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Human positioning estimation method using received signal strength indicator (RSSI) in a wireless sensor network

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Abstract

Wireless sensor networks continue to advance due to the recent dramatic progress in sensor devices. The innovative use of the received signal strength indicator (RSSI) will yield new applications in human position estimation, an important function in safe and secure services, especially for the elderly, and energy efficiency in small areas or homes. This paper proposes a simple method for estimating human position, together with a new signal processing procedure that uses RSSI. This method is simple and has the exciting benefit of compatibility with existing devices and existing wireless sensor networks, the current RSSI function is employed more effectively. Two experiments verify the performance of the proposed method. An experiment in a laboratory building showed good performance with 100 % accuracy. However, in an actual field trial in a library hosting several wireless sensor devices its accuracy fell to 75 %. Estimation performance is expected to improve with the use of multiple paths.

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Keywords: Wireless sensor network ; RSSI ; Human positioning ;

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1. Introduction

Sensors continue to advance in pace with technologies such as MEMS (Micro Electro Mechanical System), higher speed interfaces, and larger scale memories. As a result, sensors are becoming smaller in volume, lighter, more durable, less power consuming, and smarter/more intelligent. Their combination with ICT (Information Communication Technology) has yielded new sensor systems, sensor networks that can support a variety of innovative functionalities. In such systems, information coming from a lot of sensors could be integrated to produce new and unexpected results. Therefore, sensor systems are being installed everywhere for environmental management (a major traditional service), security systems covering large areas, building and geologic diagnostic systems for predicting disasters, and diagnostic systems for human health.

The authors' laboratory has conducted several studies on content transfer applications based on wireless sensors and sensor networks, with focus on the vital human information captured by wearable sensor(s)[1,2] and the environmental information captured by sensors[3,4]. Our studies have considered acceleration, angular velocity, pressure, heart rate, and FIR (Far InfraRed) image sensors for the former application, and temperature, humidity, illumination, and FIR image sensors for the latter application. Regardless of the type of sensor used, the basic information transfer process is virtually the same for all applications. In a sensor-based content transfer application, the sensors/sensor network captures environmental information, which is then processed to reduce its volume or to indicate status. Event (alert)/raw data is then transferred via a network to a node/station which extracts context and takes the appropriate action.

While researching sensor network applications, we noticed that human location recognition is still an issue, even in homes or small areas with very simple structures. The need for improvements remains even though several technologies have been proposed to recognize humans themselves and/or their location.

The most popular approach uses still/motion cameras and image processing[5]. FIR cameras[6] are also used with extended functionality to cover low light occasions e.g. at night. Cameras offer high performance in finding humans, or to recognize specific individuals. This clearly raises privacy concerns.

The use of ultrasonic sensors is another solution. However, a lot of sensors need to be installed for precise estimation and installation costs are high.

Pressure sensors located on the floor can easily capture human movements if they are widely distributed. However, installation costs are high if the floor is already constructed.

Laser range finders are a powerful tool for finding a human with high precision. Their high directivity means that only small areas can be covered.

To use the received signal strength indicator (RSSI)[7] of wireless sensor networks is another solution. This method is simple and precludes the need to alter existing devices or install new devices in an existing wireless sensor network, all that is need is to process the received signal strength values.

Several related studies on RSSI use for indoor human location have been published. References[9-13] present comparisons of location systems using UWB, RSSI, GPS, Bluetooth, Wireless LAN, GSM/CDMA, RFID, etc. Today, RF (Radio Frequency) techniques are commonly used in location systems since they need less hardware than other approaches, and exhibit lower estimation error compared to GPS and GSM/CDMA. For example, a location method using ZigBee nodes and RF signal strength has been proposed[14]. Moreover, an indoor UWB-based person detection technique has been proposed in reference[15]. In reference[16], the fluctuation in ZigBee's RSSI is used to estimate crowd behavior. A tracking system based on the RSSI of a wireless sensor network has been proposed in reference[17]. However, most of the current proposals that use RF techniques for indoor localization aim to estimate strict coordinate position of a user/object. On the contrary, this paper aims to estimate the presence (a user exists or not) in a certain region populated by several sensors. By scatting sensors in a room, the system can estimate regions in which users exist. Even though this proposal is based on RSSI, its direction differs from current research. In reference[18], a self-localization method based on RSSI has proposed. This method is relatively similar to our proposal in that it determines whether the user is located in a particular area or not. However, each user is required to have a communication device with a wireless LAN interface such as smartphone. In this paper, users are assumed to have no special communication device or tag.

This paper proposes a human position estimation method that uses the received signal strength indicator (RSSI) of a wireless sensor network, together with a new signal processing procedure. Its feasibility and performance are verified by two experiments.

The structure of this paper is as follows: Section 2 introduces an outline of the system image. Section 3 describes the two experiments and the procedure proposed for estimation. The results and performance of the estimation are given in Section 4. Section 5 gives a conclusion and future work.

2. System image

The proposed system judges whether or not a human exists in a path between a transmitter (Rx) and a receiver (Rx) in a wireless sensor network in a small area or home by processing the received signal strength indicator (RSSI) values. Figure 1 (a) depicts the basic system configuration as consisting of multiple Txs and Rxs. Each Tx has one or more sensors capturing, say, environmental information. The RF signal on the related path (pij: the path between Tx_i and Rx_j) is basically stable if nothing disturbs the link. However, the presence of object(s) on the path i.e. between a Tx and a Rx, disturbs the RF signal so the signal strength varies over time as illustrated in Fig. 1(b). The system recognize someone or object exists on the path if the signal variation exceeds some threshold. The process unit (PU) in Fig. 1(a) realizes not only captured signal processing, but also RSSI processing.

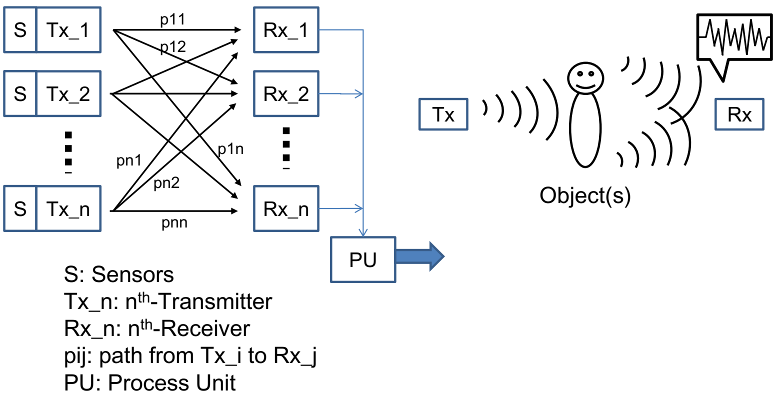

Fig. 1. (a) Basic configuration of the proposed system; (b) RF signal influenced by object(s) on the path.

3. Experiments to verify the feasibility of proposed method

In order to verify the feasibility of the proposed method, the following two experiments were conducted in a test room of the university building and the university library (actual field), respectively.

3.1. Experimental setup

ZigBee terminals (MOTE SN21140J and BU2110J, Crossbow[8]) hosting temperature, humidity, and light intensity sensors were used in the experiments. They operate in the 2.4 GHz frequency range. RSSI values are obtained by using the pre-installed function of the product.

The first experiment, which verifies the feasibility of the proposed estimation method, created two areas with 4 Txs and 2 Rxs as depicted in Fig. 2. Each area occupied 1.5 x 1.1 x 2.0 m (L x W x H). These dimensions replicate the field experiment in the university library; i.e. space between book shelves, see Fig. 3 (a).

For the second experiment that verifies the performance of the proposed method and obtains technical issues in the actual field, almost the same arrangement as the first experiment is set as depicted in Fig. 3 (b) where additional areas (area 0 and 4) plus human images are just depicted for further explanation.

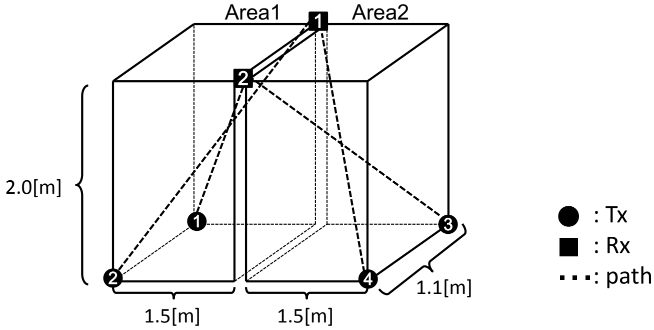

Fig. 2. Experimental configuration where 4 Txs and 2 Rxs are located. Size of each area is set to 1.5 x 1.1 x 2.0 m (L x W x H).

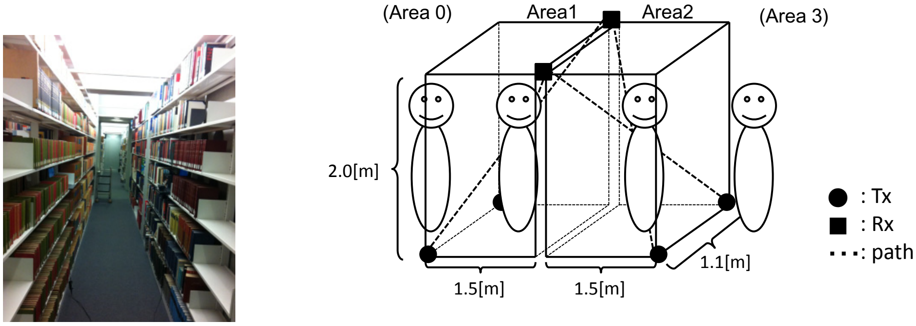

Fig. 3. (a) Photo of the space between book shelves in the university library; (b) Location of the Txs and Rxs between book shelves. Area match those in Fig. 2.

3.2. RSSI signal processing

The proposed system recognizes that someone or object exists on the path if signal variation differs from that when nothing is present. Its detailed procedures are as follows:

i) Acquiring baseline data in advance.
- Measure RSSI values on each path (pij) for a given time period, and
- Calculate standard deviation (SD) of each path.

ii) Estimation whether object (human or other) exists or not.
- Measure RSSI values on the paths in the region of interest (ROI), or specific area,
- Calculate SD of the paths,
- Calculate the sum of squared error (SSE) according to equation (1) given below, and
- Judge, for the area, whether object exists or not by comparing results of SSE output by the equation for the two conditions.

$$SSE_i = \sum_{x=1}^{n} (\sigma^{l}_{i,x} - \sigma^{m}_{i,\min(1 \le x \le n)})^2 \tag{1}$$

where i corresponds to the condition (present or not present) of the area, σ^l to the standard deviation (SD) of the baseline data for path x, and σ^m to the SD of the measured data for the path x under condition i. It is noted that *min* in the equation means to choose the minimum value among those for different paths.

This equation is an enhanced version of the previously proposed method[7]. In preliminary experiments conducted by the authors, the previous method[7] resulted in somewhat lower performance, or detection rate.

4. Experimental results and discussion

Figure 4 shows examples of measured RSSI values in area 1 in the laboratory, see Fig. 2. Left-hand values were gathered with no one present, and right-hand values with one human present. Two paths, p12 and p21 that cross each other were used. As shown in the figure, the received signal is basically stable with no one present, but varies a lot when someone is present.

SDs of these measured values were used as the baseline data as indicated in Section 3.2.

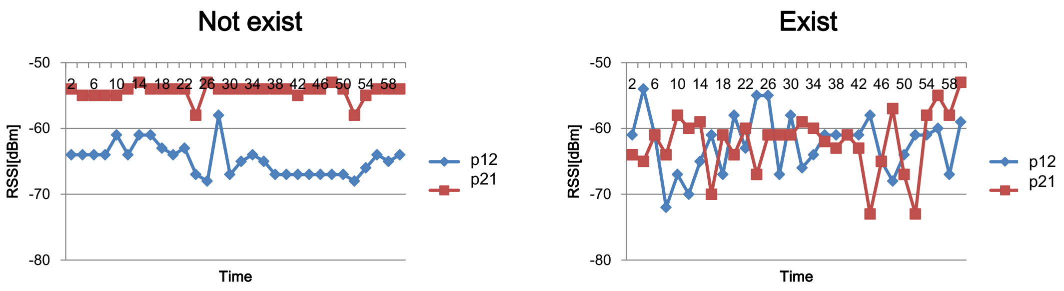

Fig. 4. Examples of measured RSSI value (a) no one is present on paths p12 and p21, and (b) a human is present.

Table 1 gives the results of the first experiment. Numbers in each cell corresponds to the calculated SSE. Case I corresponds to “no one present” in area 1 or area 2. Case II corresponds “someone present in area 1” while case III to “present only in area 2”. Not exist/ exist in area 1/2 described in the first row means that SSE was derived from the baseline data in area 1/2.

Bold numerical results for area 1/2 in the table correspond to the smaller value than others, or estimated condition in each area. In addition, G after the number expresses a good result where the estimation and the formation set are in accordance with each other. Therefore, in this experiment, 6/6 (=100 %) conditions were estimated.

Table 2 gives the results of the second experiment. Numbers in each cell also correspond to the calculated SSE. Cases I to III are the same as in the first experiment. Case IV corresponds to “people present both in area 1 and area 2.” Case V and IV correspond to someone exists in just outside area 1 (area 0) or 2 (area 3), respectively. Since the first experiment examined only a simple configuration, the second one considered other possible cases.

In this table, NG after the number expresses a not good result where the estimation and the human status are not in accordance with each other. As seen in the table, for area 1, some cases yield poor results while area 2 always achieves 100 % performance. However, for both areas, 9/12 (=75 %) could be correctly estimated. The reason why accuracy was reduced that the structure of location examined was a bit complex with a lot of shelves and books mixed together. And only two paths were used for estimation of all cases. This is the cause of the larger error.

Table 1. Experimental results conducted in the laboratory building. Numbers in each cell corresponds to the SSE calculated.

Case	Human status	Area 1 Not exist	Area 1 Exist	Area 2 Not exist	Area 2 Exist
I	No-one	**0.091 (G)**	14.1	**0.558 (G)**	17.6
II	Area 1	10.0	**0.241 (G)**	**1.36 (G)**	5.32
III	Area 2	**0.006 (G)**	12.4	37.1	**7.25 (G)**

G: Good result

Table 2. Experimental results conducted in the field (in the University Library).

Case	Human status	Area 1 Not exist	Area 1 Exist	Area 2 Not exist	Area 2 Exist
I	No-one	**0.358 (G)**	23.5	**2.01 (G)**	32.5
II	Area 1	**1.27 (NG)**	10.3	**3.46 (G)**	37.8
III	Area 2	**0.729 (G)**	26.6	7.99	**2.21 (G)**
IV	Area 1&2	**4.53 (NG)**	4.80	7.46	**2.51 (G)**
V	Area 0	8.71	**1.86 (NG)**	**0.428 (G)**	24.1
VI	Area 3	**0.139 (G)**	16.3	**2.53 (G)**	7.49

G: Good result
NG: Not good result

5. Conclusion and future work

Human position estimation is an important goal for realizing services that offer safety and security, especially for the elderly, and greater energy efficiency, even in small areas or the home. Our proposal combines a simple method with a new signal processing procedure that uses the received signal strength indicator (RSSI) in a wireless sensor network for estimating human presence. This method is simple and has the benefit of running on existing devices and existing wireless sensor networks.

Two experiments were conducted to verify the performance of the proposed method. The first experiment in a laboratory building showed good performance. However, the second experiment used a more complex site in the university library, where several wireless sensor devices have already been installed to capture environmental information for managing environmental circumstances, or energy effectiveness, there might be further issue to obtain higher performance. This might be caused by the complex structure examined and by just two paths usage for estimation.

Future works include enhancing the signal processing procedure to handle a larger number of paths in order to obtain higher performance. Use of a different frequency range, e.g. 800 MHz will also be considered.

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