Survey on Location Agent Based on Various Wireless Protocols for Indoor Localization

Syed Umar[1], Misganu Tuse Abetu[2], Tadele Debisa Deressa[3], Dr M. Paul N Vijaya Kumar[4]

Professor, Dept. of Computer Science, Wollega University, Nekemte, Ethiopia[1]

Lecture & HOD, Dept. of Computer Science, Wollega University, Nekemte, Ethiopia[2]

Lecture, Dept. of Computer Science, Wollega University, Nekemte, Ethiopia[3]

Assoc. Professor, Dept. of Information Science, Wollega University, Nekemte, Ethiopia[4]

ABSTRACT: The computer community is increasingly interested in context-sensitive systems. In order to deliver relevant services in context-sensitive applications, the first task is to locate the user, which can be dynamic and intelligent. Finding indoor mobile users isn't a trivial issue, however, as multiple devices need to be monitored and signals sent at the same radio frequency simultaneously, perhaps using the three existing wireless network protocols: Wi-Fi, Bluetooth and ZigBee. . In this direction, this document presents an agent-based architecture with the location agent module defined for context-sensitive applications, which uses three artificial neural network algorithms that are activated for the different protocols: Back propagation, Propagation Back Impulse and Levenberg-Marquardt. Taking into account the experimental aspects of the research, a study is presented to compare the neural network algorithms, including performance, regression analysis, accuracy and precision. The results show that the Bluetooth-trained back propagation algorithm gives better accuracy (the average error 0.42 meters) and the Wi-Fi-trained work-up gives better accuracy (73%). We see our approach as promising because the site agent has a service quality component coupled with neural network algorithms that can select the best signal strength to be found within users.

KEYWORDS*:* Wi-Fi, Back Propagation, ANN, Neural Networks

I.INTRODUCTION

Mobile devices enable user mobility and provide perfect access to computer resources as they move from one point to another. In this way, there is an increasing interest in context-sensitive systems that use the context to understand various current aspects of the user situation and to deal more sensitively with the environment [1]. One of the most popular context-based applications for mobile services is location-based services (LBS) [2]. LBS are value-added services that use the mobile site to provide the user with relevant information or services at a particular location. Such services may be required in indoor and outdoor environments. In outdoor environments, LBS is possible thanks to the Global Positioning System (GPS), which allows precise positioning. Most mobile devices today are equipped with a GPS receiver. However, GPS is not suitable for tracking mobile users (MUs) with acceptable accuracy as ceilings and walls can be attached to the signals. In this case, an alternative sensor can be used in mobile devices such as WLAN (Wireless Local Area Network), Bluetooth and ZigBee as alternative indoor positioning sensors. Inside is still an open research problem and central to our research. According to [3], existing indoor positioning techniques can be divided into two main approaches: (i) their precision and the installation of special additional infrastructures such as ultra-wideband or ultrasound, the accuracy of which is high frequency, but expensive and unsuitable for general use Scale; and (ii) use existing network infrastructure, such as WLAN or inertial sensors, to install them, the accuracy of which is limited, but the system is more economical and can be used at low additional cost. Of course, the wireless network is not designed to find users inside. However, measurements of signal reception strength (RSS) based on the false signal of the received signal versus distance law suggest the location of an MOSS. On the other hand, due to the properties of the hardware, they attenuate signal and noise, contributing to environmental impacts such as walls, furniture and people on the move.

II. LITERATURE SURVEY

In this research, we focus on methods that use the existing infrastructure, for example: (i) Wireless (Wi-Fi) loyalty to IEEE 802.11, which includes the IEEE 802.11a / b / g standards for WLAN and gives users access at superfast broadband internet when connected to an access point (AP) or in ad hoc mode; (ii) Bluetooth over IEEE 802.15.1, based on a wireless radio system or short-range devices and inexpensive devices to replace cables with computer peripherals; and (iii) ZigBee under IEEE 802.15.4 defines the Slow Wireless Personal Network (LR-WPAN) specifications for retrofitting simple devices that consume less energy and typically operate in the 10m Personal Operating Room (POS). According to [4], there are two main groups of internal locations based on the existing wireless network infrastructure:

Signal propagation model and construction of geometry information for converting RSS to distance measurement and information about the coordinates of the WLAN access points (AP). The triplet method can be used to estimate the position of the MOSS. ; and (ii) a site fingerprint technique that matches the RSS values found in a database of RSS models previously acquired in the region of interest. According to [5], there are two steps to fingerprint the site: offline and online. In the offline phase, the area of interest is divided into different grid points and RSS values by different APs. RSS data is collected over a period of time and stored in a database called a radio card. During the online phase, the server compares an algorithm with the fingerprint, which is measured by a fingerprint stored on the radio card, to determine the position of the mobile phones in the network. The fingerprint coordinates that specify the minimum distance for a Euclidean distance position are returned as an estimated position.

Artificial neural networks (ANN) can also be used to establish a relationship between the RSS sample model and the location [6]. In [7], ANN defines a massive parallax model with distributed processors, consisting of simple processing units called neurons. Several ANN models have been proposed, all of which should be trained. There are basically two types of training: supervised and stress-free. Although the RNA-controlled training at the desired output is known, the monitoring examines and organizes the categories under the data in the data. A faceted RNA consists of several versions of units connected by guided links using guided training. In this study, three supervised learning algorithms are used to train our networks: Retreatment (BP) [8], Retreatment with Momentum (BPM) [9] and Levenberg-Marquardt (LM) [10].The BP algorithm was often used as a guided learning algorithm in the feed-forward multi-layered RNA, which is based on the gradient extraction method. This attempts to minimize the network error by shifting the gradient of the so-called error curve. However, BP has slow compliance. As a result, much faster algorithms have been proposed to accelerate BP convergence and these can be divided into two main categories [11]: (i) Heuristic techniques developed by analyzing the performance of the steepest descent algorithm are used, e.g. BPM, for example, to prevent instability due to a too high learning rate; and (ii) uses standard numerical optimization technologies, such as the LM algorithm, which approximates Newton's method and is suitable for training minor problems and media.

According to [12], using ANN has improved performance and accuracy because it can handle noise measurements and is often used when the correlation between the system's input and output values is unclear or subject to noise data. Internal position accuracy can be measured by the error between the estimated position and the actual position of the mobile device. This feature can be improved by Quality of Service (QoS) as it selects the best RSS to find users and it is one of the most important reviews for LBS. Typically, the QoS is measured in terms of accuracy, response time, availability, and consistency [13].The multi-agent system (MAS) method is also interesting for querying the internal position with ANN and QoS [14]. According to [15], an MAS is characterized by the existence of several agents who interact autonomously and work together to solve a problem or achieve a common goal. In this way, an MAS can be used as an alternative to complexity management by developing an internal location system that combines different wireless protocols. Agents have inherent properties, such as:

(i) the ability to perceive and influence the environment; (ii) the ability to achieve individual goals; (iii) easy communication with other agents; (iv) the ability to act with a degree of autonomy; and (v) the ability to provide and Ultra Wide Band mobile nodes and the accelerometer; and (ii) uses RSS statistics and a fingerprint localization algorithm. Another approach is based on the common position of mobile users. For example, use the Bluetooth protocol to improve indoor accuracy, coverage and energy consumption by using nearby GPS bicycles [20].Unlike the initiatives presented, the focus is on exploring the modularization of complexity and the interaction of multiple wireless protocols within an agent-based model. The agent model can display complex interactions between different entities in the internal environment and allows you to make automatic decisions during execution. In addition, different wireless protocols can be contextualized in different types of agents interacting in the environment. Another important difference in our approach to the said work [16-20] is the implicit way of managing QoS mechanisms without hardware and additional costs.

III.ARCHITECTURAL OVERVIEW

In [21] earlier work, we developed a prototype for locating indoor users using the MAS approach. This prototype makes it possible to define the properties required for a more complex architecture for context-aware systems. Therefore, we improved our previous architecture with the definition of LAM together with ANN and QoS [14].

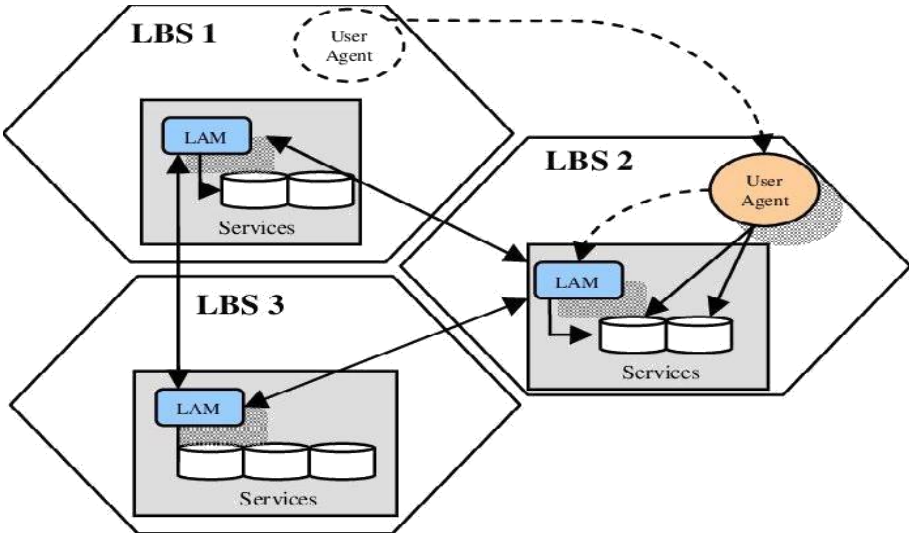

Figure1: Architecture of LAM based protocol

Fig. 1 presents LAM, which consists of three modules and a knowledge base:

Radar Agent - it initiates the user's location process in a space consisting of three submodules:

(i) Wi-Fi; (ii) Bluetooth; and, (iii) ZigBee. This sub module is responsible for monitoring the environment to collect RSS information and send it to the conflict agent; Conflicting Agent - requests RSS from the Radar Agent and consists of four sub-modules: (i) Observation (OBS) responsible for RSS requests;
(ii) Conflict Resolution (CR), which is responsible for deciding which position to use, provides access to knowledge-based;

(iii) Managed Knowledge Based (RM), is responsible for inferences using the If-Then Rule Statement; and

(iv) Tracking (TRCK), which is responsible for monitoring users;

Neurus Agent - Receives and transmits Wi-Fi RSS, ZigBee and Bluetooth infrastructure each ANN, to check its own QoS and return the location to the conflict agent. A prototype was implemented to implement the LAM architecture of FIG. 1, consisting of a set of layers for analyzing RSS signal maps and absolute coordinates as illustrated in FIG. 2. Each layer function is described in the following order:

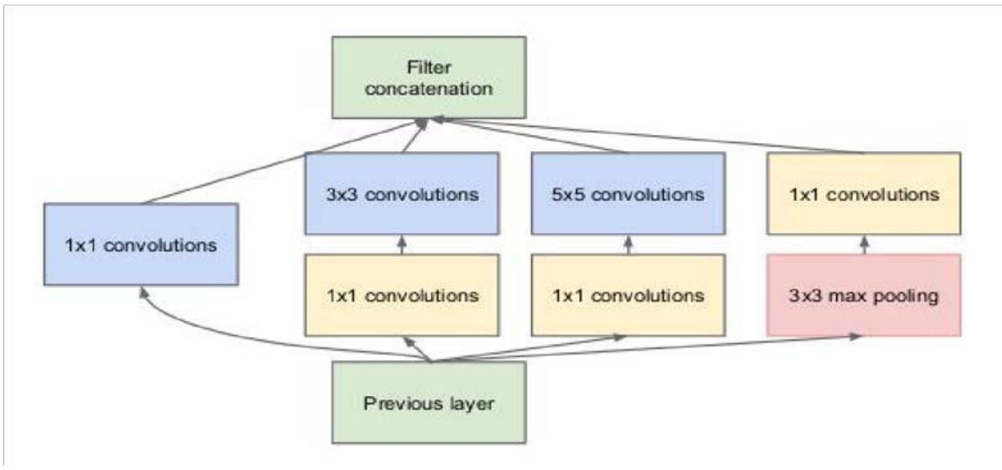

Figure2: Architecture of modular layered based

a. **LBS interface** - interface that allows communication between prototypes and other applications using the location of indoor services;
b. **QoS** - analyzes data from the LEA layer using two predetermined QoS levels: (i) the maximum acceptable error, defined as 1.5 meters according to [11]; and (ii) evaluating the signal strength to assess the proximity of an AP access point with an acceptable error rate defined as 1.0 meter;

c. **LEA** - each independent ANN is responsible for calculating the location in space and the results are obtained from the absolute coordinates of the user's mobile device;
d. **Conflict Management** - prepares data obtained at the data collection layer and implements two stages:

   (i) taking into account hardware differences; and (ii) online to prepare input values for use in the LEA layer;

e. **Data collection** - collects RSS signals from mobile users in certain parts of the indoor environment.The LAM agent-based architecture is defined as a flexible, adaptable and extensible architecture, as new agents can be added taking into account other wireless protocols, ANN algo rhythms and different QoS levels.

IV. SIMULATION AND ANALYSIS

The results presented in [14] show that the LAM architecture using different wireless protocols and QoS is suitable for the internal localization process. Using QoS allows you to select the best signal and become more precise; also improve the level of service offered. In addition, as mentioned in Section I, we compare three ANN algorithms such as BP, BPM and LM. Our experimental tests evaluated ANN performance, regression analysis, accuracy and precision. The first experimental test for the two RNAs is defined empirically with three types of layers (input, hidden and output) which vary the number of neurons in the hidden layer from 100 to 10. MLPs are trained using BP, BPM and LM algorithms. The activation function used for hidden levels and output levels is the hyperbolic tangent (tansig). The training parameters were defined by: (i) 10,000 epochs; (ii) the target of the mean square error (MSE) is equal to zero, since the formation process was supposed to be permanent, the mean root difference between production and the target is MSE; and (iii) the learning rate has been set at 0.1 according to the literature [7]. Training stops automatically when generalization stops improving, as evidenced by an increase in ESM. Other regression analyzes were performed to measure the relationship between production and the target.

To calculate the precision (ρ), our work uses the Euclidean distance which measures the distance between the RSS value acquired online (X, Y) (ob) and the expected offline training database RSS (X, Y) (expc) for each point of the network as presented in equation 1.

$$\rho_i = \sqrt{X_{obt} - X_{\exp ec}{}^2 + Y_{\text{obt}} - Y_{\text{expc}}{}^2} \quad (1)$$

Then, the mean error value for the point ρ, defined by ρp, is calculated as in equation 2. Note, n is equal to samples per Point in the environment.

$$\rho P = \frac{1}{n} \sum_{ip}^{n} \rho i \qquad (2)$$

$$\rho P = \frac{1}{n} \sum_{pp}^{n} \rho p \qquad (3)$$

The accuracy (*ρ)* is calculated as in Equation 3.

To determine the precision (δ), the standard deviation of the samples (ρi) grouped according to the expected point (δp) is calculated as in equation 4

Table:1 ANN Algorithms protocols with various parameters

ANN algorithms and Wireless protocols	Performance	Regression R	Precision (%)	Accuracy
Backpropagation Wi-Fi	0,0055	0,9859	73	3,35
Backpropagation Bluetooth	0,0068	0,985	63	0,42
Backpropagation ZigBee	0,0064	0,9844	67	2,03
Backpropagation with momentum Wi-Fi	0,0059	0,9844	72	0,64
Backpropagation with momentum Bluetooth	0,085	0,9859	65	2,95
Backpropagation with momentum ZigBee	0,061	0,9595	71	1,83
Leven-berg-Marquardt Wi-Fi	0,0062	0,998	69	0,89
Leven-berg-Marquardt Bluetooth	0,0064	0,995	70	2,15
Leven-berg-Marquardt ZigBee	0,0095	0,886	67	1,94

Table 1 summarizes the main differences between the three ANN algorithms that took into account performance, regression, precision and accuracy.

For all RNAs, the results of the regression analysis tests suggest a higher level of correlation with an increased positive value indicating a good match. In terms of accuracy, BP with trained BP performed better with the Wi-Fi protocol: 73%, followed by 72% for BPM with Wi-Fi and 71% for BPM with ZigBee protocol. With accuracy in mind, the average error was 0.42 meters for BP trained with Bluetooth, 0.64 meters for BPM trained with Wi-Fi and LM 0.89 meters for LM trained with Wi-Fi. The results presented in [14] are based on our best ANN architectures and on another level of QoS which improved accuracy by 17% for Wi-Fi, 11% for Bluetooth and 21% for ZigBee protocols.

V. CONCLUSION

As stated in Part I, the purpose of context-aware applications is to understand the location of mobile users and offer them dynamically personalized services. To achieve this goal, tools and agents must be integrated and assessed on what is possible through an agent-based approach. Our previous approach has been to present and evaluate LAM based user placement modules based on fingerprint techniques using ANN and QoS in existing wireless network infrastructure [14]. This experiment is the result of our first attempt to develop an indoor localization prototype using the MAS approach, [21] In addition, we compared the results of three guided ANN learning algorithms (BP, BPM and LM) with indoor location, trained with data from three wireless protocols (Wi-Fi, Bluetooth and ZigBee) based on fingerprint placement techniques. By analyzing the results of experiments, we can say that while the BP algorithm has slow convergence, it provides better performance in space localization than BPM and LM algorithms. In addition, using QoS with ANN can improve the accuracy of the results, as presented in the previous work [14]. For future work, we want to explore the possibility of increasing accuracy by adding other QoS levels and integrating them into the ZigBee, Wi-Fi and Bluetooth protocols. Using semantic resources, such as ontology, to characterize different texts, we plan to improve the delivery of relevant text-aware services to mobile users.

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