Real time positioning system using different sensors

Gabriel Villarrubia
Computer Science
University of Salamanca
Salamanca (Spain)
gvg@usal.es

Javier Bajo
Computer Science
Polytechnic University of Madrid
Madrid (Spain)
jbajo@fi.upm.es

Juan F. De Paz
Computer Science
University of Salamanca
Salamanca (Spain)
fcofds@usal.es

Juan M. Corchado
Computer Science
University of Salamanca
Salamanca (Spain)
corchado@usal.es

(*Abstract*) Indoor location systems can identify and locate persons in real time. The use of these systems requires the management of wireless sensor networks that can position users. WIFI networks can serve as an alternative to technologies such as ZigBee since their infrastructure can be more easily deployed in most cases. This study presents an indoor location system that uses WIFI networks and various sensors such as accelerometers and compasses to locate individuals.

Keywords—component; wireless sensor networks, WIFI, virtual organization.

I. INTRODUCTION

Indoor location is currently the subject of intensive research [13][14][15]. The main goal of researchers is to obtain a functional system capable of locating, identifying and guiding, as precisely as possible and in real time. To date, no solution has been able to achieve a location-navigation system as precise and successful as those developed in analogous research such as outdoor location. The main characteristic of a real time positioning system is to know the precise position of an object or individual within a building, which would make it possible to develop and offer a vast set of services, most notably those that aim to control access through the identification of users, security based on physical location, and applications that pursue a statistical objective or installation management. The deployment of these applications tends to take place in indoor locations such as hospitals, manufacturing plants, large warehouses or even with complementary systems such as GPS (Global Positioning System) [13].

The field of electronics has undergone numerous advances and is in state of continuous evolution. In conjunction with computer technology, the use of electronics offers limitless possibilities to improve the quality of life of all individuals. Indoor location is currently a field subject to intense research. The researchers' main goal is to get a functional system capable of making real time location, identification and guidance as accurate as possible. None of the existing solutions have achieved location-navigation systems as accurate and successful as those developed outdoors, where they have obtained much higher precision (as with the GPS system for example).

The main difficulty that characterizes an indoor location system is the ability to obtain a precision commensurate to that of an outdoor system, and with reasonable infrastructure costs [4][5].

The main reason for not having yet achieved this milestone is primarily due to technical issues and, to a greater extent, financial reasons. A GPS system simply requires a physical device that is connected in an open space to a finite number of satellites. On the other hand, a closed space requires the use of an existing infrastructure with a large number of stationary devices that act as beacons, which results in a high cost solution.

Amongst the technologies that are currently used most in the development of Real Time Locating Systems (RTLs) are[14][13], Radio Frequency IDentification (RFID) [17], WiFi y ZigBee [19][20][21]. Indoor location engines that use 802.11 technology, also known as WiFi, are very important type of technology because of their reasonable deployment costs and other numerous advantages such as: easy deployment; existing presence in the majority of electronic mobile, laptop, console and other devices; and vast number of existing networks. These characteristics allow us to refer to WiFi as the most widely used and exemplary wireless protocol.

This paper reviews the use of a multi-agent system whose main objective is to improve the assisted care of the elderly or those with some type of disability who live in a senior care facility or in their own home [2]. The virtual organization [18] proposed in this document is based on the PAngeA (Platform for Automatic coNstruction of orGanizations or intElligent Agents) [7] platform developed by the BISITE[6]

(Bioinformatic, Intelligent Systems and Educational Technology) research group. The architecture presented in this paper is composed of two primary and clearly differentiated units: the central system and the node that is carried by the person or object to be located, in this case a Smartphone. The fusion of information originating from the sensors in the device, such as the accelerometer, the compass, camera or WIFI [17] reader, provides us with the opportunity to easily pinpoint a location. The Wireless Sensor Networks (WSNs) [16] can interact with the environment and obtain information from the actual area, thus increasing the possibility of interaction between the users and the environment [3]. One of the most important WSN applications is RTLS [14][13], because of the many limitations of global positioning systems. The objective of this paper is to present an RTLS system that will enable us to obtain precise location with reduced hardware costs.

The paper is structured as follows: Section 2 presents different localization techniques. Section 3 describes the planning model. Section 4 describes a set of tests evaluating our proposal.

II. Multi-agent System

The proposed system is integrated within the PANGEA [7] architecture. The use of the architecture facilitates communication among the different system components. The system functions autonomously within the mobile device; and while external communication is not required to locate the user, it is required to track the user. During communication with the mobile device, the system updates the user's position to monitor the user's movements, and incorporates new positioning data. If the mobile devices have a connection, the location algorithm is automatically updated when the training of the algorithm and the map routes are remotely downloaded.

The PANGEA architecture incorporates its own defined roles to ensure correct operation, and specific roles for the problem it is studying. The roles specific to the case study as well those specific to the architecture are as follows:

- OrganizationManager: responsible for the management of organizations and suborganizations. It is responsible for verifying the entry and exit of agents, and for assigning roles when an agent enters for first time. To carry out these tasks, it works with the OrganizationAgent, which is a specialized version of this agent.
- OrganizationAgent: works closely to the OrganizationManager. It is in charge of performing the organization tasks.
- InformationAgent: responsible for accessing the database containing all pertinent system information.
- ServiceAgent: responsible for recording and controlling the operation of services offered by the agents.
- NormAgent: ensures compliance with all the refined norms in the organization.
- CommunicationAgent: responsible for controlling communication among agents, and for recording the interaction between agents and organizations.
- Sniffer: manages the message history and filters information by controlling communication initiated by queries.
- UserLocation: finds the location of a specific user.
- DownloadTraining: retrieves the information of the tranning and sends it to the devices.
- DownloadMap: finds training information to send to the requesting device.
- UpdateRSSI: receives Received Signal Strength Indication (RSSI) position data to incorporate new data. Filters the data from the terminals that are not able to perform this function.
- AgentTrainning: builds the classifier used to calculate positions. Uses the entry data from RSSI signal levels and from the positions. There are several agents of this type that implement different classifiers.
- User: role assigned to each mobile device that interacts with the system. Calculates the user's position by applying the available training data and information from the compass and accelerometer.

Figure 1 represents the system architecture and the interaction between different roles.

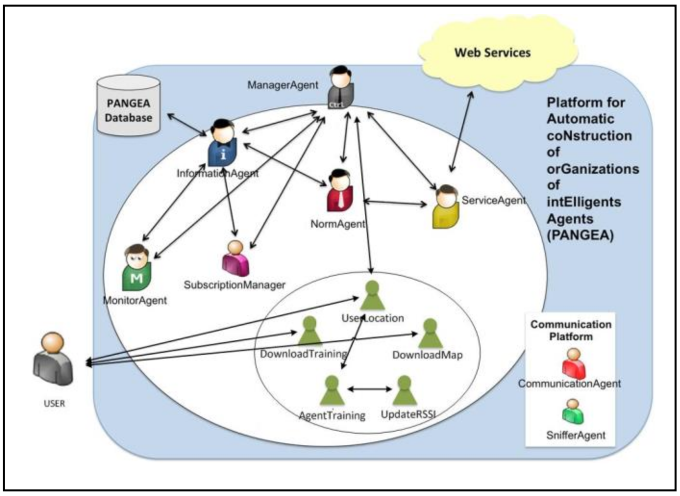

Fig. 1. Role distribution in the PANGEA architecture

A complete description of the roles specific to the architecture can be found in [7]. The roles from the case study require a more detailed explanation, which is provided below.

A. *AgentTraining*

The agent in charge of carrying out all training is the AgentTraining. This role is based on managing data that originates from the levels of the RSSI signals and the use of classifiers. The data is gathered by following possible routes and using the measurements from the WiFi routers that have been detected. The blue line in Figure 2 represents possible routes, while the red dots represent the different positions from which the signal measurements are taken. The values of the measurements are sent to the platform by the agents who are performing the User role to the agent who has the UpdateRSSI role.

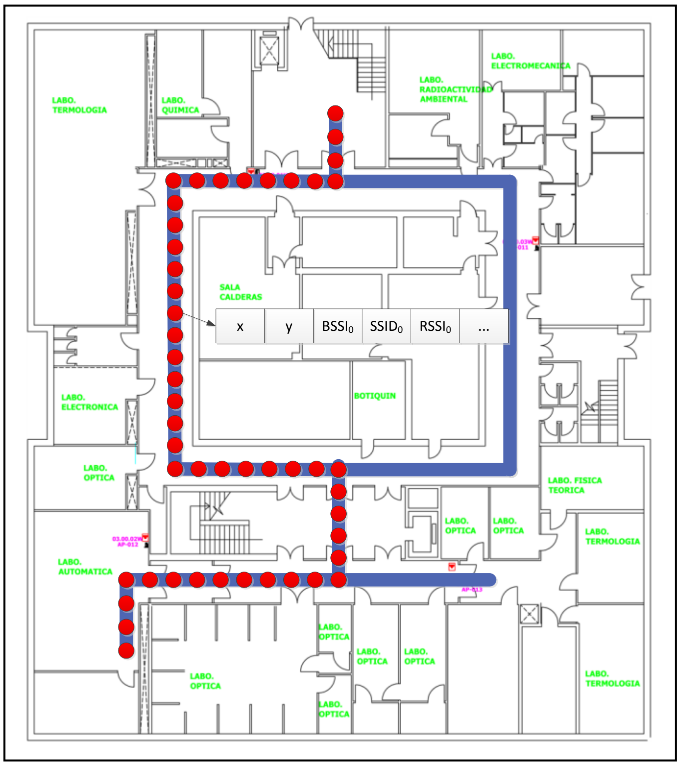

Fig. 2. Procedure for taking measurements

Using the RSSI data, the Basic Service Set Identifier (BSSID) predicts the probability of belonging to each point. The belonging probability is performed with a Bayesian network [9]. The attribute that needs to be classified is the position of each point, represented in red, while the variables used are the RSSI levels obtained from the different routers during the measurement process.

$$P(X \mid e) = \alpha P(X, e) = \alpha \sum_{y} P(X, e, y) \tag{1}$$

Where X represents a variable for an event to be calculated a priori (in the case study it refers to the location); e is a set of variables known a posteriori (where the variables are the BSSID, and the values of the variables are the RSSI signal levels); α is a constant so that the sum of the different events from variable X is equal to 1; and e, y are equal to the remaining possible values of the unknown variables,

$$\begin{aligned} &P(X \mid e) = P(X) \cdot P(e \mid X) / P(e) = \\ &P(X \mid e) = P(X) \cdot P(e_1 \mid X) \cdot \ldots \cdot P(e_n \mid X) / P(e) \end{aligned} \tag{2}$$

The values for $P(e_1 \mid X)$ are determined by the Bayesian network. In this study, we have used conditional independence. This algorithm is based on the calculation of the conditional Independence test [1] for the variables to generate a Directed acyclic graph (DAG) that can obtain the probability estimates.

B. User

The agent in the User role is in charge of locating users based on the information sent by the agent in the AgentTraining role, as well as the information available from the accelerometer and the compass contained within the device. The accelerometers can detect the steps taken by the user. The detection of the steps is easily calculated by establishing the high and low thresholds. The thresholds are determined by configuring the sensitivity of the different devices. Figure 3 shows the variations of the accelerometers from the x, y and z axes, and the steps that were detected.

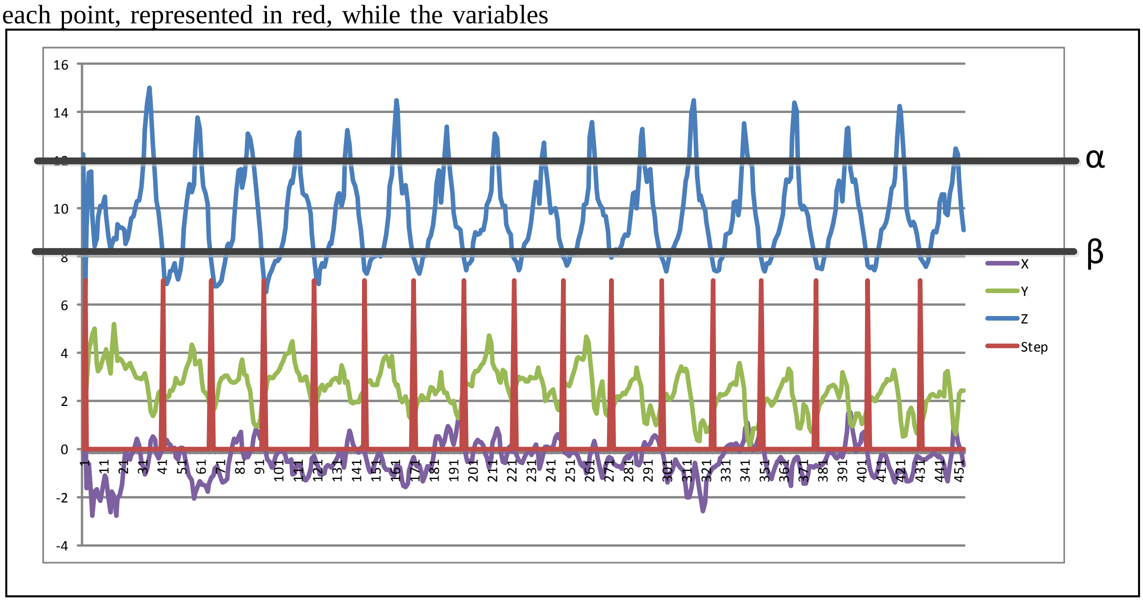

Fig. 3. Variation of the accelorometers according to the x,y and z axes and the steps detected

It is clear that the value of the accelerometers changes according to the orientation of the mobile. Instead of using the gyroscope to determine the orientation of the mobile, the axis with the greatest value is selected. This axis represents he point where the greatest force of gravity is being applied. As a result, the value used in the step detection process for each instant of time i can be defined as follows:

$$v_i = Max(x_i, y_i, z_i) \tag{3}$$

The thresholds α and β shown in Figure 3 are selected according to the values v_i. These margins are selected by using the confidence intervals from the v_i values obtained during a given timeframe t. The process of defining α and β is established empirically, and the user can modify them at any time.

Finally, the compass is used to determine changes in direction and detect steps. When a change in direction is detected and steps are detected as well, the user's position is adjusted to the position of the graph in order to increase the precision of the intersection. The location that was estimated by the compass and the accelerometer is no longer used after a predetermined distance beyond the intersection, to avoid accumulating the error generated during the step detection. During the case study, the estimate based on the steps and the compass is no longer used after the intersection has been passed by a minimum distance of 3 meters. This value was calculated empirically. The possible paths are represented by a guidance graph.

III. Results and Conclusions

The system was tested on the floor of one of the buildings of the Faculty of Sciences. The floor can be seen in Figure 2. The floor has a surface area of approximately 1700m^2. There were a total of 4 routers installed throughout the floor, although signals were also picked up from another two routers in laboratories from an unknown location.

Measurements were taken at a total of 165 different points throughout the distance covered, as shown in Figure 2. The blue line represents the path that was taken. For each point, signal levels were taken from each of the routers on the floor, approximately 4 measurements. Figure 4 shows a histogram with the number of measurements taken by various points throughout the path taken. Only one part of the 165 positions is shown.

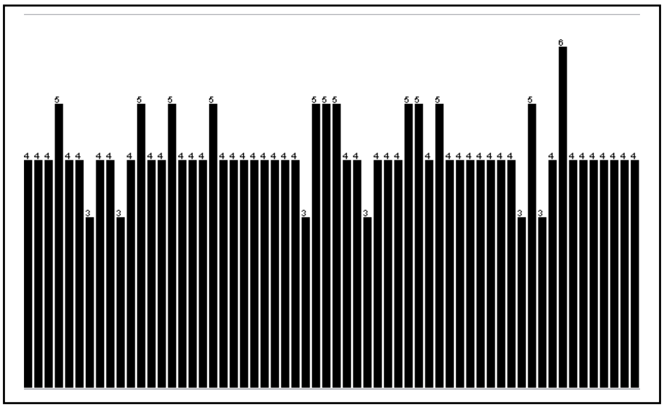

Fig. 4. Histrogram with the number of measurements taken by each point.

A 10 fold cross validation [10] was applied to train the classifier. The result obtained after the AgentTraining agent trained the classifier was only 51.6%, although the kappa index [11] of 0.51 represents a moderate degree of agreement. While the data may not seem very good at first glance, it should be noted that each of the points is separated by a distance of only one step, and that there is a total of 165 different positions, making the results much better than they would otherwise seem. This aspect can be confirmed by observing the confusion matrix [12]. Figure 5 shows part of the confusion matrix where the classes are ordered according to proximity. We can see that the estimated position is always at a diagonal, which means that the real distance from the point with the measurement is always low in case of error.

a	b	c	d	e	f	g	h	i	j	k	l	
0	3	0	0	0	0	0	0	0	0	0	0	a = 160,997
0	4	0	0	0	0	0	0	0	0	0	0	b = 160,974
0	1	2	1	0	0	0	0	0	0	0	0	c = 161,951
0	0	1	2	0	1	0	0	0	0	0	0	d = 161,928
0	0	0	0	0	3	0	0	0	0	0	0	e = 162,905
0	0	0	0	0	5	0	0	0	0	0	0	f = 181,904
0	0	0	0	0	1	3	0	0	0	0	0	g = 200,904
0	0	0	0	0	0	0	0	3	0	0	0	h = 219,903
0	0	0	0	0	0	0	1	3	0	0	0	i = 238,903
0	0	0	0	0	0	0	0	0	3	1	0	j = 257,902
0	0	0	0	0	0	0	0	0	2	0	1	k = 276,902
0	0	0	0	0	0	0	0	0	0	1	2	l = 295,901

Fig. 5. Confusion Matrix. Each column represents the instances in a predicted class, each row represents the real instances in a class. The header names (a, b, c…) represent the different point, and row points are represented on the right (a, b, c…). The coordinate of each point is represented on the right, for example the coordinate of the point a is 160, 997 .

Evidently the 51.6% success rate would have been much higher if the measurements had been taken at greater distances of separation, particularly since the distance between measurements was one walking step. Because the goal was not to improve the accuracy rate by taking fewer measurements, this aspect was not modified as it would have had an effect on the final estimation error of the positions.

In addition to the Bayesian network classifier, other classifiers also produced good results, such as Kstar [8], with a total of 60.26% correctly classified instances and a kappa index of 0.598, which would theoretically indicate that it works better. Results from some of the other classifiers can be seen in Table 1. The techniques included in this chart are primarily those that improved the results of the Bayesian network.

TABLE I. COMPARISON TO DETERMINE THE EFFICIENCY OF EACH CLASSIFIER

Model	Correctly Classified	Kappa statistic
Bayes Net	51.5789 %	0.5102
KStar	60.2632 %	0.5983
Naive Bayes	60 %	0.5956
IBK	63.4211 %	0.6302
C 4.5	59.2105 %	0.5876
SVM	37.1053 %	0.3638
RBF	0.2632 %	0
LogitBoost	58.4211 %	0.5796
JRIP	37.1053 %	0.3636
PART	56.5789 %	0.561
RandomForest	60 %	0.5955

According to the data from Table 1, it would seem that the best classification technique was not selected. However, the Bayesian networks will later reduce the estimation error of the user's position for the simple reason that when new measurements are taken, the user is not in the exact place where the the intensity maps were taken. Furthermore, the signal levels may have been affected by changes in the environment, such as open or closed doors. Taking these situations into account, the Bayesian networks are able to generalize better than the other techniques, and will function better than the others in this case study. This conclusion was reached by tracing the path shown by the red dots in Figure 2, and calculating the estimation error for the previously mentioned algorithms.

The average absolute error is shown in Table 2. As we can see, the error during the test phase was very different from the error obtained during the system's operating phase, which is why the Bayesian network was selected to calculate the person's position. During the operating phase, the agent that provided the final position also implemented the user role and obtained the classification data according to the classifier provided by the AgentTraining agent. This phase already took into account such data as the accelerometer and compass, to adjust the user's position if any changes in direction were made. In order to fuse the information from the compass with the position created, it is important to note *when* a change in direction is indicated on the compass, and to determine if the user is walking, which can be done with the accelerometer or by detecting steps. This permits locating persons at intersections with greater precision in areas that are generally more complicated due to the error that exists from locating through wifi. The error shown in Table 2 is obtained by applying all of the techniques together. Without using the compass and the accelerometer, the error for the Bayesian network would be 2.37.

TABLE II. COMPARISON TO DETERMINE THE EFFICIENCY OF EACH CLASSIFIER

Model	Error meters
Bayes Net	1.81
KStar	2.23
Naive Bayes	2.34
IBK	3,28
C 4.5	6,93
SVM	7.24
RBF	8.23
LogitBoost	7.13
JRIP	3.98
PART	6.24
RandomForest	3.12

The system created through WiFi can locate people indoors with a higher precision rate, which makes it possible to provide guidance indoors similar to how a GPS provides guidance outdoors. By using measurements taken from RSSI signals, together with a compass and accelerometer, it is possible to reduce location error and more precisely locate individuals inside a building. Future studies will attempt to improve the step detection process so that positioning at different points along the path can also be taken into account. Until now, introducing this step has always been complicated because of the need to take step length and the speed at which each person walks into account. Furthermore, the systems tested and developed in this study can detect steps, even when the user is standing still, by the subtle movements of the person's mobile. If they stop to talk to somebody, for example, the location system would show an error.

Acknowledgment

This research has been supported by the project iHAS (TIN2012-36586-C03-03) funded by the Spanish Ministry of Science and Innovation.

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