Indoor Cooperative Positioning Based on Fingerprinting and Support Vector Machines

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Abstract. For location in indoor environments, the fingerprinting technique seems the most attractive one. It gives higher localization accuracy than the parametric technique because of the existence of multipath propagation and fast fading phenomena that are difficult to model. This paper introduces a novel positioning system based on wireless the IEEE802.15.4/ZigBee standard and employs Support Vector Machines (SVMs). The system is cost-effective since it works with real deployed IEEE 802.15.4/ZigBee™ sensors nodes. The whole system requires minimal setup time, which makes it readily available for real-world applications. The resulting algorithm demonstrates a superior performance compared to the conventional algorithms.

Keywords: Location-based Services, Support Vector Machines, Radio Mapping, RSSI, Underground mines.

1 Introduction

Wireless sensor networks are becoming more and more popular in many areas such as agriculture activity, construction, industrial, manufacturing plants, large buildings, and so on. In these environments it is preferable to set up a wireless network rather than the traditionally wired sensor network because the flexibility and freedom that can provided. Based on the wireless infrastructure, a many new and promising applications are coming into our lives [1].

Even if the main applications of wireless sensor are security and environmental data monitoring, they can be used to locate and track people and objects. The technique is based on the received signal from a few anchors (node with known location) and some traditional location algorithm. This application is called the WSN positioning system [2].

Location tracking systems has brought tremendous benefits, especially to the mining industry; one of its benefits is to help keeping track of miners and equipment is a challenge in any the underground mines.

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To implement a successful WSN-based location application, the most important is to locate sensor node accurately, at least within an acceptable range, to pin-point the user's positioning.

In practice, two types of location techniques are used: the first one is based on received signal information [2]-[4] and the second is the fingerprinting technique [5]-[8].

In the first technique, an important factor is to find the mechanisms for physical distances/angles measurements [9]. Several techniques have been used. The most known are the angle of arrival (AoA), the received signal strength (RSS) and the time delay information (ToA).

However, the performance of this localization mechanism is largely determined by both physical distances measurements mechanism and radio propagation channel characteristics. As a result, this positioning algorithms may not provide optimum performance in indoor environments, which necessitates the design of new positioning algorithms for indoor geolocation systems

The second approach is fingerprinting technique. This technique assumed that the characteristics of the propagation signal are different at each location of the zone of interest. In other words, each location has a unique fingerprint or signature in terms of propagation characteristics [7].

The basic idea of the fingerprinting positioning algorithms is simple. Each location spot in the area of interest have a unique signature in terms of the RSS observed from different sensors. A fingerprinting technique determines the unique pattern features and then this knowledge is used to develop the rules for recognition.

This technique seems to be the most attractive particularly for indoor environments and small coverage areas. In fact, a judicious sensor network planning can significantly reduce the estimation errors of the location metrics caused by the both NLOS and multipath propagation condition. Therefore, the structural information of the sensor network can be easily employed in the intelligent positioning algorithms [9].

In this paper we present a new ZigBee–based sensor networks for localization in underground environments. Amongst all of the possibilities of choosing methods of positioning, we focused on the received signal strength method along with fingerprinting. So, in the first time, a measurement campaign was conducted in an experimental underground mine to collect the RSS from two transmitter sensors nodes. We use RSS as a metric instead of trying to extract the ToA or AoA which is more challenging task at the physical layer. Secondly, we introduce localization in a cooperative technique when two transmitters' nodes share the responsibility of estimating the position of mobile node.

After building the database, we introduce a new algorithm which uses the support vector machine technique as a matching algorithm to localize. Then we present the performance of localization algorithm in terms of mean localization squared error is evaluated.

The remainder of the paper is organized as fellows. Section 2 provides an overview of localization systems. The importance of the fingerprinting method is also examined. Section 3 describes the testbed development and discusses on the SVM which is used as the matching algorithm for localization. Section 4 provides the details of measurement scenarios and discusses on the result. Finally, Section 5 summarizes the results and discusses the future work which can be done through this testbed measurement.

2 An Overview of Fingerprinting Localization Techniques

The technique using the RSS fingerprint was applied for the first time in the RADAR system [5] for a mobile user's location on a second floor of a 3-storey building. It opened the door for many different techniques to be applied for the localization problem.

For example, Nibble [10] is one of the first systems to use a probabilistic approach for location estimation. To date, Ekahau's Positioning Engine Software [11] claims to be the most accurate location system based on probabilistic model; they claim a one-meter average accuracy with a short training time.

Statistical learning theory [12] and neural networks [6], [7], [8], have also been investigated for localization. Some works [13], [14] also try to aggregate localization data from different technologies (e.g., Wi-Fi and Bluetooth) in order to achieve finer accuracy.

Another emerging approach that has better accuracy and potential is Ultra wideband (UWB) technology. The large bandwidth provides high time-domain resolution which in return provides better ranging accuracy [15].

In underground mines, the geolocation can be placed in two main categories: commercial, like task optimization, logistic, traffic management in galleries and the most important factor, miners' safety.

Accurately predicting the location of an individual or an object definitely can be a difficult task producing ambiguous results because of the harsh wireless environment.

Few works have been carried out in underground mining environments [2], [6], [7], [8]. The characteristics of underground mining environments differ from other traditional indoor environments since the roughness of its walls leads to scattering of the RF signal. Thus, underground mining environments have specific radio propagation characteristics.

On one hand, the harsh site-specific multipath environment in underground mines introduces difficulties in accurately tracking the position of objects or miners. The growing interest and demand for such applications dictates examining position estimation more carefully. The underground mines propagation channel poses a serious challenge to system designers due to the harsh multipath environment.

On the other hand, the structural information of the wireless network can be used in the intelligent positioning algorithms. The small (relatively) coverage of underground mines, as compared without outdoor environment, makes it possible to conveniently conduct extensive pre-measurements in mine gallery.

The main contributions of this paper are:

(1) Investigate more profoundly on the location problem in indoor environment and particularly in underground mine. This task is considered as important for many applications.
(2) Developing a testbed for RSS-based indoor positioning systems.
(3) Using ZigBee signal as reference for our localization system. The current trend for localization is based on IEEE 802.11standard. However the main limiting factor of localization systems for underground mines is the absence of line of sight (LOS). In an underground mine, the surface and the architecture are often irregular. The localization system based on a wireless sensor network can

solve this problem. Instead of employing a few relatively expensive 802.11 access points, we can use several inexpensive ad-hoc sensor nodes to estimate the position of an object. In addition, it is easier to exploit the small size of ZigBee nodes compared to a PC Laptop for example.

(4) We adopt cooperative localization technique where more than one transmitter nodes shares the responsibility of estimating the position of the receiver node in experimental underground mines.

(5) We present an efficient algorithm based on SVM technique for location. The proposed algorithm is practical and scalable. The choice of this point is motivated by the high performance of SVM compared to other classification technique such as Neural Networks.

3 Design of Indoors Positioning System

Concurrently, there has been an increasing deployment of wireless sensor networks in many domains including mining industry. The popularity of wireless sensor networks opens a new opportunity for location-based services.

In our localization system, mobile node measure RSSI from two fixed nodes. The collected data is compared by this mobile node with a known data base in under to estimate his location.

3.1 Characteristics of the Sensor Nodes

When choosing deployment of WSN in underground mine, it should be necessary to make a compromise between conflicting requirements. The priority is to insure a robust global network with battery-operated nodes.

Wireless communication is achieved with a transceiver compliant with the IEEE 802.15.4/ZigBee^{TM} standard. ZigBee^{TM} is a global standard for wireless network technology that addresses remote monitoring, environmental data measurements and control applications. ZigBee^{TM} is an open specification that enables low power consumption, low cost and low data rate for short-range wireless connections between various electronic devices.

3.1.1 Hardware Description

The Silicon Laboratories 2.4 GHz 802.15.4 Development Board (DB) provides a hardware platform for the development of 802.15.4/ ZigBee^{TM} networks. The DB includes a Silicon Labs 8051-based MCU, a Chipcon CC2420 RF Transceiver, a JTAG (Joint Test Action Group or IEEE 1149.1 standard) connector for in-circuit programming, an assortment of programmable buttons and LEDs and a USB interface for connecting to the host computer.

3.1.2 Software Description

The 2.4 GHz ZigBee^{TM} development kit contains all necessary files to write, compile, download, and debug a simple IEEE 802.15.4/ ZigBee^{TM} -based application. The development environment includes an IDE, evaluation C compiler, software libraries, and a several code example. The software library includes the 802.15.4 MAC and PHY layers.

The ZigBee™ demonstration provides a quick and convenient graphical PC-based application. The kit also includes an adapter for programming and debugging from the IDE environment.

A Network Application Programming Interface (API) contains all necessary network primitives to build a 802.15.4 network from a user-defined application. A software example illustrates the MAC API. This example builds an ad-hoc 802.15.4 network using the included MAC API software library [16].

3.2 Support Vector Machines

SVMs (Support Vector Machines) are a useful technique for data classification. SVM is considered easier and more powerful than the Neural Networks [17].

Let $S' = (x', y')$ be the mobile node location to be determined, $\Theta' = [R'_A, R'_B]$ are the observed RSS vector form sensor A and B respectively.

A set of fingerprint is the radio signature of many known location. For each geographic location (x, y) a known vector Θ represented by:

$$\Theta = [R_A, R_B] \tag{1}$$

with $R_A = [RSS_{left}, RSS_{midle}, RSS_{right}]$

where R_A is the received signal from transmitter node A at three adjacent positions (located in left, middle and right), ditto for node B. So each physical location is characterized by six parameters.

When the mobile node changes his location, the parameter of vector Θ changed. We can get data sample $\mathrm{D} = [\Theta, S]$ by sampling $S(x, y)$ and $\Theta = [R_A, R_B]$ in grid. The input of D is RF signal (featured by RSSI) and output is location (coordinate).

Given training set (here $\mathrm{D} = [\Theta, S]$), the support vector machines require the solution of the following optimization problem:

$$\underbrace{\mathbf{min}}_{w,b,\xi} \frac{1}{2} \|\mathrm{w}^{\mathrm{T}}\mathrm{w}\| + \mathrm{C} \sum_{\mathrm{i}=1}^{\mathrm{N}} \xi_{\mathrm{i}} \tag{2}$$
$$\textbf{Subject to } (\mathrm{w}^{\mathrm{T}}\phi(\mathrm{x_i}) + \mathrm{b}) \geq 1 - \xi_{\mathrm{i}}$$
$$\xi_{\mathrm{i}} \geq 0$$

Here training vectors $\boldsymbol{x_i}$ are mapped into a higher dimensional space by the function $\boldsymbol{\phi}$. SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. C> 0 is the penalty parameter of the error term. Furthermore, $K(x, x') = \boldsymbol{\phi}(\boldsymbol{x_i})^{\mathrm{T}}\boldsymbol{\phi}(\boldsymbol{x_j})$ is called the kernel function.

We can change linear inseparable problem of (2) in lower dimension space into linear inseparable problem in higher dimensional space by kernel function $K(x, x')$. The optimization result is as follows:

$$S' = f(\Theta') = \sum_{i=1}^{N} \alpha_i K(\Theta, \Theta'_{\mathrm{i}}) + b \tag{3}$$

In localization phase, the input of system is the collected RSS vector $\Theta' = [R'_A, R'_B]$ of the mobile. The output of the system is the estimated location $S' = (x', y')$ of the mobile node.

We choose LS-SVM [18] to build model. LS-SVM is an improvement version of the standard SVM. It is simple-calculation, can improve convergence speed, and suitable for WSN for resource constraints. Here we chose the radial basis function (RBF) given by:

$$K(x, x') = \exp\left(\frac{|x-x'|}{2\sigma^2}\right) \quad (4)$$

The SVM-based localization mechanism is represented in figure 1.

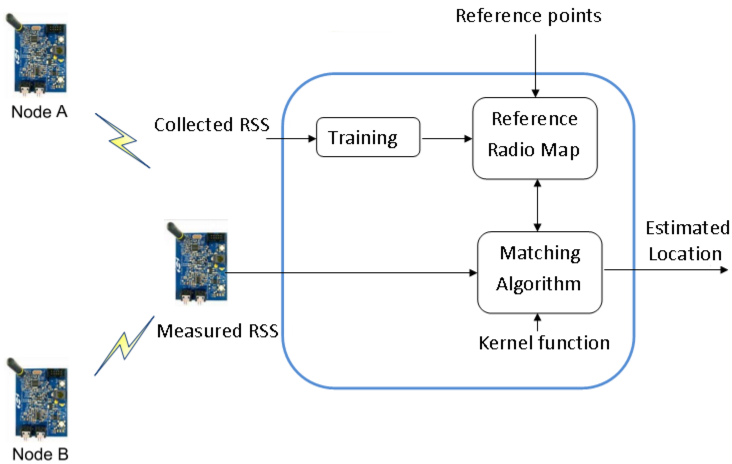

Fig. 1. Simulation procedure of sensor networks localization system

3.3 Closest Neighbor (CN)

Our algorithm will be compared with classical algorithm in pattern recognition class is called the closest neighbor (CN) or nearest-neighbor (NN) [19]. In this algorithm mobile sensor compares an observed RSS vector with all available fingerprints in the reference radio map and finds a reference point with the smallest Euclidean distance in signal space and reports that as the current location of the device. Suppose that MS observes Θ^′. The Euclidean distance between this vector and the k-th reference point entry in the radio Θ is given by:

$$d = \left(\sum_{i=1}^{N} (\Theta' - \Theta_i)^2\right)^{1/2} \quad (5)$$

The CN algorithm maps the location of MS to an entry on the radio map.

4 Measurement Setup and Results

4.1 Experimental Testbed

The measurement campaign necessary to build the fingerprints' database has been carried out in an underground mining gallery. Figure 2 shows digital picture of the underground mine gallery. It has a width of approximately 2.5 m, a length of 72 m and is located at 70 m below the level of the ground. Two transmitter node (Tx node A and B) are located on the ceil of the mine gallery.

Fig. 2. Illustration of underground mine gallery and the deployment of the node (A)

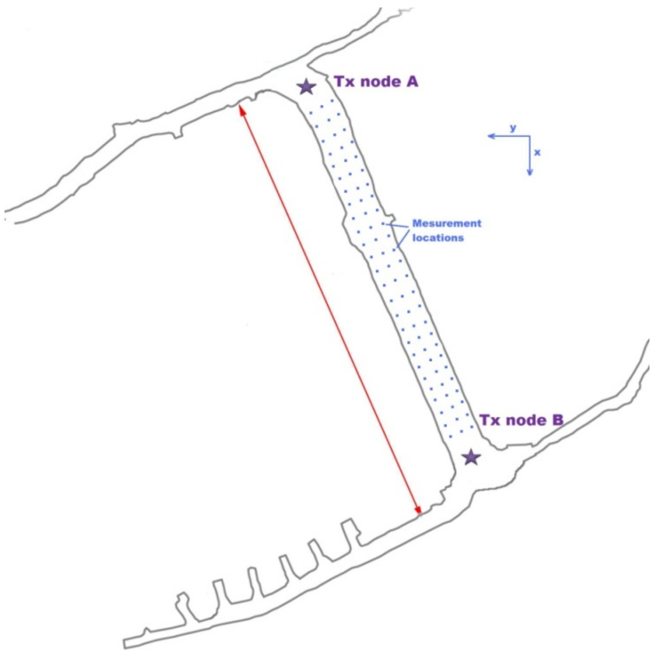

Fig. 3. Layout of the underground mining gallery used for measurements

The mobile node start form 1 m with regard to the node A (reference node) to 105 meter. The grid spacing between two adjacent mobile user's locations was set to 1 m along the x-axis and 0.8 m along the y-axis. At each location, the RSS value has been recorded in each three point (left, middle and right). A set of RSSs has been collected at 630 (105*3*2) different mobile user's locations. All the measurement locations are shown in Figure 3.

As for the pattern-matching algorithm, the SVM has been trained with the 530 location points leaving the remaining 100 points for localization purposes.

4.2 Reference Radio Map

In figure 4, received power measurements signatures are recorded follow the gallery long. The received power is recorded at uniform distance step from the source emitter following a route located at the gallery center, a route following the right lateral wall and the route following left lateral wall of the gallery. So for each separation distance three data were collected (middle, left, and right).

4.3 Separation of Location Fingerprint

The performance of indoor positioning systems depends greatly on the separation of location fingerprints. A location fingerprint corresponding to a location can be identified correctly if it is difficult to classify it (incorrectly) as another fingerprint by a pattern classifier [20].

Theoretically, a change in RSS is proportional to the logarithm of the distance between a transmitter and a receiver. Therefore, two different locations with different distances from the same transmitter node should have different average RSS values. However, in practice the RSS is a random variable that has its value fluctuating around the average value due to the dynamics in the environment. These fluctuating values can be grouped to get her as patterns of RSS at a particular location.

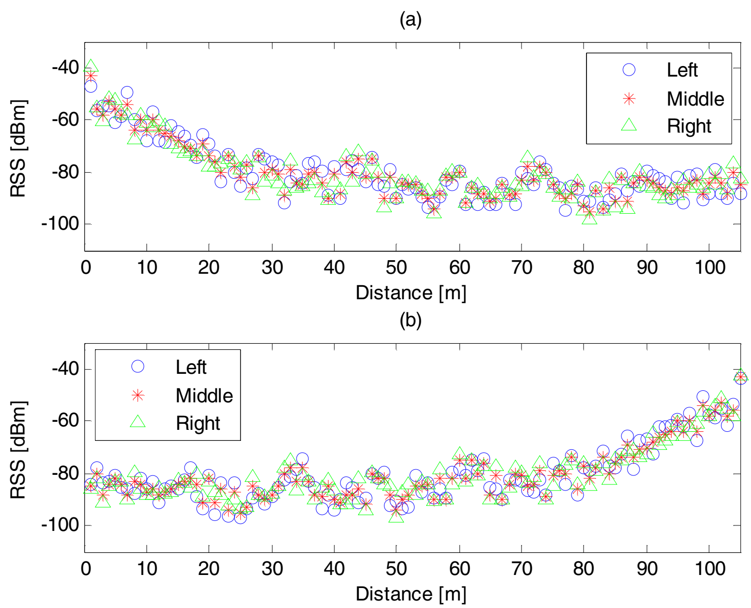

Fig. 4. The received power measurements signatures

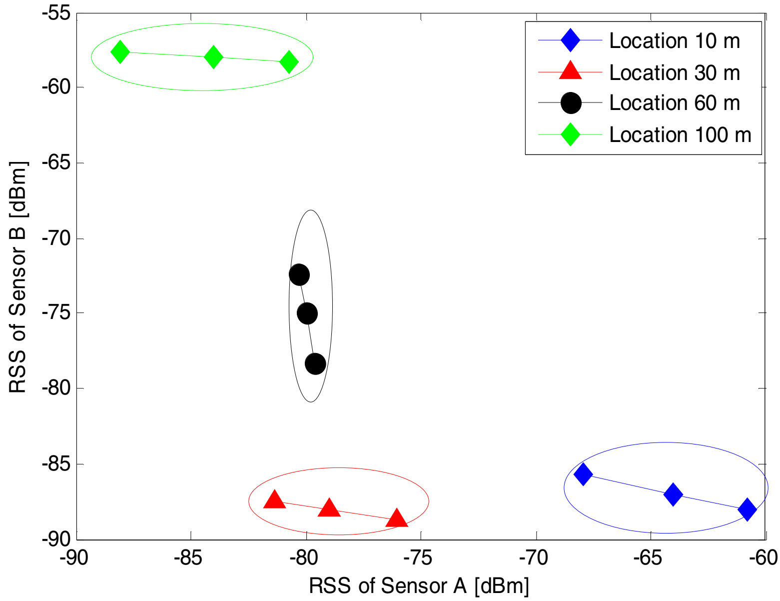

Fig. 5. Signature separation problem of four location

Figure 5 shows two-dimensional plots of patterns form node A (x-axis) and node B (y-axis). The group of patterns at each location can be called the location fingerprint of that particular location. From the plot, patterns of each location can be grouped together as a cluster.

This figure indicates that RSS's patterns can be separated by a separate cluster. Each signature is well distinct. This good indication is useful for localization mechanism.

4.4 Localization Results

The performance of the presented localization techniques will be evaluated using the CDF graph. The first two plots show the results of the SVM localization technique based on cooperative localization (node A and node B). The third plot represents the position errors when using SVM with only one transmitter node. The last plot shows the results of using the localization technique based on closet neighbor.

As shown in Figs. 6, closet neighbor algorithm provides the worst results. Form the results 3.03 meter of localization error is needed to cover 90 % of the testing data. The positioning error when only one transmitter is used is around 2.2 m for 90% of the testing data. However, when two nodes are used for localization (the cooperative localization), this error decrease to 1.45 m for 90 % of testing data. This can be explained by the size of signature location (six parameters instead of three when one transmitter is used).

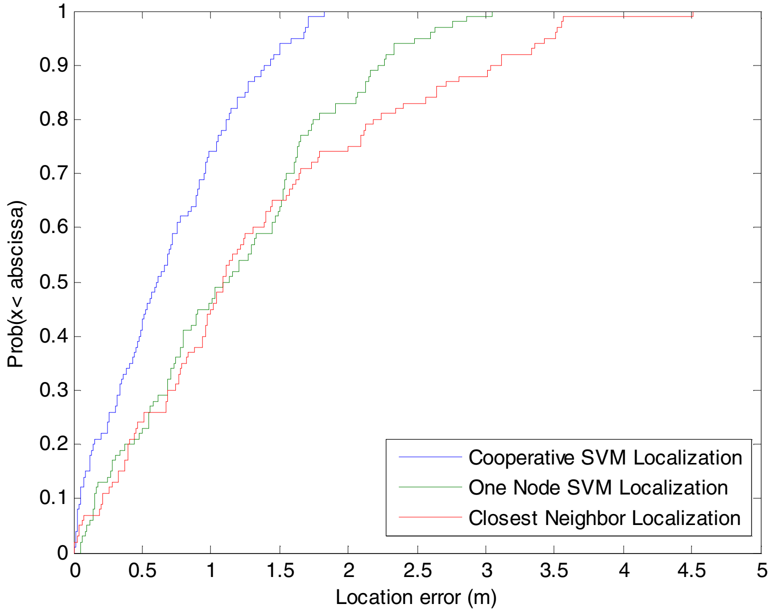

Fig. 6. CDF plots of the position estimation errors at a receivers' several localization techniques

5 Conclusion

This paper has described the implementation of a novel algorithm, based on a set of support vector machine (SVMs) applied to ZigBee RSS fingerprinting technique in an underground mining gallery. We investigated the performance of our system experimentally. The advantage of our technique is that it does not use coordinates, special hardware is not required, and it is simple and robust in dynamic environments. The performances in terms of localization accuracy of algorithm is evaluated and compared to a conventional algorithm. The experimental results showed that the percentage of measurement points where our system could localize the mobile node with a median distance error of 0, 67 m. The algorithm performs slightly better than the conventional closet neighbor algorithm (median error distance is 1. 4 m).

In the future our algorithm will be compared with other more sophisticated algorithm such as generalized radial neural network.

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