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Enhanced Weighted Centroid Localization Algorithm for Indoor Environments

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Abstract**—**Lately, with the increasing number of location-based applications, demand for highly accurate and reliable indoor localization became urgent. This is a challenging problem, due to the measurement variance which is the consequence of various factors like obstacles, equipment properties and environmental changes in complex nature of indoor environments. In this paper we propose low-cost custom-setup infrastructure solution and localization algorithm based on the Weighted Centroid Localization (WCL) method. Localization accuracy is increased by several enhancements: calibration of RSSI values gained from wireless nodes, repetitive measurements of RSSI to exclude deviating values from the position estimation, and by considering orientation of the device according to the wireless nodes. We conducted several experiments to evaluate the proposed algorithm. High accuracy of ~1m was achieved.

Keywords**—**Indoor environment, received signal strength indicator, weighted centroid localization, wireless localization.

I. Introduction

In recent years, localization became the essential process for many applications such as environmental monitoring, medical care, tourist applications, goods transportation, as well as location-aided network functions such as network routing, topology control and coverage [1].

Nowadays, when it comes to outdoor environments, GPS remains the most common positioning technique. However, it does not work well in indoor environment due to the presence of obstacles between satellites and the receiver, such as building walls, so other technologies are used: infrared radiation, radio frequency (RF) and ultrasound system technology [2], [3]. The most prevalent is radio frequency. Since radio waves are able to penetrate through the walls and human bodies easily, it is applicable to almost every indoor environment, has a larger coverage area and needs less hardware comparing to other systems. RF-based technologies are further divided into RFID, Bluetooth, Wi-Fi, FM and UWB technologies.

Positioning based on Wi-Fi has some comparative advantages over competing technologies, due to its easy setup, reasonable cost [2] and, since it is present in almost every mobile phone or tablet device, requires no additional specialized software or hardware, eliminating the need for carrying any extra devices along. It can be easily set up using existing infrastructure - access points already installed trough the cities or buildings and user mobile phones or tablet devices. Due to the low cost, nowadays it is even affordable to setup own wireless network intended solely for positioning.

Developing an indoor localization technique is a challenging problem, due to the complex nature of indoor environments, including the impact of obstacles such as walls, equipment, other people in the room, and other factors [3]. Furthermore, another problem is the measurement variance, because of imperfect hardware, presence of obstacles or user orientation [4].

II. Related Work

One of the most common Wi-Fi localization methods is fingerprinting. Fingerprinting is based on creation of a so-called radiomap, a collection of pre-measured signal strengths for all visible access points in a particular location [5]-[7]. This process is usually called calibration. After a radiomap is created (which is, theoretically, performed only once for each area of interest), signal strengths measured by different users are compared to the values in the radiomap, and the location is determined. Although this method is rather simple, and does not require any specialized hardware, it has some serious drawbacks. The process of creating a radiomap is time-consuming, and since radiomaps are "static" and cannot adapt to environment changes, e.g. people walking around the room, or a new piece of furniture, calibration should be repeated every time a significant change in environment occurs [3]. Similarly, installation of a new access point would also require repeating the calibration process, to include new signal strength measurements into the radiomap. Accuracy of fingerprinting depends on the number of access points in specific area, and on the density of radiomap points.

Other methods like lateration and centroid methods are based on the conversion of measured RSSI into distance [8], [9]. These solutions are usually simpler than fingerprinting, and much better adapt to changes in the environment. The main drawback of such methods is computation of path loss exponent which is extensive and error-prone.

Today, many projects and systems that enable localization exist. The Open Beacon project [10], used for indoor positioning in the Jewish Museum in Berlin uses RFID technology, with custom RFID tags carried by users, and EasyReaders, base stations that receive beacon packets emitted by tags in the vicinity. RADAR [6], from Microsoft Research, is the first system for indoor localization using the existing wireless LAN infrastructure. It is based on the fingerprinting method, with calibration measuring taken in

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different times of day, in an attempt to adapt the application to changes in the environment. The Awiloc [11], developed at Fraunhofer IIS, also uses RSSI fingerprinting as a basis of its localization algorithm, with some optimizations which, according to the authors, make the algorithm robust and more resistant to small changes in the environment. Google Location Services APIs [12] use different techniques to determine user's location, from GPS in the outdoor scenarios, to mobile base stations and wireless access points when GPS signal is not available. iBeacon [13], the Apple's indoor proximity system launched last summer, uses Bluetooth Low Energy devices, defines only the hardware and communication protocols, while the implementation of localization algorithm is left to the application developers.

There is a lack of mobile applications with high accuracy indoor positioning and unobtrusive and simple usage. We argue that user should not need additional device other than her mobile phone or a tablet, and the positioning application should minimize additional user involvement for its operation, e.g. requiring her to take a picture of a QR code, do a manual location correction, etc.

The solution proposed in this article addressed the abovementioned issues and aims to be accurate to locate a person not only inside the room but at certain location in the room. According to properties of Wi-Fi, accuracy is expected to be between 1 and 5 meters [3]. In practice, accuracy of 3m is usually satisfactory [14], [15]. Still, we claim that higher accuracy should be achieved for feasible functionality of many indoor applications. Furthermore, our solution aims to be easy to setup, easily customized, reusable and have the ability for self-correcting without additional user involvement.

III. Enhanced Weighted Centroid Localization Method

A. Setting up the Environment

Solutions for indoor localization usually use an existing wireless network since Wi-Fi infrastructure is available almost everywhere in the cities and buildings [16]. Although such infrastructure has expensive initial deployment, there are also low-cost and simple wireless access points (AP-s) available nowadays which are cheaper than standard Wi-Fi routers. Moreover, if the aim is accurate positioning inside the room, one usually cannot rely on existing infrastructure which is in most cases not dense enough to locate the object with satisfactory precision.

So, setting up the environment requires setting several (at least four) AP-s at known positions in the room (advisable in the corners) such as shown in Fig. 1.

One should be aware that algorithms used in the following sections work well only if the places where the object can be positioned, are covered by convex hull of set of AP-s (as shown by dotted lines in the Fig. 1).

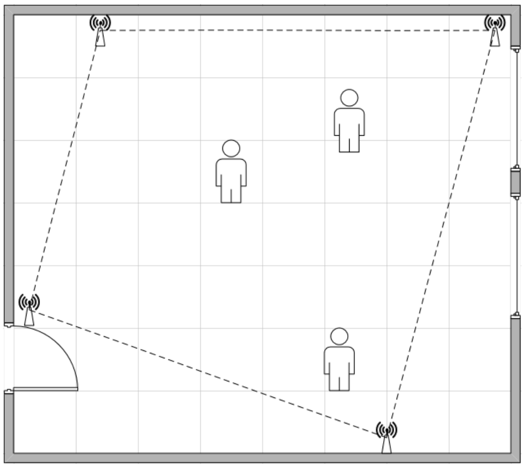

Fig. 1 An example of AP setup

B. Localization Algorithm

There are several approaches to wireless localization [1]-[3]. In practice, most of the wireless localization algorithms calculate object's location using properties of the received signal with received signal strength indicator (RSSI) - the most widely used signal-related feature. The disadvantage of RSSI measurements is that they are sensitive to the environmental interference.

To estimate the distance from object to AP using RSSI, several formulas can be used [14], [17], following the most common one:

$$RSSI = -(10n\, log_{10}d + A) \tag{1}$$

where *A* refers to RSSI value at one meter distance to certain AP and *n* is computed by measuring RSSI at various distances.

Calculated distance is used to estimate position of the object, either by lateration [14], [17], [18] or centroid method [9], [15]. We will further focus on the class of centroid methods, since they show good results, are computationally less demanding than lateration, and lately, some enhancements that improve centroid methods accuracy emerged, as we will show in the following text.

1) WCL

Weighted Centorid Localization (WCL) uses weights to ensure an improved localization comparing to the centroid method where arithmetic centroid is calculated as object's location [9]. Weights are measure of AP-s' attraction to object. The bigger the weight is, the closer the object is to the AP.

To calculate the weight, following formula is used:

$$w_{ij} = \frac{1}{{d_{ij}}^{g}} \tag{2}$$

where d_{ij} refers to the distance between *i*-th object and *j*-th AP and *g* to the degree which determines the contribution of AP. Distance d_{ij} can be calculated using aforementioned formula. In most of the related work, *g* is set to 1 [9] [15], although every application scenario could require a different *g* due to the different environment conditions.

Estimated objects' positions are further calculated by formula:

$$P_i(x,y) = \frac{\sum_{j=1}^{n_{AP}} (w_{ij} \cdot AP_j(x,y))}{\sum_{j=1}^{n_{AP}} w_{ij}} \quad (3)$$

where n_{AP} is number of AP-s in the setup.

Disadvantage of this method requires computation of path loss exponent (n in (1)) which is computationally extensive and is not accurate by computing.

2) WCWCL-RSSI

The great improvement of WCL is presented in [15]. The method needs no computation of distance which makes it faster and more accurate than original WCL method.

The formula by which the weight is calculated is based solely on RSSI values:

$$w_{ij} = \frac{\sqrt{\left(10^{\frac{RSSI_{ij}}{10}}\right)^g}}{\sum_{k=1}^{n_{AP}} \sqrt{\left(10^{\frac{RSSI_{ik}}{10}}\right)^g}} \quad (4)$$

Furthermore, through the measurements of accuracy of binding the estimated position to actual position where closer AP-s are not recognized well, authors suggested the improved weight which increase the weight closer to the AP-s:

$$w'_{ij} = w_{ij} \cdot n_{AP}{}^{2 \cdot w_{ij}} \quad (5)$$

Estimated object's position is further calculated with formula (3) by replacing w_{ij} with w'_{ij}.

3) Enhanced WCWCL-RSSI

By performing the real experiment, we discovered additional problems and proposed a solution to them.

Calibration of Values Gained From AP-s

Different brands, WiFi chipsets, circuit board and antenna design and placement inside the casing of the AP, but also placement of AP in the room (e.g. by the wall, behind the wardrobe etc.) result in different AP signal strengths, and in the end, in different RSSI measurements by client devices. Of course, similar measurement uncertainty applies to the client side hardware. We considered the need of correcting RSSI measurements from different devices carried by the user (different mobile phones or tablets can report different RSSI values under identical measurement conditions [14]) but this is unnecessary due to the independence of A and n from (1) in (4). The same device would measure all RSSI-s with the same error, so it can be disregarded.

Readings from different access points, on the other hand, have to be "normalized" to allow the algorithm to perform correctly. We propose an additional initialization phase in the localization process, in which a device should detect differences between AP-s to achieve more reliable estimations of object's position. This, for example, can be achieved by simply measuring RSSI at 0m or 1m from the AP for 10 consecutive times and calculating the average RSSI. Difference or ratio between these pre-calculated values can later be used to correct the live RSSI readings in the localization process.

Repetition of Measurements

Due to the signal variance, RSSI gained from AP at certain moment is not reliable. We propose a solution that consists of repetitively RSSI measuring and taking the most reliable measure into further computation. The pseudo code is given in Table I.

TABLE I
ALGORITHM FOR CALCULATING AVERAGE RSSI WITH REMOVAL OF DEVIATED MEASUREMENTS

Algorithm *CalculateAverageRSSIs*

Input:
$RSSI = [RSSI_{ij}]: i = 1..n_{AP}, j = 1..n_m$
values of RSSI-s measured n_m times from object *O* to each *AP* at time *t*
Output:
$RSSI' = \{\mu'_i: i = 1..n_{AP}\}$ average values of RSSI-s

Algorithm:
```
for i := 1 to n_AP
    R ← set of RSSI-s measured from object O to AP_i at time t
    Calculate μ(R) and δ(R)
    foreach RSSI ϵ R
        if | μ(R) − RSSI | > 2 · δ(R)
            R ← R\RSSI
    Calculate μ'_i ← μ(R)
```

Weight formula for fixed object *O* becomes:

$$w_j = \frac{\sqrt{\left(10^{\frac{RSSI'_j}{10}}\right)^g}}{\sum_{k=1}^{n_{AP}} \sqrt{\left(10^{\frac{RSSI'_k}{10}}\right)^g}} \quad (6)$$
$$w'_j = w_j \cdot n_{AP}{}^{2 \cdot w_{ij}}$$

and estimated location:

$$P'(x,y) = \frac{\sum_{j=1}^{n_{AP}} (w_j \cdot AP_j(x,y))}{\sum_{j=1}^{n_{AP}} w_j} \quad (7)$$

Disadvantage of this method is that it consumes more time. Still, the incremental improvement method, where the first result is presented to the user right away, and then as the other measurements are collected, is improved, could successfully solve that issue.

Considering Object's Orientation

In real experiment, the big role plays the surrounding environment like obstacles. One permanent obstacle between the device and AP is the object (person) carrying it. Since all modern mobile phones are equipped with compass, orientation of the object can be used to enhance the estimation of the object's position. Based on orientation and known positions of

AP-s, we can infer whether the person represents the obstacle between the AP and device (did she turn her back to the AP). This situation usually results in unrealistically lower RSSI measurements. The example of angle calculation between object and AP is shown in Fig. 2. Angle between object at estimated position P and north is marked by $\alpha(O_P, North)$ and angle between object at estimated position P and AP_i by $\alpha(\overline{O_p AP_i}, North)$. Difference of these two angles is angle between object and AP.

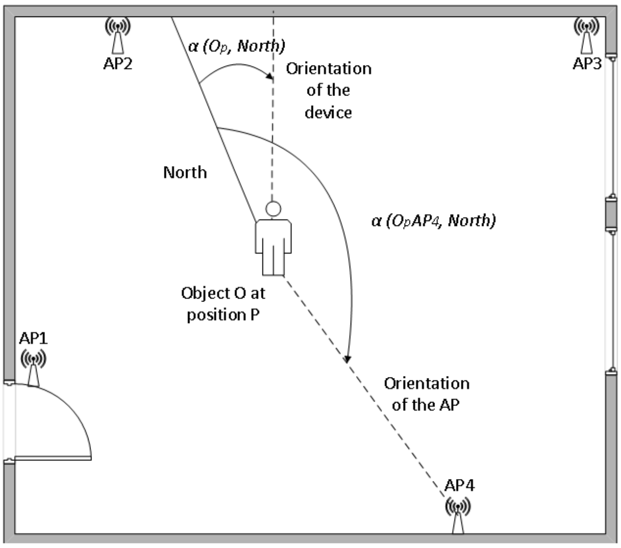

Fig. 2 Example of device orientation and angle between device and AP

We propose the following correction (Table II) to originally estimated position.

TABLE II
ALGORITHM FOR CALCULATING CORRECTED RSSI-S CONSIDERING OBJECT'S ORIENTATION

Algorithm *CorrectRSSIByOrientation*

Input:
P estimated location of object O
$RSSI = \{ RSSI_i :\ i = 1 .. n_{AP} \}$ values of RSSI-s measured from object O to each AP at time t
α' trashold angle
$RSSI_{add}$ initial value RSSI to add at distance of 1m from AP

Output:
$RSSI' = \{ RSSI'_i :\ i = 1 .. n_{AP} \}$ corrected values of RSSI-s

Algorithm:
for $i \coloneqq 1$ to n_{AP}
  $\alpha \leftarrow \left| \alpha(O_P, North) - \alpha(\overline{O_p AP_i}, North) \right|$
  if $(\alpha > 180°)$ $\alpha \leftarrow 360° - \alpha$
  if $\alpha > \alpha'$
    $RSSI'_i \leftarrow RSSI_i \cdot (\alpha/\alpha') \cdot (RSSI_{add} / \sqrt{d(O_p, AP_i)})$

The formulas for weight and estimated position calculation are the same as (6) and (7), with only difference in taking corrected values of RSSI-s.

Algorithm which encompasses aforementioned enhancements is given in Table III.

TABLE III
LOCALIZATION ALGORITHM

Algorithm *Locate*

Input:
$RSSI = [RSSI_{ij}]:\ i = 1 .. n_{AP}, j = 1..n_m$ values of RSSI-s measured n_m times from object O to each AP at time t
α' trashold angle
$RSSI_{add}$ initial value RSSI to add at distance of 1m from AP

Output:
P'' ← estimated position

Algorithm:
$RSSI'$ ← ***CalculateAverageRSSIs(RSSI)***
P' ← estimated position using RSSI'
$RSSI''$ ← ***CorrectRSSIByOrientation(RSSI', P, α', $RSSI_{add}$)***
P'' ← estimated position using RSSI"

IV. EXPERIMENTAL RESULTS

We evaluated proposed algorithm through the real experiment. Four wireless nodes (access points - two PQI Air Pen express and two Portable Wireless Wi-Fi Express Pocket Router AP) are placed in the university meeting room of $50m^2$ (7.7 m x 6.6 m) at the following coordinates (lower left corner is (0,0)): AP1(0, 2.2), AP2 (1.5, 6.6), AP3(5.6, 0), AP4(6.5, 6.6) at height of 0.5m. The room is equipped with chairs and tables not higher than 0.9 m. There is interference from other wireless devices at university which we could not avoid.

We conducted two experiments in two different time periods each consisting of measurements with two mobile devices of different brands. One experiment contains 25 and the other 32 positions, with three repetitive measurements for each of the four AP-s, at each position. The accuracy of each experiment is presented in Table III. We set parameter g = 1 in each experiment. The first column shows accuracy of WCWCL-RSSI algorithm. The accuracy is in average higher than presented in [15]: 1.79 m in the first and 1.91 m in the second experiment. In the second column the accuracy of WCWCL-RSSI with AP calibration is given. The accuracy is higher than accuracy without calibration (1.74m and 1.75m in the first and second experiment respectively), as expected. Further on, third column shows even higher accuracy (1.39m and 1.64 m) by applying algorithm proposed in Table I. In the last column is given accuracy of localization taking into account calibration orientation of the device using algorithm proposed in Table III with parameters $\alpha' = 90°$ and $RSSI_{add} = 10$. Accuracy increases to 0.97m in the first and 1.25m in the second experiment, which is a significant improvement of existing WCWCL-RSSI method. The accuracy ranges from 0.24 m to 2.17 m for single location.

TABLE IV
ACCURACY OF LOCALIZATION EXPERIMENTS

	WCWCL-RSSI	*WCWCL-RSSI with AP calibration*	*WCWCL-RSSI with AP calibration and average*	*WCWCL-RSSI with AP calibration, average and orientation*
Exp1	1.79m	1.74m	1.39m	**0.97m**
Exp2	1.91m	1.75m	1.64m	**1.25m**

We believe that, in bigger room, the same AP setup will lead to lower accuracy but it is possible (especially due to the low-cost setup) to install extra AP-s in the room, for example in the middle, to create several smaller configurations like the one presented, each considering the closest 4 or more AP-s.

Fig. 3 shows an example of movement estimation gained from the experiment we conducted using the proposed algorithm. Solid line represents actual movement and the dashed line estimated movement.

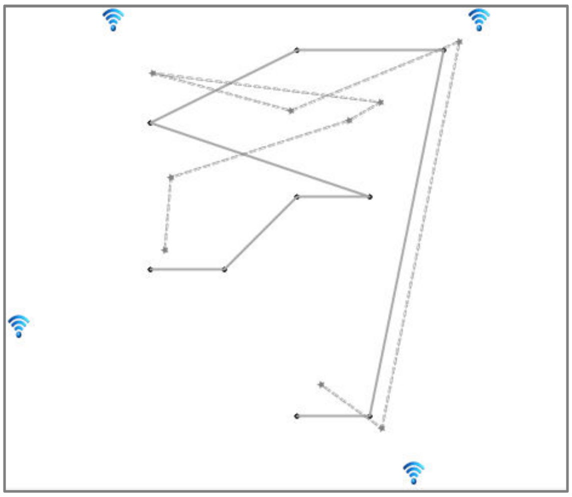

Fig. 3 An example of movement estimation

V. CONCLUSION

We propose localization method which takes into account differences among the various access points, orientation of a client device, and by calculating the average signal strengths from several repetitive measurements, to minimize the unpredictable external interference. We conducted series of experiments which showed that our method gives more accurate results than the other algorithms which we tried out. It should be noted that our method is suitable for use with a variety of different low-cost, off-the-shelf Wi-Fi access point devices, does not require any additional or specialized hardware, and uses the features that are widely available on almost every mobile device (mobile phone or tablet) today. Also, since the localization process can be completely carried out by software on the device, the location and movement history are known only to the user, so user's the privacy is not violated at any time.

As a next step in our research, we would like to test our method in larger premises, such as sports halls, and with more access points. In future work, we also plan to further improve the quality and accuracy of the localization system, by proposing and developing the context-aware extension to our model, i.e. the system that determines location taking into account a range of other factors from the environment, like existing obstacles (e.g. furniture), time periods between localizations or the other nearby users.

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