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ENHANCING LOCATION ESTIMATION THROUGH DATA FUSION

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ABSTRACT

In this paper* we discuss a system that exploits observations derived from sensors, in order to estimate a key factor for pervasive computing and context aware applications: the location of a user. The term "sensors" includes Wi-Fi adapters, IR receivers, etc. The core of the system is the fusion engine which is based on Dynamic Bayesian Networks (DBNs), a powerful mathematical tool for integrating heterogeneous sensor observations. In closing, is provided an evaluation of the system as it comes out from the experimental results.

I. INTRODUCTION

In pervasive computing environments, location is essential information as it is an important part of the user's context. Applications can exploit this information for adapting their behaviour. Such applications are termed location-aware applications (e.g., friend-finder, asset tracking).

The location of a user is derived by various positioning methods. The majority of indoor positioning systems relies on different technologies usually of the same kind (wireless LAN signal strength measurements [2], IR beacons [3], or ultrasonic signals).

At this point we will quote the definitions of accuracy and availability, the most important characteristics of a positioning system.

- *accuracy* is a measure of how close is the position provided by the system to the user's true position (e.g. error smaller than 10 meters).
- *availability* denotes the percentage of time the system provides location results at a specified accuracy level, (e.g. error smaller than 5 meters on 80% of the time).

The accuracy and availability are tradeable and it is clear that if we need less accuracy the availability of the system increases.

During the last years several location systems have been proposed that use multiple technologies simultaneously in order to locate a user. One such system is described in this paper. It relies on multiple sensors readings from Wi-Fi access points, IR Beacons, RFID tags, etc. to estimate the location of a user. This technique is known better as sensor information fusion which aims to improve accuracy and availability by integrating heterogeneous sensor observations. The proposed location system uses a fusion engine that is based on Dynamic Bayesian Networks (DBNs), thus, substantially improving the accuracy and availability.

The paper is organized as follows: Section 2 discusses the related work and the differences of the proposed system from other positioning systems. In Section 3, we present the basic location sensing technologies and the respective devices. In Section 4, we present the layered architecture of the system and discuss the structure of each layer. In Section 5, we define the experimental setup environment and provide the results from the evaluation of the system. Section 6 discusses open research issues and Section 7 concludes the paper.

II. RELATED WORK

Indoor positioning systems have been an active research area since the Active Badge [1] project. Since then, several indoor location systems have been proposed. A large number of them use IEEE 802.11 (Wi-Fi) access points to estimate location. RADAR [2] is a radio-frequency (RF) based system for locating users inside buildings. It operates by recording and processing received signal strength (RSS) information. The RSS method is used also by the commercial system Ekahau [4].

The Cricket Location Support System [5] and Active Bat location system [6] use the ultrasonic technology. Such systems use an ultrasound time-of-flight measurement technique to determine user's location. The previously mentioned systems provide accurate location information but have also drawbacks like poor scaling and a high installation and maintenance cost. For these reasons they are rather inaccessible to the majority of users.

Another category of location systems use multiple sensor readings (Wi-Fi access points, RFIDs) and sensor fusion techniques to estimate the location of a user. Location Stack [7] employs such techniques to fuse readings from multiple sensors. Another similar approach is described in [8]. The drawback of these systems is their inability of supporting mobile devices with limited capabilities (CPU, memory) as the location estimation is performed at the client side, hence devices incur the cost of complex computations.

The location estimation system described in this paper relies on data from sensors to determine the location of a user. Our work differs from previous approaches in various aspects.

Firstly, we use Dynamic Bayesian Networks (DBNs) for location inference. Along with heterogeneous sensor data that are processed in real-time we can also "fuse" past information about the user. Secondly, our system can support a variety of mobile devices (PDAs, palmtops) with low computing power. Location estimation takes place in a server residing in the

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fixed network infrastructure. Mobile devices are just transmitting observations from sensors to this server and receive the location estimations. Finally, the adopted system architecture has the advantage of easy management and scalability (e.g. the installation of a new access point is completely transparent to users).

III. Positioning Technologies

In this section we present the principal technologies that are used for indoor positioning and describe their characteristics. We also discuss a categorization of the devices related with each technology.

The most important wireless LAN standard today is the IEEE 802.11 (Wi-Fi) that operates in the 2.4 GHz band or 5GHz band. Wi-Fi is used by several positioning systems which measure the signal strength from access points (RSS) to locate a user.

Radio Frequency Identification (RFID) is the technology used for security tags in shops, ID cards, etc. Tags are powered by the magnetic field generated by a reader and transmit their ID or other information. Such tags do not require any battery and can be deployed in a building to detect object and person passing or proximity.

Infrared (IR) Beacons are programmable devices that periodically emit their unique ID in the IR spectrum. Usually the range of these beacons is approximately 10-20 meters and the infrared receiver should have line of sight with the beacon in order to receive its ID.

Ultrasonic signals are vibrations at a frequency greater than 20 kHz. The devices used to receive and transmit ultrasonic signals are called transducers and are commonly used for distance measuring. In general, they integrate a sensor that can receive or transmit an ultrasonic signal and another RF transmitter/receiver which is used for synchronization.

All the previously mentioned devices (elements) of different technologies (access points, beacons, tags, etc.) can be found in indoor environments either deployed in the building or attached to mobile devices. Some of them emit information and others detect (read) information. According to their position and functionality the elements can be categorized as follows:

- Portable elements are those carried by users or attached to their mobile devices (RFID tags, Wi-Fi adapters)
- Infrastructure elements are those attached to the building (Wi-Fi access points, IR beacons, RFID tag readers)
- Active elements (sensors) are those which detect a phenomenon or take measurements (RFID tag readers, Wi-Fi adapters)
- Passive elements are those that emit information which is detected by active elements. Wi-Fi access points, IR beacons, etc., fall in this category.

IV. System Architecture

The architecture of the proposed location estimation system is organized in three layers: the sensing layer, the collection layer and the fusion layer. **Figure 1** illustrates the generic architecture of the proposed system. We also present location aware applications and databases where the personal profile of users or historical data about their behavior is stored. The layered approach aims to facilitate effortless inclusion of new elements in order to improve the accuracy and the availability offered by the system. In the following paragraphs we provide a more detailed presentation of each layer.

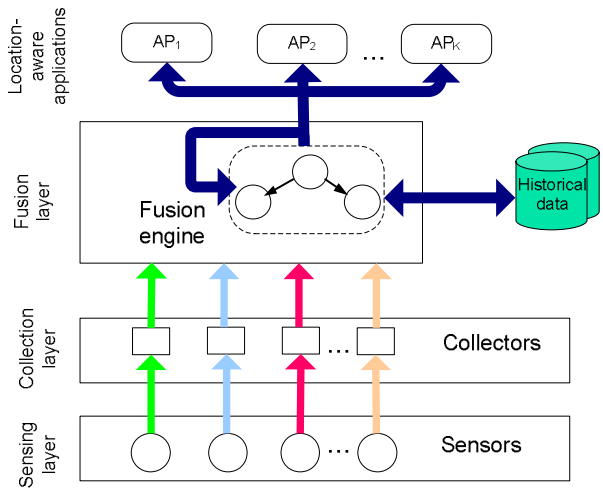

Figure 1. Architecture of the indoor location estimation system

A. Sensing layer

This is the lowest layer of the architecture and comprises sensors of different technologies. Sensors are attached either to the user's mobile device (portable active elements) or are attached to the building (infrastructure active elements). Below, we briefly discuss these two categories.

1) Portable Sensors

A Wi-Fi adapter, can measure the received signal strength (RSS) from a Wi-Fi access point. Similarly, the IR port of a handheld device or a laptop is used as reader for infrared transmissions from IR beacons that are wall-mounted.

2) Infrastructure Sensors

RFID tag readers belong in this category. Such readers detect an RFID tag and read its ID when the latter is in proximity. Users can carry RFID tags which have unique IDs. Furthermore, ultrasonic devices, which estimate the distance of a user from a known point, also belong in this category.

B. Collection Layer

This layer consists of software components called *collectors*. The role of a collector is to interact with the appropriate sensor and collect measurements or events. Sensors may produce raw data in a variety of formats according to their type. Hence, the output of a Wi-Fi adapter is a stream consisting of RSS measurements from access points; IR and RFID tag readers generate a stream of proximity events. When such raw data arrive at the collection layer, a preprocessing procedure is performed as described below.

1) Preprocessing of raw data

Assume that a new RSS measurement arrives from a Wi-Fi adapter. Then, the appropriate collector (Wi-Fi collector) quantizes this on N discrete levels (values): S_1, S_2…S_N. If, for example, the value from the access point with ID *AP2* is between -70 dBm and -60 dBm the value "S_1" is assigned to this infrastructure passive element.

An IR Beacon collector, during this preprocessing procedure operates differently. The two possible states of an IR Beacon are: *Visible* and *Not_Visible*. Assume that an IR receiver is in the range of the IR Beacon with ID *IRB3*. This situation will cause a proximity event which will be detected and the collector will assign the value "*Visible*" to the *IRB3*. The functionality of an RFID tag reader collector is similar to the IR Beacon collector.

2) Tuple formation

After the preprocessing of raw data from the sensing layer, each collector forms a tuple of the type:

(*user_ID, IE_ID, value*)

where *user_ID* is the unique identifier of a user, *IE_ID* is the unique identifier of an infrastructure element and *value* is a measurement or an event.
A Wi-Fi collector may form the following tuple:

(userA, AP1, S1)

which denotes that the Wi-Fi adapter (portable active element) of the mobile device of *userA* measures the RSS from access point *AP1* (infrastructure passive element) and the (quantized) RSS has value *S1*.

A possible tuple generated by a RFID tag reader collector would be:

(userB, RFR1, Visible)

which denotes that an RFID tag (portable passive element) worn by *userB* (or attached to his/her mobile device) is in proximity of RFID tag reader with ID *RFR1*.

In the next section (Fusion layer), we will show how such values are exploited for location estimations.

C. Fusion layer

As mentioned in the *Introduction*, the fusion engine is based on a Dynamic Bayesian Network (DBN) which is used for location inference. Below, we briefly discuss the basic concepts of Bayesian and Dynamic Bayesian Networks and, next, we discuss the adoption of DBNs in the proposed system. We assume that the reader is familiar with the theory of Bayesian and Dynamic Bayesian Networks. For a more complete introduction the author is referred to [9], [10].

1) Bayesian and Dynamic Bayesian Networks

Bayesian Networks (BNs) present a statistical tool that has become popular in the areas of machine learning. They are well suited for inference because of their ability to model causal influence (cause - effect) between random variables.

A BN consists of two parts. The first part is a directed acyclic graph (DAG), representing random variables as nodes, and relationships between variables as arcs between the nodes. If there is an arc from a node *A* to a node *B* then it is considered that *B* is directly affected by *A* (*A* is the parent of *B*). Each node is conditionally independent from any other node given its parents.

The second part of a BN is a probability distribution associated with each graph node. This describes the probability of all possible outcomes of the variable given all possible values of its parents. The parameters of this probability distribution would be estimated using observed data (Bayesian Network learning) [11]. The DAG and probability distributions together define the joint probability distribution.

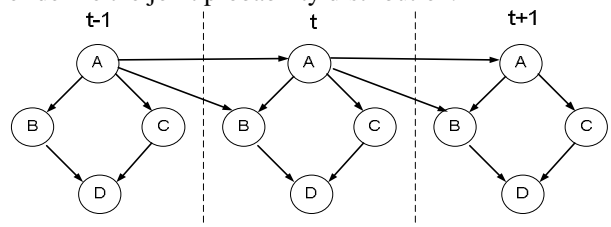

Figure 2. A Dynamic Bayesian Network (DBN) showing dependencies between variables in different time-slots (*A* at *t-1* affects *A* and *B* at *t*)

A DBN extends the static BN by modeling changes of stochastic variables over time. Random variables in a DBN are also affected by variables from previous time slots (see **Figure 2**). For simplicity, it is assumed that the parents of a node are in the same or in the previous time slot (First Order Markov Chain).

2) DBN integration in the location system

The DBN that is used in our location estimation system is depicted in **Figure 3**.

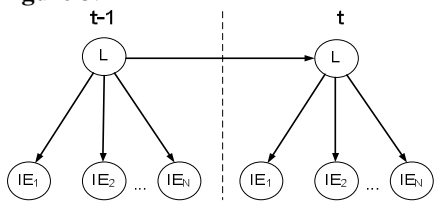

Figure 3. DBN for location estimation representing the dependencies between random variables at different time slots

The incorporated random variables are:

- the location *L* of the user, which may take values from a set of *K* locations {*L1, L2,…LK*}.
- the *N* infrastructure elements IE_1, IE_2,…IE_N. The range of values of those random variables depends on the type of element. Hence, an access point may take a value from the set {*S1, S2,…}* and an RFID tag reader from the set {*Not_Visible, Visible*}.

The random variable *L* at time *t*, $L^{(t)}$, is directly affected by the random variable *L* at time *t-1*, $L^{(t-1)}$, so $L^{(t-1)}$ is the cause and $L^{(t)}$ is the effect. This is a reasonable assumption as the location of a user is depended on his/her previous location. Also, the infrastructure elements at time *t* are affected by location at time *t*, $L^{(t)}$; the location of the user affects the value of an infrastructure element (e.g., the signal strength measured from a Wi-Fi access point depends on the location of the user).

The probability distributions that are associated with each node of the DBN are estimated with Bayesian Network learning techniques. In particular, for every infrastructure element (IE_1, IE_2,…IE_N) we estimate the probability distribution $P(IE_i \mid L)$. This can be achieved by taking into account the fixed positions of infrastructure elements, the indoor propagation models of RF and IR signals, the time of flight of ultrasonic signals, etc. A simpler technique of learning that can be used is the method of sampling (signal, events) at every location for determining the values of infrastructure elements and the frequency of appearance of these values. According to this frequency we are able to form the probability distributions. In **Table 1** we present a probability distribution of a passive infrastructure element (Wi-Fi access point) with ID *AP1*.

Table 1. A possible probability distribution for access point with identifier *AP1*. It can be shown that the probability $P(AP1=S2 \mid L=L1) = 0.3$

	L_1	L_2	…
S1	**0.5**	**0.0**	…
S2	**0.3**	**0.8**	…
…	…	…	…

Furthermore, the probability distributions $P(L^t \mid L^{t-1})$ for location transition can be generated according to the structure of the building, the distance between two locations and the time required by a mobile user to cover this distance. The determination of probability distributions takes place once, at system initialization (training phase).

3) Location inference queries

After having structured the DBN of the fusion engine we can use it for location estimations. A location inference query might be: "*Where is user X given his/her previous location and given the values (observations) of infrastructure elements associated with this user?*".

To answer this we calculate for each of the *K* locations {L_1, L_2,…L_K } the following conditional probability:

$$P(L^{(t)} \mid L^{(t-1)}, O^{(t)}) . \quad (1)$$

which is the mathematical representation of the location inference query and denotes the probability of being at location $L^{(t)}$ at time *t* (the requested location) given the already known value of the previous location $L^{(t-1)}$ and given the values of the *N* infrastructure elements at time *t*, $O^{(t)}$. For simplicity reasons we write

$$\{IE_1^{(t)}, IE_2^{(t)}, ...IE_N^{(t)}\} = O^{(t)} . \quad (2)$$

Equation (**1**) can be converted to the following equation:

$$P(L^{(t)} \mid L^{(t-1)}, O^{(t)}) = \frac{P(L^{(t)}, L^{(t-1)}, O^{(t)})}{P(L^{(t-1)}, O^{(t)})} . \quad (3)$$

Taking into consideration that each node of our DBN is conditionally independent from any other node given its parents, we can compute the joint probability that appears in the numerator of (**3**). Also, as the denominator of (**3**) does not depend on the random variable $L^{(t)}$, it can be treated as a normalizing constant. Hence, the following equation is derived:

$$P(L^{(t)} \mid L^{(t-1)}, O^{(t)}) = \frac{P(L^{(t)} \mid L^{(t-1)}) * P(O^{(t)} \mid L^{(t)})}{\sum_{i=1}^{K} P(L_i^{(t)} \mid L^{(t-1)}) * P(O^{(t)} \mid L_i^{(t)})} . \quad (4)$$

The probability distributions $P(O^{(t)} \mid L^{(t)})$ and $P(L^{(t)} \mid L^{(t-1)})$ are known from the training phase, so we can now compute the probabilities for each location {L_1, L_2,…L_K}. The problem of location estimation is to find the location L_i, that maximizes the probability.

$$\max\{P(L_i^{(t)} \mid L^{(t-1)}, O^{(t)})\} . \quad (5)$$

The location with maximum probability is stored in the database and the profile of the user is updated. Moreover, the location information is forwarded to LBS applications.

V. SYSTEM EVALUATION

A. Experimental setup

The evaluation of our system was performed using two technologies, Wi-Fi access points and IR Beacons. The experimental setup was the 2-floor building of the *Department of Informatics and Telecommunications (University Of Athens)*. Each floor has dimensions of *30 X 100 meters*. A user equipped with a mobile device was roaming inside the building at walking speed (*~4 km/h*).

In total, we used *4* Wi-Fi access points (exploiting the wireless infrastructure of the building) and *5* Lesswire IR Beacons. Moreover, we used *35* symbolic locations (*room1, room2,…*). During the DBN training phase, a training sequence (number of samples-measurements) from all locations and infrastructure elements was compiled and fed to the system. This resulted to the formation of probability distributions. The length of the training sequence was *60* samples for each location

The overall architecture of the system (collectors, fusion engine) was implemented in Java programming language. The server, where the fusion procedure and location inference is performed, was executed on an Athlon 1800+. At the client (user) side, we used an iPAQ™ Pocket PC equipped with an Orinoco™ wireless adapter and a "built-in" IR port.

B. Experimental results

In **Figure 4** is illustrated the availability of the system at a specified accuracy level (error <*10 meters*) if we use only IR Beacons, only Wi-Fi access points and their combination[1]. The availability for the first case is *31%*. If we only use Wi-Fi access points availability climbs to *48%*. Finally, the location estimation system that uses the combination (fusion) of the two heterogeneous technologies reaches availability *65%*. As

[1] The accuracy determination of the location estimation results was achieved by comparing the estimations with known reference points in the building.

anticipated, the integration of heterogeneous technologies into the system improves its performance.

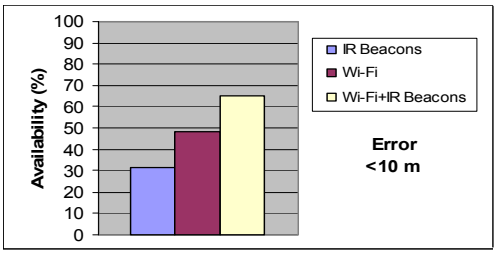

Figure 4. Availability of different technologies for a specific accuracy level (error less than *10 meters*)

As discussed in the description of the *Fusion layer*, the system computes the probabilities for each location and the estimated location of the user is the location with the maximum probability. We define this maximum probability as *confidence probability* of the system.

Figure 5 illustrates the *confidence probability* (mean value) of the system using a static Bayesian Network and a Dynamic Bayesian Network for the location inference process. In the first case we do not take into consideration the previous location of the user for the estimation of the current location. The mean value of *confidence probability* was *75%*. Conversely, through the use of a DBN, the mean value of *confidence probability* increased to *89%*. It is obvious that the use of DBNs for location inference instead of static BNs increases the certainty on the user position estimation, thus improving the performance indicators of the location system.

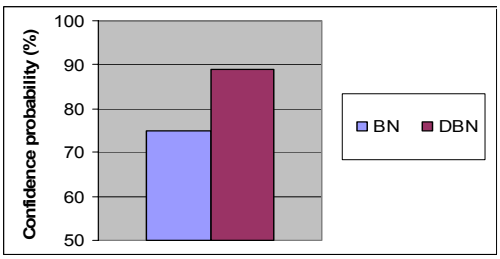

Figure 5. Mean confidence probability of the system, using static BN and DBN

VI. FUTURE WORK

Currently we are working on two issues which will have a direct impact on system's performance and scalability. The first issue is the use of "dead reckoning" techniques to improve the availability and accuracy that the system provides. A user's mobile device which is equipped with an electronic compass and an accelerometer could provide information about the direction and speed of its owner. Taking also into account the last known position of the user and the time elapsed since then, we can predict the current position and make more accurate estimations.

The second issue that we are working on is the adoption of a distributed architecture for the system. In this distributed architecture the building is divided in regions (cells). For each region there is one server responsible for location estimations. Servers of adjacent regions are interconnected in order to interchange information about the users (handovers between regions, etc). The distributed approach of the system will enhance its performance, improve its scalability and make it more robust in case of server failures.

VII. CONCLUSION

In this paper we presented a layered fusion system architecture which exploits information from sensors of different technologies to estimate the location of a user. A key difference from similar systems is the use of Dynamic Bayesian Networks for location inference. The use of DBNs improves our estimations. Along with sensor information we take into consideration the previous location of the user thus improving the performance. Additionally, the system supports a variety of mobile devices including those with restricted computational capabilities (PDAs, etc.) as they do not incur the burden of complex location calculations. Finally, the evaluation of the system in real conditions proved its appropriateness for indoor positioning.

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