at a height of 75 cm above the ground, so they are lower than the fingerprint collection points. This was done in order to be as close as possible to the real-life situation. The environment was characterized by the presence of seven people who continued to act in a natural way.

2.2 Error Reduction

Human influence on electromagnetic waves

Studies to date on the influence of the body on waves have been carried out to determine the general consequences of the presence of the body, but also of its orientation in one direction (north, south, etc.). Authors in [17] points out that more than 70% of the human body is made up of water and show that the operating frequency of Wi-Fi 2.4 GHz absorbs electromagnetic radiation. This is due to the resonance created with water at this frequency. It one can conclude that, given this composition of more than 70%, the impact of the presence of the body is not negligible. [18] shows that apart from multipath, which already causes the received value of a power level to oscillate around an average, the presence of a body increases the distribution of this power variation. The standard deviation rises from 0.68 dBm to 3.00 dBm when the user is close to the mobile receiving the signal. The average of the samples collected rises from -70.4 dBm to -71.6 dBm, a difference of -1.2 dBm. In the present study, the "body effect" phenomenon has not been considered in this work.

Measurement of Values by Average of Samples

The idea of sampling comes from Xiao-Min Yu who [19], with the help of an image, shows the various fluctuations in the power level of the signal received at an identical position over an extremely short period of time. He records the power levels for one minute at a static position. Noting that the value was not stable for all the samples, he suggested taking the average. In this work, the same logic to both the database records and the measurements taken in real-life situations during the online positioning phase is . In fact, basing our calculations solely on the first value obtained could lead to errors which could have a devastating effect on the positions obtained. By using this procedure, we can at least guarantee that the fluctuations in the power level oscillate around an average value. However, for our work we have chosen to sample the power variations over a period of 30 seconds every three seconds.

Sorting using the residual method

After conducting a short experiment on signal power level fluctuation, R. Zhou [20] concluded that this fluctuation relationship is non-linear. So that, it is impossible to predict these variations in power levels. It can be seen that this fluctuation can easily reach a 10 dB difference.

Over time, depending on variations in the environment, the climate and the nature of the transmitting and receiving equipment, the signal fluctuates unpredictably. To attenuate this fluctuation, which causes errors in position calculation, the absolute RSS difference (RSS-ABS-DIFF), which is around 10 dB, needs to be reduced. To do this, we propose a method of pre-processing the RSS database to eliminate large errors and abnormal entries.

Considering a measurement taken at a given position over a period of time and during this time p measurements are performed.

The residual r_q is defined to measure the degree of deviation $RS^{(q)}$ from the mean of the p RSS denoted $\overline{RSS}$ by :

$$r_q = RSS^{(q)} - \overline{RSS} \text{ with q} \in [1, p] \text{ and } \overline{RSS} = \frac{1}{p}\sum RSS^{(q)} \qquad (1)$$

This allows to calculate the square root of the mean of the squares of the residuals previously obtained.

$$\sigma = \sqrt{\left(\frac{1}{p}\sum_{q=1}^{p} {r_q}^2\right)} \qquad (2)$$

Table -1: criteria for assessing deviation using the residual method.

Pt N 45	72	72.8	52.56	63.2
	AcPo 1	AcPo 2	AcPo 3	AcPo 4
1	78	79	55	60
2	72	79	49	68
3	74	69	51	72
4	75	69	51	65
5	74	70	55	65
6	69	69	51	58
7	68	73	54	62
8	69	73	72	61
9	55	72	54	61
10	69	75	53	60
Mean	70.3	72.8	54.5	63.2

Average obtained after sample elimination by residual calculation

Average obtained before sample elimination by residual calculation

At this point, we apply the criterion of the centred reduced normal distribution, which consists of keeping only the values of $RSS^{(q)}$ such that: $|r_q| > 3\sigma$ to obtain a confidence interval of 99.7%. Once these values have been retained, it can then perform the average to obtain final results. Table -1 illustrates the calculation of the deviation using the residual method. It can be seen that the 55 dB and 72 dB samples have an influence on the mean deviation. Those samples have been eliminated from the calculations.

Database of positioning fingerprints

The fingerprinting stage consist of two operations, the data collection and the creation of the fingerprint database. The result of the fingerprinting operation, illustrated in table 2 below, is a dataset consisting of 138 points (or fingerprints). Each point, as shown in Fig. 1, is defined by its coordinates in the plane (X_LONG and Y_LONG), the identity of the item to which the point belongs, and the powers of the four signals received at this point. This dataset has been split in two to make it easier to handle: the first part contains the ID of the point, the target room column and the powers received, while the second contains the ID and the coordinate columns.

Table -2 : fingerprinting data base

POINTS	X_LONG (cm)	Y_LONG (cm)	AcPo_1 (dBm)	AcPo_2 (dBm)	AcPo_3 (dBm)	AcPo_4 (dBm)	Target Room
1	20	30	-54,11	-60	-65,13	-61,25	Main Living Room
2	20	150	-54,14	-63,66	-64,2	-62,8	Main Living Room
3	20	270	-51,12	-62,87	-64,25	-63,71	Main Living Room
4	20	390	-54,44	-63,5	-64,3	-64,2	Main Living Room
5	20	510	-48,89	-63,8	-75,5	-67,1	Main Living Room
6	140	30	-59,4	-63,83	-68,6	-67,7	Main Living Room
7	140	150	-71,125	-69,4	-76,8	-68,9	Main Living Room
8	140	270	-61,2	-59,1	-66	-63,9	Main Living Room
9	140	390	-55,44	-58,8	-65,6	-56	Main Living Room
10	140	510	-56	-60	-66,7	-61,2	Main Living Room
11	260	30	-62	-70,2	-72	-59,9	Main Living Room
12	260	150	-49,1	-63,6	-69,6	-65,6	Main Living Room
13	260	270	-53,2	-59,6	-65,3	-64,8	Main Living Room
14	260	390	-56,5	-64	-56,7	-61,5	Main Living Room
15	260	510	-51,3	-68,9	-69,33	-55,9	Main Living Room
16	380	30	-54	-66,7	-71,1	-71,8	Main Living Room
17	380	150	-51,9	-64,7	-66,2	-61,4	Main Living Room
18	380	270	-51,5	-65,4	-71,6	-69	Main Living Room
19	380	390	-49,7	-59,3	-70,7	-64,3	Main Living Room
20	380	510	-60	-69,44	-83,1	-69,3	Main Living Room
21	500	30	-57,1	-64	-70,1	-67,4	Main Living Room
22	500	150	-51,6	-65,8	-73,8	-66,7	Main Living Room
23	500	270	-61,3	-55,9	-70	-65,7	Main Living Room

Prediction and position calculation algorithm

The process used in this work consists of reducing noise and thus reducing the algorithm's error rate by calculating the residual. Most authors apply an asymmetric process. The operations applied to the data during the offline fingerprint collection phase are not applied to the data entered during the online phase. We therefore applied the same measures in this phase as in the offline phase. Prior to the online phase, we collected the RSS data that will be used to search for the nearest contacts by recording them over a period of 30 seconds every three seconds. We therefore obtained 40 RSS samples per point (10 for each APs). After harvesting, we look for any significant discrepancies between the RSS data collected and then the residual is calculated. If a discrepancy is found, the value responsible for the discrepancy is removed and the average of the remaining values is calculated and used to estimate the position. The data can then be used in a MW-KNN algorithm to estimates the position. The overall process of position fingerprint algorithm location is given as follow.

1- Definition and initialisation of the KNN Model
model = KneighborsClassifier()
2- Hyper-parameters initialisation
N_neighbors = 3
Metric = 'euclidean'
3- Model Training
Model.fit(X_train,Y_train)
4- Initial Prediction
a- Arguments initialisation
(AcPo_1, AcPo_2, AcPo_3, AcPo_4)
b- Prediction
N=model.predict(model, AcPo_1, AcPo_2, AcPo_3, AcPo_4)
5- Determination of K_nearest_neighbors (here 3)
print (kneighbors(N))

Distances	k_1	k_2	...	k_m
Index_Dataset	i_1	i_1	...	i_m

6- Defining the MW-KNN prediction function : MW-KNN weighting
for j in range k_m
$P1_j$ = Dataset['AcPo_1', j]
$P2_j$ = Dataset['AcPo_2', j]
$P3_j$ = Dataset['AcPo_3', j]
$P4_j$ = Dataset['AcPo_4', j]
$W_1 = 1/10^{(P1)}$ ... $W_4 = 1/10^{(p4)}$ (W is the weight assigned for the weighting) (3)
7- Coordinate calculation
for j in range K_m
x = (W_j * Dataset ['X_LONG', j]) + x
X_Targert = x * (1/4) (same procedure to calcute Y_target)
(X_Target and Y_Target : abscissa and ordinate of the point on the moving body that we are trying to locate).

Implementation
The position calculation algorithm was implemented in Python.

3. RESULTS AND DISCUSSIONS

3.1 Wifi terminal signal strength

To start, analysis of available Wi-Fi signal was done. The measured signal strength at 3 m from the access point (AP) is shown in Fig -4. it has been observing that the Wi-Fi signal emitted by the APs was very unstable, even when the receiving equipment is stabilised on a single position. One reason that comes to one's mind is because of wall and other objects obstructing the signal. Also, interference because of other wireless networks and the poor quality of APs device.

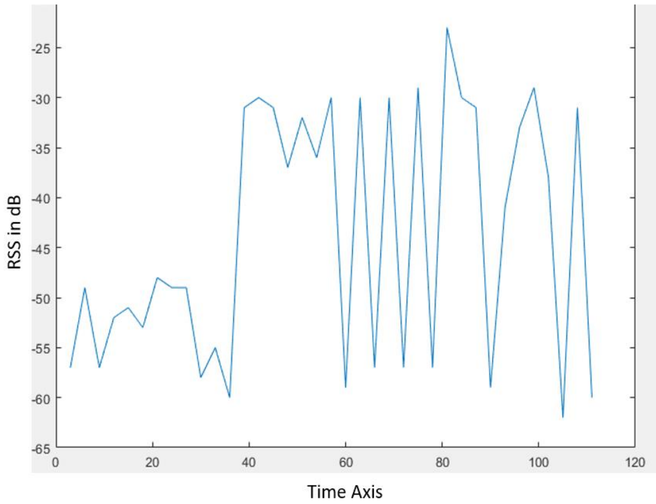

Fig -4: profile of the access point signal

3.2 Tests with KNN, WKNN and MW-KNN algorithm

In order to verify the validity of the proposed algorithm, MW-KNN algorithm is compared to two traditional algorithms KNN and WKNN. Having selected random points in the experimental environment, the measurements have run from these points through the three machine learning algorithms. For this purpose, the measurements used were taken in the same way as for the offline phase.

Once the results obtained, it can see that the proposed approach produce better results comparing to KNN and W_KNN algorithm. The MW-KNN algorithm and error reduction measures deliver an average improvement of 43% over KNN and 15.35% over WKNN. The best result of the tests carried out gives an improvement of 76.5% over KNN and 58.5% over WKNN.

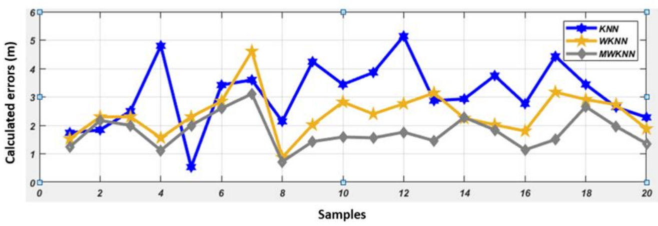

Fig -3 *:* Error of different algorithms in the experimental environment. KNN, WKNN and M-WKNN

3.3 Analysis and interpretation of errors

Quantitative data analysis

Figure 4 shows the validation and training curves as a function of the percentage of data used. Both curves show very rapid growth with the number of data. The training curve shows an early peak at around 27 sampling point.

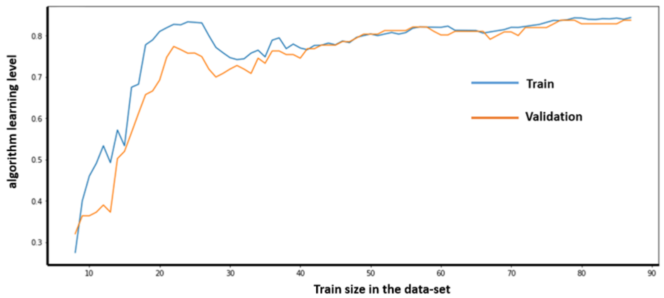

Fig -4: Analysis of data quantity

This number represents the number of dataset entries required for the algorithm to produce a training score of 82%. We can see that the curve decreases slightly and then rise at below 30 sampling point. The experiment indicates that the algorithm will learn better with a large amount of input data. By using 138 sampling points, we obtained an efficiency of 91.8% for our algorithm. The curve shows that for 63% of the points used for testing, the algorithm is already 83% efficient for validation.

Impact of the temperature

Most of studies on temperature impact in positioning system have been done in outdoors environment [21 - 22]. So fare, in this work, experiments are conducted in the proposed indoor environment to evaluate the impact of the temperature on the signal level emitted by APs.

We therefore collected signal level values received at several different times of the day and over several days. A least squares regression criterion to these points. Figure 5 shows the effect of temperature on the signal power. In the scatterplot, we can observe a negative relationship exist between indoor temperature and captured signal level. The signal level decrease with the increasing of temperature.

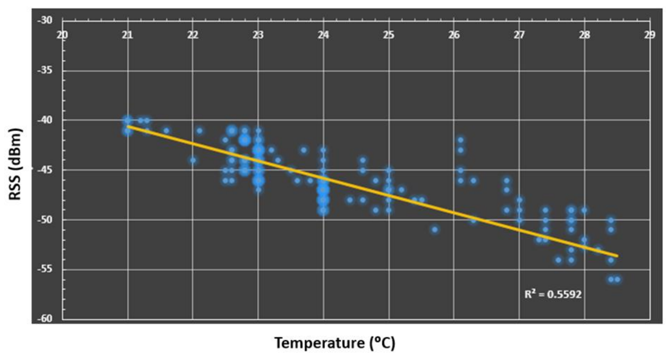

Fig-5: Study of the relationship between noise and temperature indoors.

Impact of walls and openings on radio signals

In indoor environments, the presence of walls, floors, furniture or people may have a strong impact on the radio waves propagation. Previous works have shown that walls absorb hertzian waves and thus reduce the power of the propagating signal either by absorption, diffraction or reflection. The level of absorption depends not only on the frequency of the radiation but also on the material composition of the wall or slab in question.

To assess the impact of walls and other structures on the electromagnetic wave, the multi-wall propagation model is used [23]. This model takes into account all the walls and all the floors crossed by introducing transmission loss coefficients depending on the thickness and the nature of the material. Therefore, the received power PL (in dB) can be expressed as:

$$PL = 10nLog(d) + Lc + \sum_{j=1}^{p} m_j\, l_j + K_f l_f \qquad (4)$$

with ;

n: attenuation factor
Lc : is a constant
m_j: number of walls of type j
l_j: loss factor of walls of type j
K_f : number of slabs
l_f: slab loss factor

Figure 6 shows the number of walls crossed dependence of the electromagnetic wave attenuation of single-layer material as well as of multi-layer one calculated using the multi-wall model. The experiments show that free space reduces signal power less than the other materials presented in this study. For a signal passing through a breeze-block wall, a metal cupboard and a wooden door, the losses evaluated using the multi-wall propagation model are around 75dB. This value is already significant and is enough to destroy the quality of the signal and therefore the quality of the proposed algorithm. Finally, cement produces more losses than metal, which in turn produces more losses than wood. In terms of signal quality, it would therefore be preferable to use wood rather than metal and the concrete.

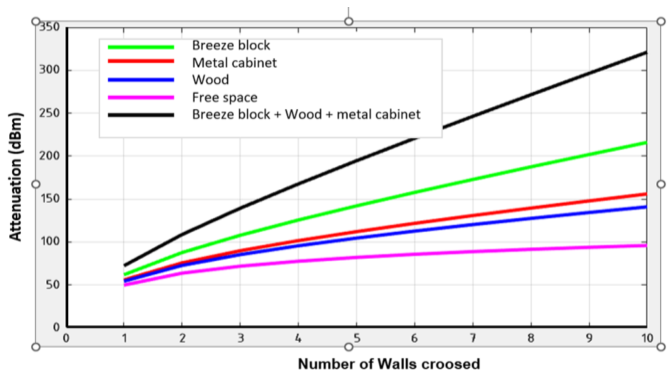

Fig -6: Calculated attenuation of building materials as function number of walls crossed.

4. CONCLUSIONS

A Modified Weighted K-Nearest Neighbor (M-WKNN) algorithm to position determination based on listening to the power levels of Wi-Fi terminals have been discussed in this paper. The work carried out throughout this study was conducted in a real indoor environment, and the experimental results indicated that the positioning performance of the proposed algorithm is considerably convenient for Wi-Fi based indoor positioning system for areas such as dwelling house or shopping malls than the traditional WKNN and KNN algorithm. Also, the approach consists of carrying out all the noise and error reduction operations upstream, which are usually only carried out when the position is calculated. On the basis of almost 138 points in the database and 4 access points, for the proposed approach, the average positioning error is 1.77 m, with a maximum of 3.11 m and a minimum of 0.72 m.

The work carried out shows that the temperature, the 'human body' factor and the presence of walls and objects have a major negative influence on the Aps signal. The results of this study thus offer a simple and effective work support for indoor localization at a lower cost.

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