Received signal strength based room level accuracy indoor localisation method

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***Abstract*— our goal is to achieve room-level accuracy indoor localization of a target, using already deployed WLAN infrastructure, but without actually interfering with the network. The target device only performs passive scans of the existing access points. The currently used methods targets maximum precision and therefore use computationally intensive algorithms. In this paper, a simple covariance based method is presented which can achieve room level accuracy but in the meantime is simple to implement.**

Keywords—received signal strength; WLAN; WiFi; covariance;

I. INTRODUCTION

As stated in [14]: "Cognitive infocommunications (CogInfoCom) investigates the link between the research areas of infocommunications and cognitive sciences, as well as the various engineering applications which have emerged as a synergic combination of these sciences". In this respect, location awareness, achieved by any localization technique is inside the scope of CogInfoCom.

Received signal strength (RSS) based localization methods relay on inter-cognitive communication. One can speak of inter-cognitive communication when "information transfer occurs between two cognitive beings with different cognitive capabilities…"[14]. Indeed, from our localization system prospective, one of the actors only sources RF energy (we are talking about any reachable WLAN AP in the area) whiles the other actor (an intelligent mobile device) is capable of locating himself by performing RSS readings.

We can also talk about representation-bridging here (see [14] for a definition) because a representation of the information at the receiving end (mobile device) is totally different from the representation at the transmitter end (WLAN infrastructure). These statements may be a little foggy at this point but would be obvious after the lecture of this paper.

The paper is organized as follow. Section II presents a brief presentation of main localization methods while section III reviews in some detail the RSS based localization techniques. In section IV our own method is presented while in section V some early results are shown.

II. LOCALISATION METHODS

Unlike outdoor localization which is generally speaking resolved by GPS technology, indoor localization is still an open issue, with several different technologies competing for a place on the market. Although indoor-applicable GPS technologies exists, there are far less popular then their outdoor parent. That is because the technology is costly (expensive infrastructure must be deployed in order to ensure indoor reception of GPS signals). Instead, a handful of other techniques are available for indoor localization. The most important are [1]: infrared based technologies, ultrasonic localization techniques, GSM based indoor localization methods, Döppler effect radio localization systems, RFID technology-based localization and finally, radio (especially 2.4GHz ISM band) signal strength based methods.

With the advent and unprecedented expansion of wireless technologies: WiFi (IEEE 802.11), Bluetooth (IEEE 802.15.1), ZigBee (IEEE 802.15.4), received signal strength (RSS) based methods are gaining momentum. That is mainly because all radio chips complying with these standards provide a so called RSS index (RSSI) than is related to RSS in a manner that depends on the specific radio chip. So one can use an already deployed WiFi, Bluethooth or ZigBee network to perform indoor localization related tasks too, without any or very low additional costs.

III. REVIEW OF RSS-BASED LOCALIZATION METHODS

According to Luo [2] RSS based technologies use *range-free* or *range-based* techniques for localization. *Range-free* techniques assume no prior knowledge about RSS except for the fact that RSS decrease with distance (to the sender). *Range-based* techniques relay on a priori knowledge about RSS values in certain points in the area under test. One can distinguish two types of algorithms in this class: *model based* and *map based* algorithms.

Modell based algorithms use a mathematical model (the so called path-loss model) to relate RSS readings to distance in a deterministic manner. *Map based* algorithms (also known as fingerprinting methods) relay only on a RSS map, trying to match actual RSS readings with templates from the map, in a stochastic manner. Table I summarizes these methods.

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TABLE I. Classification of RSS based localization algorithms.

<table>
<tr><td colspan="4">range based</td><td>range free</td></tr>
<tr><td colspan="3">path-loss model</td><td rowspan="2">finger printing</td><td rowspan="2">over-lapping circles</td></tr>
<tr><td>Trilate-ration</td><td>MinMax</td><td>Maximum Likelihood</td></tr>
</table>

A. *Overlapping rings method*

The overlapping rings (OR) method is detailed in [3]. As one can see in table I, this is a range-free technique, which requires no a priori RSS mapping. Instead, a number of beacon stations must be deployed in some convenient points. No elaborate path loss model is required. I emphasize "elaborate" because a very basic path-loss model is still used: it is assumed that RSS decays with distance.

Applying this principle, beacon station A in figure 1 perform RSS readings for all stations in range, including the tracked device (T). All RSSI readings are compared with target's RSSI ($RSSI_T$). All readings, greater than $RSSI_T$ are discarded, except for de smallest value, let that be $RSSI_B$. All readings smaller than $RSSI_T$ are also discarded, except for the greatest value, let that bee $RSSI_C$. So we have two RSSI readings related to $RSSI_T$ as in (1):

$$RSSI_B > RSSI_T > RSSI_C \qquad (1)$$

From beacon A's prospective that implies that T is closer to A than C but farther apart from A than B. So based solely on these assumptions T can be anywhere on a ring centered in point A and having the inner radius AB and the outer radius AC (fig.1).

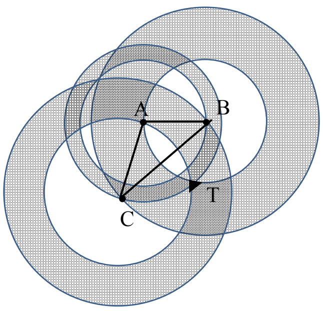

Fig.1 An illustration of overlapping rings method.

From beacon B's prospective a similar ring but centered in B can be constructed. If we add the third ring, generated from beacon C's prospective, the area of residence of T is located. T is supposed to be located in the gravity center of that specific area.

B. *Path-loss model based methods*

Model based algorithms use a path-loss model to determine distance based on RSSI readings. According to [4] the Log-distance Path Loss equation (2) is usually used.

$$P_d = P_{1m} - 10 \cdot \log(d^n) + X_\sigma \qquad (2)$$

where:

P_d is the power level at distance d from the transmitter

P_{1m} is the power level at 1m from the transmitter

n is the path loss exponent

d is the distance

X_σ is a zero mean Gaussian variable with σ standard deviation to account for fading effects.

P_d can be derived from RSSI readings. Measuring RSS values at various distances the values of n and σ can be estimated. So eq.(2) represents a mathematical model which enables us to convert RSSI reading into distances. If used for location, path loss model based methods use, according to Luo [2], one of the following localization algorithms:

- Trilateration
- MinMax
- Maximum likelihood

Trilateration [5] is a well-known positioning algorithm (GPS systems use it). It can be proved that if one knows the exact distance to a target (T in fig. 2) from three fixed points (A,B,C) than the position of T is determined by the intersection of the three circles having a radius of AT, BT, and CT respectively. Due to errors in distance determination (especially RSSI based determination) one can find a locus of position rather than a singular point (this is what we've tried to suggest by shadowing the sharp contour of circles in fig. 2). Due to this fact, the implementation is complex and computationally intensive.

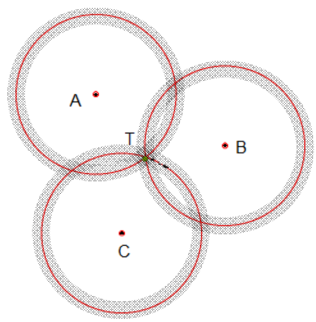

Fig.2 An illustration of trilateration method.

The MinMax algorithm [6] eases the computational burden by considering squares instead of circles. If A sees T at distance AT than T is supposed to be located in a square with a side length of 2AT, centered in A (see fig. 3). The same assumption goes for all beacons that can see the target. The locus of positions for T is the intersection of these squares.

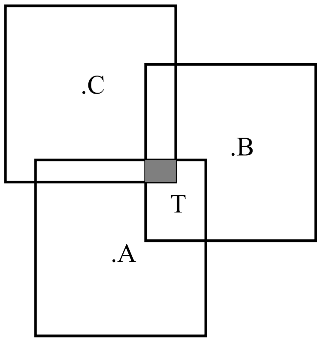

Fig.3 An illustration of MinMax method.

Maximum likelihood (ML) based algorithms are also used [7]. These are very effective in minimizing the estimation error when the probability density function of the random variable (distance in our specific case) is known. Even so, a large number of bacon nodes must be used, in order for the algorithm to be effective [8].

C. Fingerprinting methods

Fingerprinting-based location techniques do not assume any deterministic relationship between distance and RSS. Instead, for a limited number of points of a map, a n-tuple of RSSI readings is recorded (n being the number of access points (AP) in range). These n-tuples, just like fingerprints, are stored as templates, in a so called radio map, for further reference. When a tracked device reports his fingerprint, this is compared to the templates in the radio map.

The similarity of fingerprints can be estimated in a variety of ways, but usually the closest Euclidean distance in template space is used. For better accuracy, a number (k) of closest neighbor's location is averaged in order to estimate the tracked device. This method is known as the k-nearest neighbor (kNN) algorithm [9].

D. Performance comparison

In [2] the performances of these localization methods are reported. The authors used Crossbow Technologies Mote 2 devices as beacon nodes in three different test beds. Table II summarizes their findings on average error. Of course these results depend on the specific test bed and number of beacon nodes but they are consistent with results published in other papers [10-12].

TABLE II. Average error of different localization algorithms

Method	Average error [m]
Overlapping rings	1.69 – 2.76
MinMax	1.55 – 2.58
Maximum Likelihood	2.52 – 3.76
k-Nearest Neighbors	1.49 – 2.93

As a conclusion we emphasize the following facts:

- RSS based indoor localization techniques represent a way to go if a localization error in the order of 1 to 3 meters is acceptable.
- Among all these methods only fingerprinting based methods can use existing WiFi, ZigBee or other wireless sensor network infrastructure for localization purposes. All the other techniques require beacon stations especially deployed to perform localization related task.
- Moreover, fingerprinting methods can be used on existing WLAN infrastructure, without any interference with the current networking tasks and without the need to know the position of APIs.

IV. COVARIANCE BASED FINGERPRINTING METHOD

Our goal is to achieve room-level accuracy indoor localization, using already deployed WLAN infrastructure. Taking into account the state of the art in this domain the only way to go is fingerprinting method. But the algorithms currently used with this method are optimized for maximum precision and therefore very elaborate and computationally intensive, as the kNN algorithm. And still the best performance reported is an average error of 1.5m [13]. We assume that the kNN algorithm by itself is perfect; the RSS map is the limiting factor. Indoor, RSS is affected by many factors (reflections, movements, door or window opening or closing) that makes impossible to have an accurate enough RSS map.

For room level localization, an average error of 2 to 3 meters is fairly acceptable; moreover, rooms are surrounded by walls which attenuate the radio signals. So it is likely to have distinct RSS patterns at room level rather than at point level.

Our covariance based fingerprinting is derived from a signal processing method: matched filtering. A matched filter correlates a template signal, with the input signal in order to detect the presence of the template in the input signal. The decision is taken by comparing the output of the correlator to a threshold. If the threshold is exceed one can presume a match between the input signal and the template signal. In our case the input signal would be an n-tuple of RSSI readings from the tracked device. This is to be correlated with the set of room templates. The resulting correlation coefficients are ordered and the template which produces the maximum output is assigned to be the correct match.

On the other hand the correlation coefficient is a normalized version of covariance, since σ in (3) is constant for both random variables x and y.

$$cor(x,y) = \frac{\mathrm{cov}(x,y)}{\sigma_x \cdot \sigma_y} \tag{3}$$

where:

cor(x,y) is the correlation coefficient of x and y

cov(x,y) is the covariance of x and y

In order to ease computation we would not compute standard deviations but use instead his scaled up equivalent, the covariance (4).

$$\text{cov}(x,y) = E[(x - E(x)) \cdot (y - E(y))] \qquad (4)$$

where:

E(x) is the expected value of the random variable x.

We will assume that the expected value is the mean value of the random variables and both *x* and *y* have *n* elements. Than (4) can be written as:

$$\text{cov}(x,y) = \frac{1}{n} \cdot \sum_{i=1}^{n} [(x_i - \bar{x}) \cdot (y_i - \bar{y})] \qquad (5)$$

Our method in a nutshell goes as follows:

A. Record RSSI reading in each room of interest.

B. Create interim room templates (IRT)

C. Normalize IRTs to obtain room templates (RT)

D. Program the target to transmit RSSI readings in RT format

E. Compute the covariance of the target's RT with RT of all rooms.

F. The location of the target is the room with the greatest covariance.

A. Recording RSSI reading

In this stage, n two dimensional variables are recorded, n being the maximum number of APs seen from the room.

$$x_i = (AP_i, RSSI_i) \qquad (6)$$

where:

APi is some identifier of the AP (SSID or MAC adress).

RSSIi is the received signal strength index for *APi*.

Observing RSSI recordings one can decide which AP to take into account and which is to be discarded for each room.

For example fig. 4 shows a snapshot of RSS recording (taken with inSSIDer 3) from three APs for an approximate period of 90s. As one can see two APs with RSS around -60dB are constantly seen by the receiver while the third AP's signal is lost for relatively long periods of time. That is because his RSS is somewhere near -90dB and common Wi-Fi radios are unable to sense signals under that threshold.

Therefore we discarded any AP with RSSI less than -80dBm. (This is the sensitivity limit for many cheap WiFi radio chips). In this way the constellation of AP seen from within a room is stable. One also can observe in fig. 4 the apparently random variation of RSSI reading. That is why we recorded the mean value of several readings rather than one single reading.

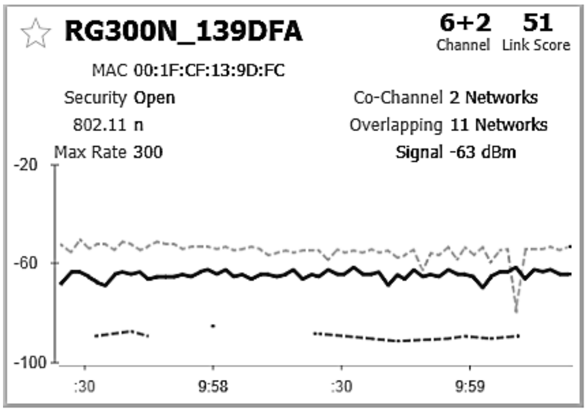

Fig.4 A snapshot of RSS recording.

As an example table III shows the RSS records taken in a room, situated in a residential building. AP-4 would be discarded because RSS is under 80dBm. AP-7 will also be discarded because 4 times out of 10 his signal was not sensed.

By consequence the RSS record for this room would be like:

R = {(1, 66); (2, 42); (3, 58); (5, 61); (6, 71)} *(5)*

TABLE III. Example of RSS records

AP	RSS readings (absolute values)										avg.
1	66	66	66	66	64	67	65	68	65	70	66
2	43	43	41	43	43	41	42	42	42	42	42
3	60	57	59	59	60	59	54	55	59	56	58
4	82	83	84	89	82	82	84	83	82	82	83
5	60	61	63	63	59	61	59	60	61	62	61
6	71	72	72	72	-	70	70	71	72	70	71
7	80	-	-	-	78	-	79	79	79	78	79

B. Interim room templates

Since we intend to use covariance, we intend to construct a zero centered random variable from the RSSI records previously taken, and store these along with AP's id.

$$x_i = (AP_i, RSS_i\text{-}mean(RSSi)) \qquad (7)$$

So, the interim room template will ok like:

$$IRT = \{x_1, x_2, ...x_n\} \qquad (8)$$

with *n* being the number of AP seen from that room.

After we generated an IRT for each location a number of *m* IRT of different lengths will be available.

C. Room templates

In order to equalize IRT record lengths we use 0 padding in RSS_x position if AP_x is not seen in a given location. In the next step, we associate a unique index for each AP (we use i instead of AP_i) and thus IRT records are transformed in vectors of equal length. These are the rom templates. For example, columns (A), (B), (C) in table IV are RT example for three rooms (A,B,C) .

TABLE IV. RT examples

API index	template (A)	template (B)	template (C)
1	6,4	-13,5	9,5
2	-17,6	-13,5	-4,5
3	-1,6	9,5	0
4	1,4	7,5	-16,5
5	11,4	0	0
6	0	2,5	0
7	0	-2,5	0
8	0	8,5	0
9	0	1,5	0
10	0	0	11,5

We may look at data in columns (A), (B) and (C) as samples of a pseudo-signal. Figure 5, 6 and 7 represent these pseudo-signals graphically.

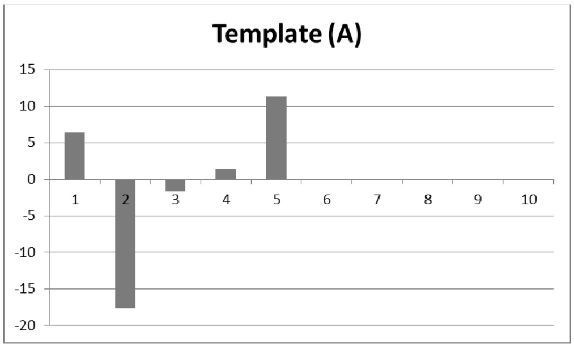

Fig.5 Graphical representation of RT(A)

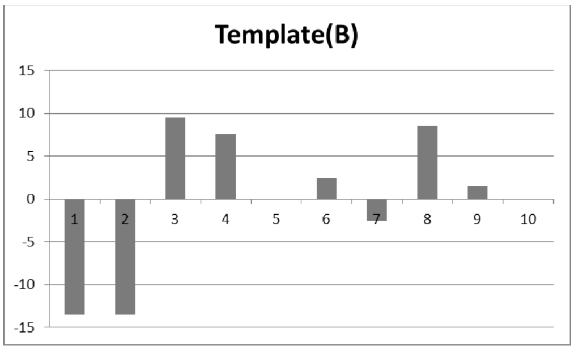

Fig.6 Graphical representation of RT(B)

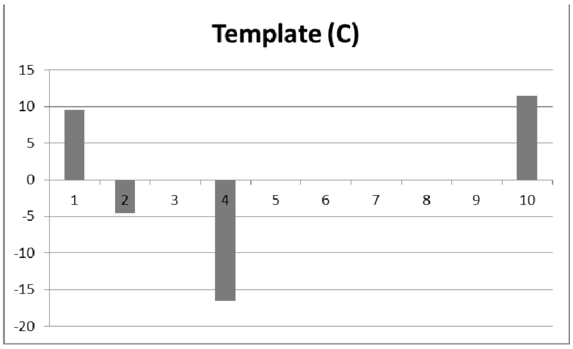

Fig.7 Graphical representation of RT(C)

If, as an example, the normalized fingerprint of the target would be like in figure 8 than the result of covariance applied to templates A, B, C respectively will look like in figure 9.

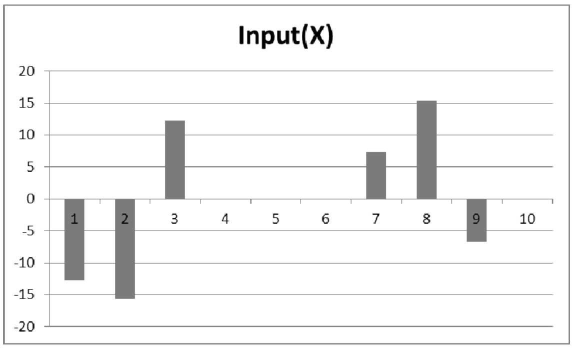

Fig.8 Graphical representation of target fingerprint

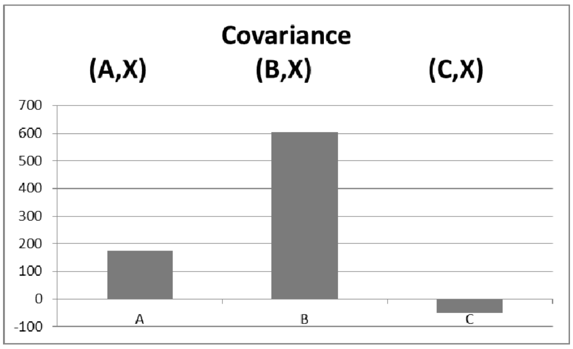

Fig.9 Graphical representation of covariance

It is obvious that using covariance as a matching method the target is supposed to be in room B since covariance of the input with room B's template is greater than the others. This is in fact true because the fingerprint in figure C was taken in room B, in the same spot where the room template (B) was taken but at about one month distance in time.

V. CONCLUSIONS

The method needs further testing but the actual results are promising. If the number of AP sensed in a room is large enough (which is the case with modern residential or office buildings) then long term variation in one or two AP's signal does not affect the correct decision. As an example, in figure 10 the fingerprint and the template are represented together.

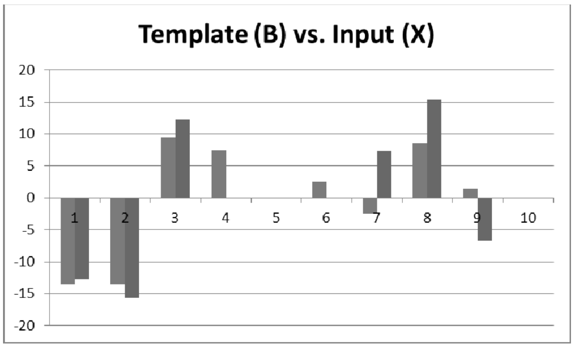

Fig.10 Comparison between the signal and the template

Although AP 4 and 6 don't appear in the input signal and AP's 7 and 9 have opposite signs still the match in figure 10 is very clear because of the effect of APs 1,2,3 and 8.

As a conclusion, these results look promising but still a large number of tests must be performed, with various types of devices in different indoor environments.

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