Fuzzy Location and Tracking on Ambient Networks

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Abstract

This paper describes user location and tracking on indoor scenarios through an ambient network. User location and tracking are considered in order to provide complete intelligent location based services. Imprecise location based on radio-frequency estimations can be processed by a fuzzy location algorithm in order to provide high location near to 90%. Fuzzy tracking is also provided by means of a fuzzy automaton. Fuzzy location techniques here presented allow increasing location ratios even when the user triangulation can not be as precise as desired.

Keywords: fuzzy location, fuzzy tracking, ambient networks, indoor location.

1 Introduction

There is an increasing interest towards location technologies for mobile devices [8]. Location-based services is an active field of research, because applications increase user satisfaction due to the possibility of service adaptation to user location.

Since nowadays there are an intensive use of mobile communication terminals such mobile phones and PDAs, we consider interesting to use them to increase the information flow between the user and the system. This consideration implies an utilisation of the location technologies available at the mobile terminal (MT): GPS; Bluetooth, WiFi, etc; and its use as a representation interface allowing the user to interact with the information provided by the system taken into account its location.

The Global Positioning System is nowadays the most common location-sensing system used (instead its prize) since the world-wide satellite constellation has reliable and ubiquitous outdoor coverage and allows to determine geographic positions with a reasonable precision (in terms of a few meters).

Furthermore, GPS techniques can be successfully used in wide open areas, but there are ineffective on indoor scenarios. Then other location sensing techniques including triangulation (multiple distance or angle measurements between known points), proximity measures nearness to a known set of points and scene analysis must be also considered. Location system implementations use one or more of these techniques to locate equipment, people, or both.

User indoor location can be performed using different kind of sensors and technologies as: infrared [11], radio-frequency (RF) [7], ultrasound and radar. Radio waves provide a powerful mean of location detection because of its ability to penetrate various materials. Rather than using differences in arrival time, as done by ultrasound systems, RF based location systems usually determine location based on the received signal strength [10, 2, 3].

Sometimes the scenario can change, and then the environment representation must be rediscovered dynamically. Some different techniques have been proposed to match the observed scenario with the known environment representation as K-nearest neighbour averaging (KNN) [2], bayesian networks [5], neural network models [4] and others.

In general, Location based services (LBSs) are focused to users and their location. LBSs require knowledge of the scenario where users are located in order to locate a user by triangulation bearing in mind the exact location of the emitters. Location estimation when using stationary emitters for indoor RF wireless networks [9] is quite easier than using mobile emitters. Location uncertainty is due to attenuation and multipath propagation of RF signals, to the movement of MTs, to evolving scenarios where certain elements can move, to the presence of certain variable obstacles, to the existence of different access points and so on. There are several parameters in the system that make possible that sensor measures could be different for a given location. Such differences can be interpreted as a fuzzy view of the measures. Henceforth, location estimation is so uncertain and fuzzy that we must to consider the use of fuzzy techniques to solve this problem.

Ambient networks enable the cooperation of heterogeneous networks, integrating the fuzzified location information collected by each sensor of an ambient network and the fuzzified set of measures of the mobile device for the access points.

The main contribution of this work is a fuzzy location and tracking system that can deal with the problem of uncertainty of user location estimation. Since it is often difficult to be sure about the measures obtained by the sensors in terms of received signal strength, it is also difficult to obtain by triangulation a precise estimation of the location of a user. In addition, we base the decision on a set of measures that do not require knowing the precise location of the access points. This fact makes a big difference with the traditional triangulation schema. The proposed algorithm obtains location rates higher than 90% and tracking rates higher than 85%.

The rest of the paper is organised as follows: section 2 is devoted to introduce location services and the system architecture; section 3 describes the location problem and proposes a fuzzy inference system to solve it; section 4 is devoted to describe a user tracking mechanism based on a fuzzy automaton; experimental results obtained for user location and tracking proposals are described in section 5; and finally, conclusions and references end the paper.

2 Location based services architecture

A small piece of software placed in the MT scans for access points. It then calculates a user's location by selecting several signals and comparing them to the reference database. The more densely populated the area is with WiFi signals, the more accurate the software is at locating the device. In the same way, sensors can determine the presence of a certain MT in their own influence area. The location of sensors can be easily known if they are fixed (static and fix sensors) or can be rediscovered dynamically if the scenario changes. This information is stored in a database. If a certain access point detects a certain MT, the location system can start the location process. Both, sensors and access points are nodes of the ambient network.

In our case, we consider sensors and access points at the same level in order to build the location system. The distinction between sensors and access point is very interesting in dynamic environments, because sensors are referred to access points. Then, transitively we can define user/MT location based on access points through the information offered from the sensors. However, for simplicity we focus this work in the user/MT positioning based on incomplete and/or imprecise information obtained from access points.

The system we are considering takes into account that an MT is under the influence of different access points. Such access points cover a complete area, which is subdivided in different zones. For example, a museum with different rooms; or a hotel with an access point for a set of rooms in each floor. In addition, the signal strength received in a room could be different along the day because of the interferences of other electronic devices, precise location of the user in the room, etc.

In this way, we consider that the normal situation is to have a lower number of access points than zones. Then, the location system must integrate the information of the different access points. Moreover, it should be easily reconfigured in case of failure of some access points. In addition, we assume the imprecise location of the access points.

The location system alone is prone to detect situations where is possible to estimate even different locations for the same user in an instant time. We resolve this situation using a fuzzy tracking system in order to select the actual user location, because its next location depends on its previous ones. The tracking system takes into account the trajectory followed by the user, henceforth the new location should be included in the trajectory ignoring location estimations far away the trajectory.

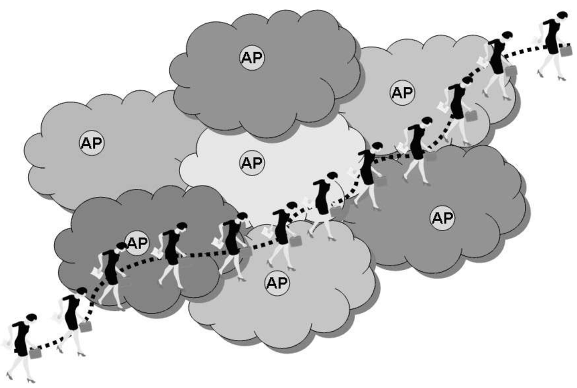

Figure 1: Communication abstraction.

In figure 1 we illustrate the situation of different access points covering completely an area; and dividing it in different zones of main influence. Each user/MT will receive signal strength information from at least one (but not necessary all of them) access point, which could be used to determine its location. In addition, the trajectory followed by the user helps it to determine its actual location. In this case, a businesswoman moves across a building where different WiFi networks are defined. Its MT can be located and tracked by means of the signal strength measures obtained by its MT from the access points operating in its influence area, even if the precise location of the access points is not known.

3 User Location

User location is based on the position of the access points. We consider a two dimensional lattice, which defines an area. Such area is divided in regular zones. Access points are dispersed randomly through the area, being possible the presence of more than one access point in the same zone. Considering homogeneous access points, we determine the value of the signal strength in some zones of the area. We use such values as inputs to train a fuzzy system. As output we use the zone where the user is located. The use of the zone as output of the system allows us to integrate fuzzy values for the signal strength.

Location estimation is performed in terms of the membership degree of the user to a certain influence area. We have used the Matlab fuzzy optimisation toolbox to tune the parameters of a fuzzy inference system (FIS). It generates, using grid partitioning, fuzzy rules by enumerating all possible combinations of membership functions of all inputs. The training is performed using the Sugeno hybrid method, and the rule base is initialised based on examples.

Figure 2 shows the indoor wireless scenario where 9 cells and two hubs to cover the complete area are considered. We consider 15x15 possible positions for the user into each cell. When considering more hubs, the number of rules and the surface complexity increase. The FIS must be re-tuned each time the scenario changes.

The fuzzy location algorithm takes as inputs the fuzzy values of the membership to the influence zone of the access points and offers as output the location area. When the location of an object is sensed by more than one sensor, the location estimation can be more precise by the aggregation of the knowledge. Figure 3 illustrates the triangulation of a user location considering the signal strength received by two MTs from two access points. However, depending on the number of access points and the user location, the output of the location system could be imprecise and/or erroneous.

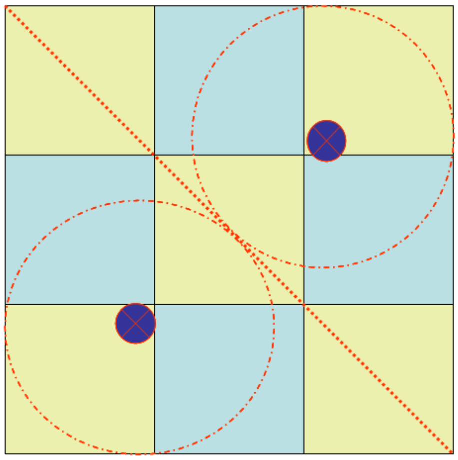

Figure 2: Indoor wireless scenario of 9 15x15 cells with two hubs.

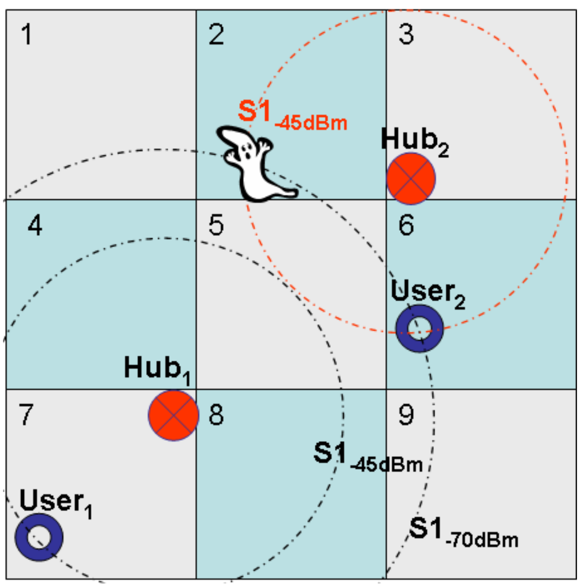

Figure 3: Indoor wireless triangulation.

The algorithm obtained is a set of fuzzy rules provided by the FIS as depicted in figure 4. For $user_1$ in figure 3, we obtain a high membership degree only for the *zone 7*: "*IF* S_1 *is HIGH AND* S_2 *is NULL THEN loc_zone_7=0.9*". But something happens for $user_2$, since the system provides a high membership degree for both zones 2 and 6: "*IF* S_1 *is MEDIUM AND* S_2 *is HIGH THEN loc_zone_6=0.7*" and "*IF* S_1 *is MEDIUM AND* S_2 *is HIGH THEN loc_zone_2=0.7*". The membership degree obtained for $user_2$ is the same for zones 2 and 6, since the number of access points considered is insufficient. A reduced number of access points can introduce phantom users in the system, as it occurs in zone 2 (see figure 3). The number of access points to consider, and their location, determine the occurrence of erroneous location estimations.

User tracking can also aid to reduce the phantom phenomenon since the system can estimate the location of the user taking into account the location estimation and the trajectory followed by it (tracking).

User tracking can be performed considering the evolution of the user location during a time interval as it is depicted in next section. However, there are situations in which it is impossible to differentiate two paths despite the use of user tracking. For example, it is the case of two access points to cover the complete area. In such cases, it is necessary to have an initial point to distinguish between the paths. In other cases, with more than two access points, this problem is not present because we can make a classical triangulation process to discriminate between the paths.

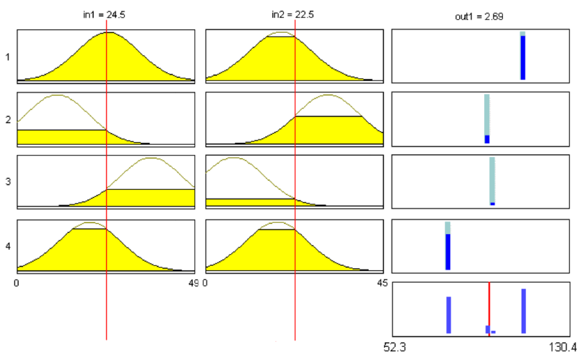

Figure 4: Fuzzy rules.

4 User tracking

The accuracy of location based services can be improved via mobility tracking. In [1] we proposed the use of fuzzy logic techniques to track the trajectories of the MTs and to provide user friendly interaction among MTs and services. In such approach, each zone of a scenario is represented by a symbol of an alphabet. Thus, each possible path is modelled as a string of symbols.

The system builds an estimated string $\alpha = x_1x_2x_3 \dots x_m$ which is obtained by the concatenation of symbols representing the location of the user tracked during a time interval. Each symbol represents the influence area of a certain hub of the network, where the system estimates where the user is located. The system estimates the user location evaluating the rules provided by the FIS according to the signal strength detected at the mobile terminal for all the hubs of the lattice. For each estimation, the system provides a zone location represented by the associated symbol of the alphabet. Location estimation can be performed on demand by the user, or periodically by the system. Then, the estimated path is classified taken into account a dictionary containing the pattern paths existing in the current coverage area.

For each pattern path in the dictionary ω, we provide a fuzzy automaton $MF(\omega)$ which gives a fuzzy similarity value between the estimated path and the pattern path [6]. The fuzzy automaton is able to deal with imperfections of the estimated path because it implements a fuzzy imperfect string matching. The estimated path is finally classified as the pattern path in the dictionary with the highest similarity value. In the following we define the fuzzy automaton for a pattern path.

Let Σ be a finite set of symbols, and let Σ^* be the set of strings over Σ. Let $\omega \in \Sigma^*$, $\omega = a_1a_2a_3 \dots a_n$, be a string that representing a certain path of the lattice. A fuzzy automaton $MF(\omega)$ for a path ω that deals with an imperfect string of symbols as input, is defined as $MF(\omega) = (Q, \Sigma, \mu, \sigma, \eta)$, where $Q = \{q_0, q_1, \dots, q_n\}$ is a non-empty finite set of states, being n the length of the pattern ω, Σ is a non-empty finite set of input symbols (set of zones), σ and η are the fuzzy sets on Q that representing the initial and final states respectively. Finally, the state transition function μ is defined as:

i) $\mu(q_{i-1}, q_i, a_i) = 1$ for $i : 1..n$, transition without error.
ii) $\mu(q_{i-1}, q_i, \varepsilon) \in [0, 1]$ for $i : 1..n$, transition for insertion of symbol a_i.
iii) $\mu(q_{i-1}, q_i, x) \in [0, 1]$ for $i : 1..n$, $x \in \Sigma$ and $x \neq a_i$, transition for substitution of symbol x by a_i.
iv) $\mu(q_i, q_i, x) \in [0, 1]$ for $i : 0..n$ and $x \in \Sigma$, transition for deletion of symbol x.
v) the rest of fuzzy transitions values are set to 0.

The main advantage of this fuzzy method is that it deals with a non limited number of signal propagation errors.

5 Experimental results

We consider an area of 30 x 30 possible user positions, where we place 2, 3, 5, 7, 10, 15, 18, 27 or 40 access points. The real position of the access points is not know *a priori*, making impossible to use a traditional triangulation schema to locate the user.

The objective is, on one hand, to determine the rules to provide user location taking into account the vagueness and uncertainty information from access points, minimising the occurrence of phantom locations; and on the other hand, to improve user location using the user tracking based on a fuzzy automaton.

In figure 5 we represent the location rates obtained when different zones are defined for the same area. The figures take into account the relation between the number of access points and the number of zones. In addition, access points are randomly distributed, which allows to extract some conclusions about a dynamic system where access point are added or deleted from the system. In particular, figure 5 shows the location rates obtained when considering 9 cells with 10 x 10 possible user positions, 4 cells with 15 x 15 user positions or 36 cells with 5 x 5 user positions respectively.

In order to compare the performance of the system we consider as comparative metric the position given by the access point from which it receives the highest signal strength (the access point at the minimum distance). *Minimum* label in the figure legend indicates the recognition rate obtained when estimating the location considering the minimum distance (maximum signal level) to the emitter. In a similar way, *fuzzy* label identifies the location rate obtained when the location is performed using the proposed fuzzy algorithm.

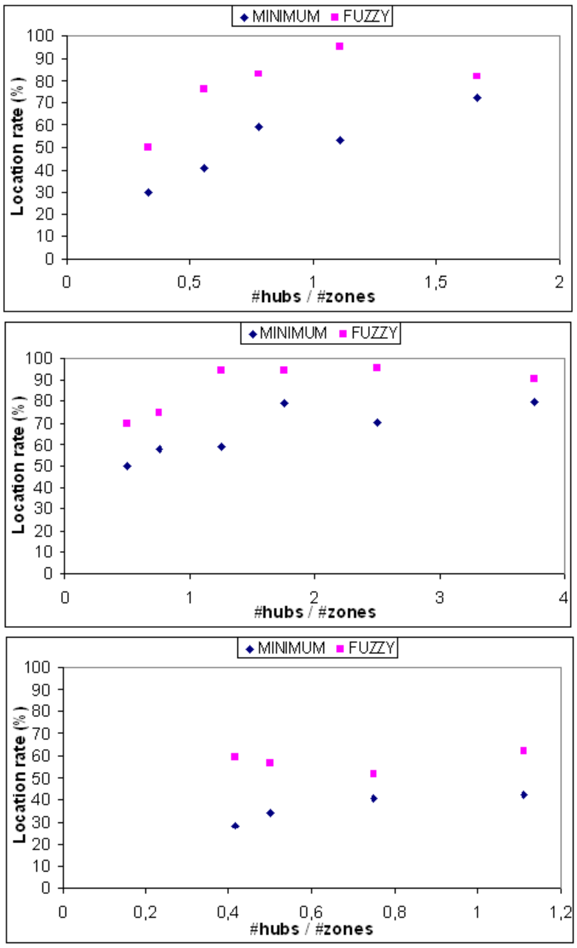

Figure 5: Location rate for 9 10x10 cells (up), 4 15x15 cells (middle) and 36 5x5 cells (down).

As it can be seen in figure 5, fuzzy method performs better than minimum, and the higher the number of hubs per zone is the higher recognition rates are obtained. The algorithm performs better whenever more access points are added to the system. In fact, with one access point per zone, we obtain good positioning rates. Real situations must take into account the possibility of access point failure. Then, we assume that access points are located independently of the zone definition in the area.

The number of zones affects the location rate. The more zones are defined, the more access points are needed. An increase in the number of access points reduces the presence of more phantom users if they are adequately placed.

Then, the increase in the number of access points improves the location rate. However, as this number increase, grows the number of phantom users as well. There are more access points and different combination of them produce different user positioning.

For the tracking experiment, we have considered a scenario where MT tracking is performed by demanding the ambient network the current location of an MT once per 480 milliseconds during its presence on the scenario. Figure 6 shows the five different trajectories defined for a certain 3x3 cells area. Results obtained are depicted in Table 1, where ER indicates the error rate introduced when problems as multipath propagation and attenuation of the signal are considered. The string of symbols representing the movement of the MT contains edit errors (insertion, deletion and change). These strings are compared with all the possible paths that an MT can follow for a certain scenario, that are contained in a dictionary. RR indicates the recognition rate, and represents the amount of correct tracking estimations in %. Results have been obtained for a set of 5 predefined paths (see figure 6) and 50 different trajectories.

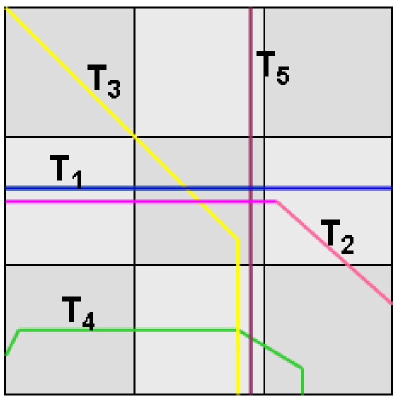

Figure 6: Trajectories for a 3x3 cell area.

ER (%)	RR (%)
87.64	84.6
71.73	88.1
58.74	88.8
44.58	89.3
31.40	89.5

Table 1: User tracking rates.

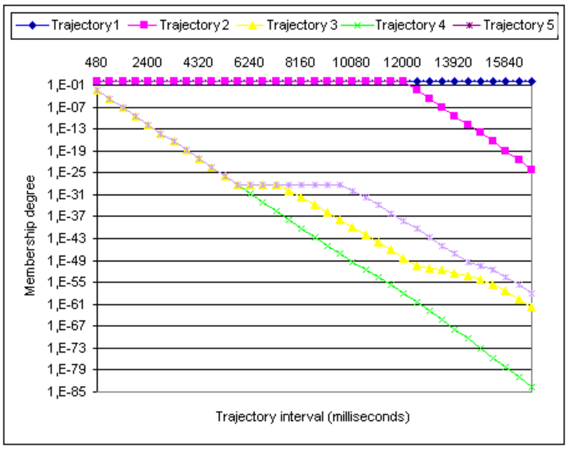

Figure 7: Membership degree when error-free trajectories are considered.

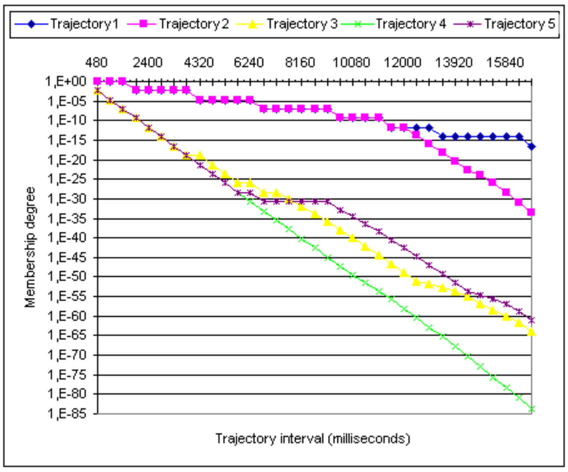

Figure 8: Membership degree when trajectories containing errors are considered.

Figures 7 and 8 show the membership degree obtained for each trajectory when applying the fuzzy automaton to the movement of a mobile terminal. The trajectory followed by the MT is the $Trajectory_1$. Figure 7 represents the membership degree obtained for each trajectory when precise location estimations (error-free) are considered. In figure 8 location estimations are imprecise. The 31.4% of the location estimations are incorrect. As it can be seen, it is possible to discriminate certain trajectories quickly, however discrimination requires more tracking time for trajectories 1 and 5.

Combining the proposed fuzzy location algorithm with the tracking automaton, location rates increase. Phantom locations are discriminated from correct location estimations by means of user tracking. A great number of erroneous location estimations are incompatible with the trajectories followed by mobile terminals when moving across a certain scenario. This fact allows eliminating the erroneous location information, increasing the location ratio.

6 Conclusions

This paper presents a location and tracking system for location based services (LBSs) on indoor scenarios where user location is performed using RF imprecise triangulation. Imprecise location estimation due to signal attenuation, multipath propagation and obstacles presence can be processed by a fuzzy location algorithm in order to provide high location near to 90%. Location by triangulation becomes less restrictive since the LBS do not require knowing the exact location of the mobile terminals.

Transmitters location can be modified due to node failures, sensor movements or imprecise positioning. This fact causes either imprecise or erroneous user location estimations. The fuzzy location algorithm here presented allows increasing location ratios even when the user triangulation can not be as precise as desired.

The use of fuzzy techniques allows obtaining good location estimation for mobile terminals using the RF facilities of the ambient networks. Fuzzy inference systems can be used to locate mobile users on ambient network scenarios and user movements can be tracked using fuzzy automata if an adequate number of hubs are considered, and adequately placed. The user tracking allows resolving indefiniteness or imprecisions in the location process.

The combination of the proposed fuzzy location and tracking techniques allows obtaining a high location ratio for mobile terminals on ambient networks.

Acknowledgements

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