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Research Article

A Fusion Approach of RSSI and LQI for Indoor Localization System Using Adaptive Smoothers

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Due to the ease of development and inexpensiveness, indoor localization systems are getting a significant attention but, with recent advancement in context and location aware technologies, the solutions for indoor tracking and localization had become more critical. Ranging methods play a basic role in the localization system, in which received signal strength indicator- (RSSI-) based ranging technique gets the most attraction. To predict the position of an unknown node, RSSI measurement is an easy and reliable method for distance estimation. In indoor environments, the accuracy of the RSSI-based localization method is affected by strong variation, specially often containing substantial amounts of metal and other such reflective materials that affect the propagation of radio-frequency signals in nontrivial ways, causing multipath effects, dead spots, noise, and interference. This paper proposes an adaptive smoother based location and tracking algorithm for indoor positioning by making fusion of RSSI and link quality indicator (LQI), which is particularly well suited to support context aware computing. The experimental results showed that the proposed mathematical method can reduce the average error around 25%, and it is always better than the other existing interference avoidance algorithms.

1. Introduction

Due to the ease in deployment, inexpensiveness and potential applications in the smart building, security, and healthcare, indoor localization system gets significant attentions in these recent years. Mobile positioning has become increasingly interesting system most notably for context-aware application and emergency services, which works in ad hoc manner. Global positioning system (GPS) has been the mainstream technology for location and tracking for outdoor environment but the positioning within indoor environments does not permit a positioning with GPS (or only with poor quality). It generally requires a direct view to several satellites, resulting in limited performance for indoor environments. GPS signal in an indoor environment is too faint to provide sufficient accuracy. Development of non-GPS-based solutions is thus of great interest for indoor use based on existing signals and hardware, as well as new systems and sensor modalities.

A number of commercial systems and research prototypes are developed with different kinds of localization methods. This method usually use infrared (IR) [1], ultrasound [2–4], or radio-frequency (RF) system [5–7]. Different sensors provide a different range of accuracy from centimeters to room level. It seems as if the accuracy is smaller than a room. But in practice, when we directly transform (x, y) coordinates to room level information, it often causes mistakes. The reason is that the wireless signal is easily disturbed, making localization unusual jumping in a split second or over a short span, and such situations may affect the location estimation from one room to another. Infrared system has been popularly used for containment-based location systems [1]. The response speed of infrared transducers allows a fair amount of data to be transmitted.

Although localizing techniques using ultrasound have been actively researched because ultrasound has a number of merits such as low cost and relative easiness of application; but, ultrasound is still considered as a low-guaranteed sensor since it is too sensitive to be used for precise localization. RF-based positioning systems are probably the most popular for indoor tracking. But there is a significant amount of time that the localization accuracy may suffer from the bursts of background noise [8]. The reason was investigated by recent experimental studies [9], which show that the various indoor fading effects are the main causations of the localization error [10]. The fading effects can be divided into the slow fadings and the fast fadings. Slow fadings are effects caused by the environment, such as the radio block or shadow fading. Fast fading is temporary or random effect, such as the interference, random noise, and the multipath effects. They work together making the RSSI value hard to predict the distance, thus introducing a large localization error. Current localization systems use different methods to improve the localization accuracy.

Mainly these algorithms are categorized into two—signature based and beacon based. Most indoor localization systems employ an RSSI-signature-based approach which exploits temporal stability in the RSSI of wireless signals. In that, at every known location, the RSSIs collected from a set of predeployed beacons form an RSSI signature for the corresponding location. When a target carrying a receiving tag enters the space, the RSSI values collected on the tag are compared to the RSSI signatures. The location of the target is identified by the corresponding location with the closest RSSI signature. To tackle the temporal variation of RSSI signatures, methods of ensuring robust mapping between the measured RSSI values and the prerecorded RSSI signatures have been studied intensively in recent years [11]. *RADAR* was one of the first RF signal strength-based positioning system used to track people inside buildings [6]. The major disadvantages of the fingerprinting method include the need for dense training coverage and poor extrapolation to areas not covered during training.

In contrast to fingerprinting, model-based positioning techniques express the RF signal attenuation using physics-based "path loss" model [12, 13]. From an observed RSSI, these methods triangulate the person based on a distance calculation from multiple access points. However, the position-RSSI relationship is highly complex due to multipath, metal reflection, and interference noise. Thus, the RSSI propagation may not be adequately captured by a fixed invariant model.

In this paper, the proposed protocol improves the existing algorithms using RSSI and LQI values. RSSI and LQI [13] are considered as two parameters which play a pivotal role in the beacon-based localization of sensor nodes. Typically RSSI is a measure of dBm, which is ten times the logarithm of the ratio of the power (P) at the receiving end and the reference power (P_{ref}). Power at the receiving end is inversely proportional to the square of distance.

Hence, RSSI could potentially be used as an indicator of the distance at which the sending mote is located from the receiving mote. When data from many such neighboring motes are combined, the location of the sending mote can be judged with reasonable accuracy. The localization systems presented in this paper are based on the RSSI as a strength indicator and LQI as a quality indicator of a received packet and it can also be used to estimate a distance from nodes to reference points. The LQI has been used as an assistant indicator of RSSI indicator. The proposed protocol provides a filtering process of an object based on its distance.

Table 1: Low and high RF range of LQI and RSSI.

	Low RF	High RF
LQI	105	108
RSSI	−75 dBm	−25 dBm

LQI exhibits a very good correlation with packet loss and is therefore a good link quality indicator. However, one of the contributions of the present work is to show that RSSI is a reasonable metric if it is processed correctly, and if interference can be distinguished from noise. Given that LQI is a superior metric, it should not be forgotten it is only made available by 802.15.4-compliant devices. It therefore makes sense to make the most out of RSSI. Low and high RF range of LQI and RSSI is depicted in Table 1.

In our paper we use an adaptive filter as it performs well to track an object under such changing conditions in the RF signal environment. In this paper, the proposed protocol tries to improve the existing algorithms [5, 13], using RSSI and LQI values. The indoor localization systems presented in this report are based on the RSSI as a strength indicator and LQI as a quality indicator of received packets. It can also be used to estimate a distance from a node to reference points. This system uses the LQI and RSSI in a different way and therefore it could lead to better and more predictable results than the other existing system. Several experiments were conducted to investigate the performance of the proposed scheme. Firstly, this system performs with respect to the signal analysis to understand the characteristic of the LQI and RSSI values on three types of environments to decide how the environment effects on RSSI and LQI strength. The effect of distance on received signal strength (RSS) can be measured by RSSI and LQI provided by the radio. Secondly, this scheme performs with respect to the signal analysis which is to filter the original signals in order to remove the noise. Besides, the noise could be estimated by using adaptive filtering algorithms. Sudden peaks and gaps in the signal strength are removed and the whole signal is smoothed, which eases the analysis process. We propose three different types of new filtering to smooth the real RSSI, that is, "LQI" filtering, fusion filtering, and "BOTH" filtering, and compare the results.

The remainder of this paper consists of six subsections. Section 2 describes brief explanation of some properties of RSSI, LQI, and two simple filters which could be used to smooth the RSSI values. In addition, it also explains the proposed localization algorithm briefly. Section 3 reveals the experimental testbed. The system implementation of "A Fusion Approach of RSSI and LQI for Indoor Localization System using Adaptive Smoothers" and its probability of returning the correct location are explained in Section 4. Section 5 compares the experimental performance. And Section 6 concludes the section with conclusions.

2. System Configuration

This section gives a brief explanation about RSSI, LQI, and two common filters, which are simple averaging and feedback filters and then will focus on how this effective protocol has been implemented, and implementation issues were considered. To measure the radio strength, two useful radio hardware link quality metrics were used in this experiment, that is, (i) LQI and (ii) RSSI. Specifically, RSSI is the estimation of the signal power and is calculated over 8 symbol periods, while LQI can be viewed as chip error rate and is calculated over 8 symbols following the start frame delimiter (SFD). The specific point in a system where position estimates are calculated is an important design parameter. In this scheme, the mobile device itself calculates the position. The device calculates its own position based on its own measurements.

2.1. Received Signal Strength Indicator (RSSI). Majority of the existing methods leverage the existence of IEEE 802.11 base stations with powerful radio transmit powers of approximately 100 mW per base station. Such radios are in a different class from the low power IEEE 802.15.4 compliant radios that typically transmit at low power levels ranging from 52 mW to 29 mW. The wide availability of larger number of IEEE 802.15.4 radios has revived the interest for signal strength-based localization in sensor network. Despite of rapidly increasing popularity of IEEE 802.15.4 radios and signal strength localization, there is a lack of detailed characterization of the fundamental factors contributing to large signal strength variation. The analysis of RSSI values is needed to understand the underlying features of location-dependent RSSI patterns and location fingerprints. An understanding of the properties of the RSSI values for location can assist in improving the design of positioning algorithms and in deployment of indoor positioning systems. The characteristics of RSS will decrease with increased distance as the equation shows below:

$$\text{RSSI} = -(10n \log 10\, d + A), \tag{1}$$

where, n: signal propagation constant, also named propagation exponent; d: distance from sender; A: received signal strength at a distance of one meter.

Lots of localization algorithms require a distance to estimate the position of unknown devices. One possibility to acquire a distance is measuring the RSS of the incoming radio signal. The idea behind RSS is that the configured transmission power at the transmitting device (PTX) directly affects the receiving power at the receiving device (PRX). According to Friis' free space transmission equation, the detected signal strength decreases quadratically with the distance to the sender (Figure 1(a)):

$$\text{PRX} = \text{PTX} * \text{GTX} * \text{GRX} \left(\frac{\lambda}{4\pi d}\right)^2, \tag{2}$$

where, PTX: transmission power of sender, PRX: remaining power of wave at receiver, GTX: gain of transmitter, GRX: gain of receiver, λ: wave length, and d: distance between sender and receiver.

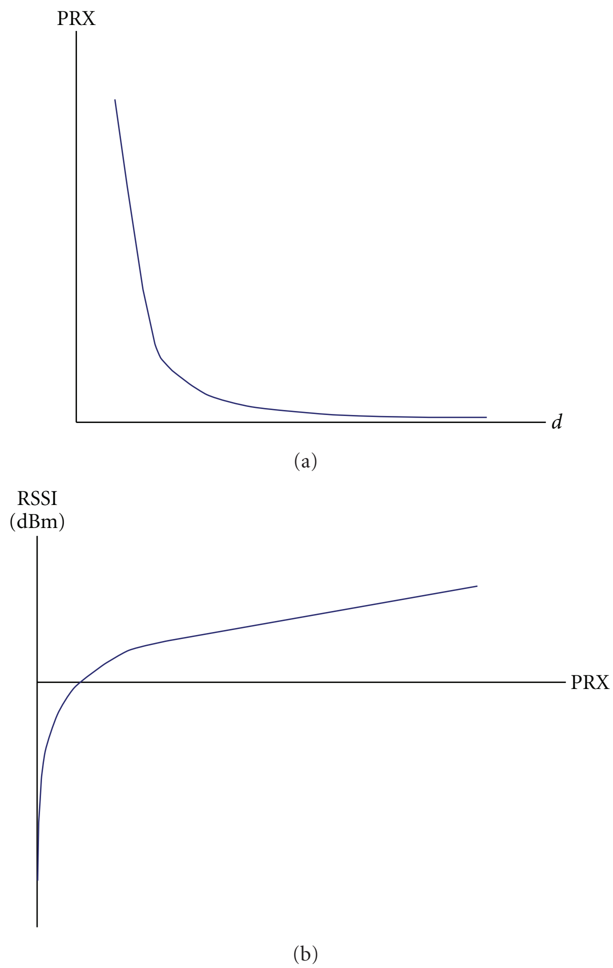

Figure 1: (a) Received power PRX versus distance to the transmitter. (b) RSSI as quality identifier of the received signal power PRX.

In embedded devices, the RSS is converted to RSSI which is defined as ratio of the received power to the reference power (P_{Ref}). Typically, the reference power represents an absolute value of $P_{\text{ref}} = 1$ mW.

$$\text{RSSI} = 10 * \log \frac{\text{PRX}}{\text{PRF}} [\text{RSSI}] = \text{dBm}. \tag{3}$$

An increasing received power results a rising RSSI. Figure 1(b) illustrates the relation between RSSI and the received signal power. Plotting RSSI versus distance "d" results in a graph, which is in principle axis symmetric to the abscissa. Thus, distance "d" is indirect proportional to RSSI. In practical scenarios, the ideal distribution of PRX is not applicable, because the propagation of the radio signal is interfered with a lot of influencing effects.

2.2. Link Quality Indicator (LQI). For communications IEEE 802.15.4 radios provide applications with information about the incoming signal [14]. The effect of distance on RSS can be measured by the packet success rate, RSSI, and LQI provided by the radio. LQI is a metric introduced in IEEE 802.15.4 that measures the error in the incoming modulation of successfully received packets (packets that pass the CRC criterion). The LQI metric characterizes the strength and quality of a received packet. It is introduced in the 802.15.4 standard [15] and is provided by CC2430 [14]. LQI measures each successfully received packet and the resulting integer ranges from 0×00 to $0 \times \mathrm{ff}$ (0–255), indicating the lowest and highest quality signals detectable by the receiver (between −100 dBm and 0 dBm). The correlation value of LQI range from 50 to 110 where 50 indicates the minimum value and represents the maximum. The 50 is typically the lowest quality frames detectable by CC2430. Software must convert the correlation value to the range 0–255, for example, by calculating

$$\mathrm{LQI} = (\mathrm{CORR} - a) \cdot b, \tag{4}$$

where, CORR: correlation value and a and b are found empirically.

The CORR (correlation value) is the raw LQI value which can be obtained from the last byte of the message. The raw value can be gotten from CC2430 (CORR) which is between 40 and 110. Limited to the range 0–255, "a" and "b" are found empirically based on PER measurements as a function of the correlation value. A combination of RSSI and correlation values may also be used to generate the LQI value. LQI values are uniformly distributed between these two limits. Different form RSSI, LQI measures the qualities of links while RSSI measures the strengths of links. LQI is a measure of the error in the signal, not the strength of the signal. A "weak" signal may still be a very crisp signal with no errors and thus a potentially good routing neighbor. If there is no interference from other 2.4 GHz devices, then LQI will generally be good over distance. Note that scaling the link quality to an LQI, compliant with IEEE 802.15.4, must be done by software. This can be done on the basis of the RSSI value, the correlation value, or a combination of those two. Signal strength and link quality values are not necessarily linked. But if the LQI is low, it is more likely that the RSSI will be low as well. Nevertheless, they also depend on the emitting power. Even though they do not describe how far from each other the sender and the receiver are located, it illustrates perfectly that both low and high power emissions guarantee a good link quality. The low RF emissions could be more sensitive to external disturbances. LQI exhibits a very good correlation with packet loss and is therefore a good link quality indicator. However, one of the contributions of the present work is to show that RSSI is a reasonable metric if it is processed correctly, and if interference can be distinguished from noise. Given that LQI is a superior metric, it should not be forgotten that it is only made available by 802.15.4-compliant devices. It therefore makes sense to make the most out of RSSI.

Various filters can be used to smooth the RSSI value [7, 8, 16, 17]. Two common filters are simple averaging and feedback filters. Averaging is the most basic filter type, but it requires more data packets to be sent. Feedback filters use only a small part of the most recent RSSI value for each calculation. This requires less data, but increases the latency when calculating a new position.

2.2.1. Averaging Filter. The average RSSI value is simply calculated by requiring a few packets from each reference node, each time the RSSI values are measured and calculated according to the equation below:

$$\overline{\mathrm{RSSI}} = \frac{1}{n}\sum_{i=0}^{i=n}\mathrm{RSSI}_i. \tag{5}$$

2.2.2. Feedback Filter. If a filter approximation is used, this can be done as shown below. In this equation the variable $a$is typically 0.75 or above. This approach ensures that a large difference in RSSI values will be smoothed. Therefore, it is not advisable if the assets that should be tracked can move long distances between each calculation:

$$\mathrm{RSSI}n = a * \mathrm{RSSI}n + (1 - a) * \mathrm{RSSI}n - 1. \tag{6}$$

This means that the averaged RSSI value corresponding to the signal strength at distance depends on both the previous averaged value and the most recently measured value. As the value of "a", which should be between zero and one, determines the degree of filtering if "a" is chosen to be close to one; the new measurement barely plays a role in the calculation of the new average. If on the other hand the value of "a" is nearly zero, virtually no filtering is performed. An optimal filter, that is, a value for "a", specifically for this project will be determined in this section. In this paper we are going to propose three filtering processes. At first, we use an LQI filter to smooth the RSSI value. In our second filtering process, we proposed a fusion filter which is the fusion of RSSI and LQI where we decided to use LQI as a reference aid when the RSSI or LQI is below RSSI and LQI threshold. Lastly, we proposed a BOTH filter, which is also a fusion of RSSI and LQI where we decided to use LQI as a reference aid when the RSSI or LQI is below RSSI or LQI threshold.

2.3. Localization Algorithm. This scheme decides to use a private and scalable system. It features an active base station that transmits both RSSI and LQI signals. The mobile devices receive the signals, but they do not transmit anything themselves. The base station transmits the RSSI and LQI signals at the same moment in time. A mobile device measures signal and is able to calculate the distance to the transmitter. By this scheme the location privacy of the user, who carries the mobile device, can be easily guaranteed because the mobile device does not send out any signals that might disclose its presence or its location. A further advantage of this architecture is scalability to many mobile devices. As the mobile devices do not transmit any signals, there can be an unlimited number of mobile devices in principle. Due to its privacy and scalability features, this architecture might be particularly suitable for large-scale professional location systems or systems in public spaces. Each mobile device calculates its own position, based on the received signals.

As we know, for environmental change the log model also changes, so the proposed system uses a scaling factor for adjusting the log model with the measured data. This system includes a scaling factor "s" with the basic RSSI log model equation, which adjusted the log model based on the received signal:

$$\mathrm{RSSI} = -10n\log_{10}(sd+1)+A. \tag{7}$$

To get the best performance of filtered data, this scheme uses triplicate filtering process for smoothing the received RSSI data. To do this experiment, we determine the value of filtering factor "a" and applied that value to the existing feedback filtering equation. To filter the received RF signal, firstly we applied the LQI filter based on the received packet quality. For our second experiment we used a fusion of LQI and RSSI values based on the filtering conditions to smooth the measured RSSI. There is a detail explanation in section IV-B. BOTH filter is our last experiment, where we filter the received RSSI values with both LQI and RSSI values. Section IV-C gives a detail explanation about this filtering process.

We apply the LQI filtering by using the following equation:

$$\mathrm{smooth\_RSSI}_{t(\mathrm{LQI})} = a * \mathrm{RSSI}_t + (1-a) * \mathrm{RSSI}_{t-1}. \tag{8}$$

Secondly, we proposed a fusion filtering of RSSI and LQI values, for smoothing the measured RSSI:

$$\mathrm{smooth\_RSSI}_{t(\mathrm{Fusion})} = a * \mathrm{RSSI}_t + (1-a) * \mathrm{RSSI}_{t-1}. \tag{9}$$

At last we proposed a BOTH filtering of RSSI and LQI values, for smoothing the measured RSSI. Then we compared the resulted values of these three filters. We, however, used the following equation for smoothing the measured RSSI for BOTH filter:

$$\mathrm{smooth\_RSSI}_{t(\mathrm{BOTH})} = \mathrm{a} * \mathrm{RSSI}_t + (1-\mathrm{a}) * \mathrm{RSSI}_t - 1. \tag{10}$$

3. Experimental Testbed

Adaptive filter contains a set of adjustable parameters. In design problem the requirement is to find the optimum set of filter parameters from knowledge of relevant signal characteristics according to some criterion. This mathematical system combines the general principles of a proximity-based localization system with the analysis of the radio signal strength behavior over distance. This system uses the LQI and RSSI in a different way and therefore it could lead to better and more predictable results than the other existing system. Several experiments had conducted to investigate the performance of the proposed scheme.

To implement our proposed protocol we decided to use 10 m of an indoor environment as our experimental testbed. We implemented our experiment in three kinds of environments. The first step of this system performs with respect to the signal analysis to understand the characteristic of LQI and RSSI values on three types of environments.

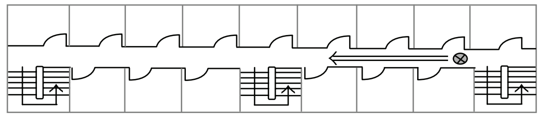

Figure 2: Close space indoor environment (path 1).

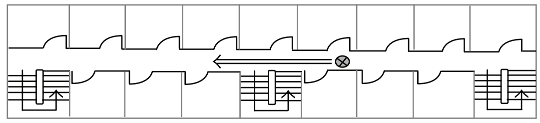

Figure 3: Half-open space indoor environment (path 2).

The effect of distance on RSS can be measured by RSSI and LQI provided by the radio. Equation (1) describes the basic model formula for RSSI where RSS decrease with increased distance, but this scheme decided to use a scaling factor "s" in the basic log model equation to adjust the log model with measured RSSI values. So, to find the accurate log model for specific environment we use a scaling factor "s" in (7). The experiment is conducted on three types of following environment, that is, Figures 2, 3, and 4 to decide how the environment effects RSSI and LQI strength. The first experiment is conducted in close space indoor environment (Figure 1). The second experiment is deployed in half-open space indoor environment, where few meters of the corridor were open (Figure 2) and the third experiment (Figure 3) is conducted on the open space indoor environment to decide the variation of the RF and LQI from the other two experiments.

To determine the accurate distance, the following distance equation has been used:

$$\mathrm{Distance} = \frac{(\mathrm{RSSI}-A)/(10-10n)-1}{s}. \tag{11}$$

And for measuring the signal attenuation factor the following equation has been used:

$$N = \frac{\mathrm{RSSI}-A}{-10\log 10(sd+1)}. \tag{12}$$

Figure 5 represents the measured RSSI and LQI values. These figures are also representing how the log model curve adjusted with the measured RSSI values in half-open space indoor environment.

Figures 6 and 7 provide the reliability of the RSSI and LQI for all testbeds.

Figures 8 and 9 represent the average distance error according to RSSI and LQI values for all three testbeds. Figure 8 shows that in 8 meters the LQI value is 100. From our experiment we found that when LQI = 100, it gives 20% reliability. Whereas, Figure 9 reveals that in 8 meters RSSI value is −77, from our experiment we found that it gives 10% reliability. So, we conclude that over long distance LQI reliability is better than RSSI. According to this finding; we decide to use LQI as an assistance filtering factor for RSSI, which we are going to discuss next.

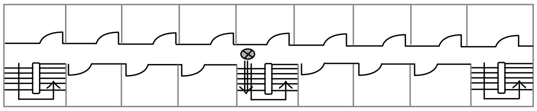

Figure 4: Open space indoor environment (path 3).

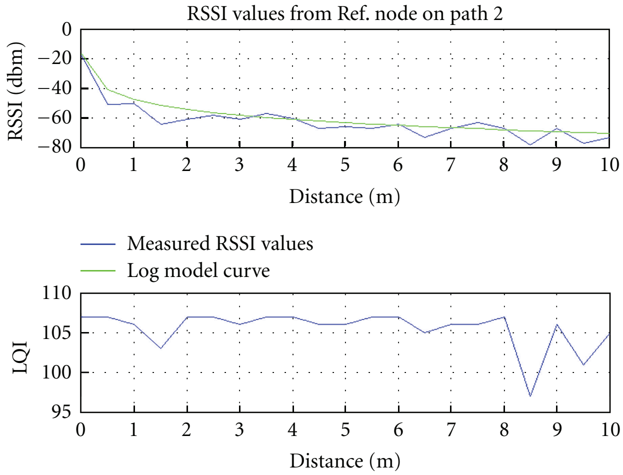

Figure 5: Characteristics of RSSI and LQI in half-open space indoor environment.

It is found that LQI gives best performance when the value was 108 in about 2 meters distance, which indicate that it gives 80% reliability (Figure 8). The results show that when the value is 100, it gives lowest performance in about 8 meters. As our measurement testbed was 10 meters, we decided to determine the value below 10 meters. So, we determined the LQI reliability from 100 to 108, where the reliability varies from 20% to 80%, which means LQI filtering factor "a" varies between 0.8 to 0.2 for LQI filtering. And we also determine that if "a" value is below 101 then it should be negligible. The following equation has been used for LQI filtering:

$$\text{smooth\_RSSI}_{t(\text{LQI})} = a * \text{RSSI}_t + (1 - a) * \text{RSSI}_{t-1},$$
$$a = 0.8 - 0.6 * \frac{108 - \text{LQI}}{8}. \tag{13}$$

Furthermore, RSSI gave best performance when its value was -15 in about 0 meter distances, by which we determine that it gives 100% reliability (Figure 9). It has also been seen that when its value was -75 it gave the lowest performance in about 5 meters, which means 50% reliability. So we decided the reliability for RSSI between -15 to -75, where the reliability varies from 50% to 100%. So this system decided to use the RSSI filtering factor a around 1 to 0.5 according to RSSI value. We also determine that if RSSI value is below -75 then the RSSI reliability will be 10%, which could be

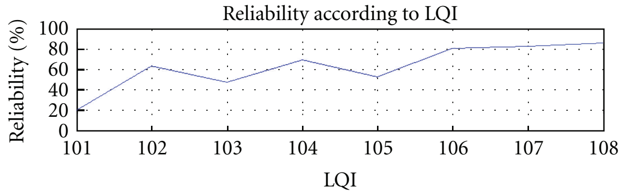

Figure 6: Reliability according to LQI in all three paths.

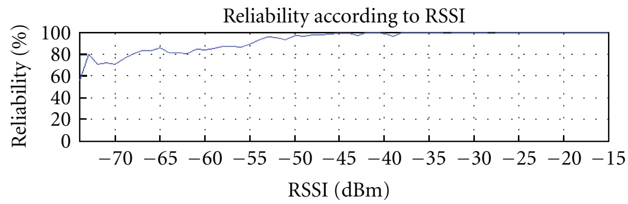

Figure 7: Reliability according to RSSI in all three paths.

neglected. However, the following equation was used for RSSI filtering:

$$\text{smooth\_RSSI}_{t(\text{RSSI})} = a * \text{RSSI}_t + (1 - a) * \text{RSSI}_{t-1},$$
$$a = 1 - 0.5 * \frac{-15 - \text{RSSI}}{60}. \tag{14}$$

The proposed system was implemented with TinyOS 2.x and the ZigBee device (Hybus, Hmote 2430), which were designed to operate in environments where they are approximately coplanar, therefore constrained in 3 of their 6 degrees of freedom (pitch, roll, and z-axis). Hardware had already been developed as a research platform. This section will describe these devices. The performance of the systems has been analysed by implementation and simulation using MATLAB.

4. System Implementation

The proposed scheme performs with respect to the signal analysis to filter the original signals in order to remove the noise. By smoothing, sudden peaks and gaps in the signal strength are removed and the whole signal is smoothed, which eases the analysis process.

4.1. LQI Filter. LQI is a metric, provided by radio. It measures the error in the incoming modulation of successfully received packets. LQI exhibits as a quality indicator of a received packet and helps to estimate the distance between the nodes. For smoothing the measured RSSI values we use LQI filter based on only LQI values. The condition for this filter is as follows: if the LQI value is smaller than 100 then

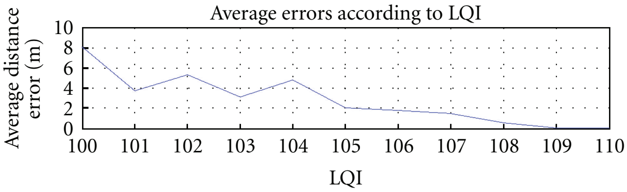

FIGURE 8: Average errors according to LQI in all three paths.

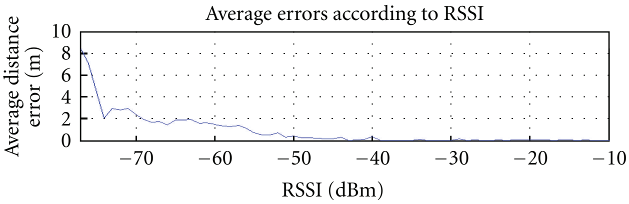

FIGURE 9: Average errors according to RSSI in all three paths.

the filtering factor α will be 0 otherwise the measured RSSI signal will be smoothed by the LQI filter:

$$\begin{aligned}&\text{if LQI} < 100\\&\qquad \alpha = 0\\&\text{else}\\&\text{smooth\_RSSI}_{t(\text{LQI})} = a * \text{RSSI}_t + (1-a) * \text{RSSI}_{t-1}.\end{aligned} \tag{15}$$

After applying the filter, the program analyses the behavior of the filtered signal strengths over distance. Figures 10, 11, and 12 provide the results. Figures 10, 11, and 12 show the analysis results of LQI filter for 3 different paths. To analyse the filter result, we measured the log model using the scaling factor for adjusting the log model with the measured data. These figures (Figures 10, 11, and 12) show the difference between filtered RSSI value and raw RSSI values and also how the proposed scaling factor helps to adjust the log model based on three different paths. LQI filter gave the best performance in closed indoor environment.

4.2. Fusion Filter. In our second experiment we make a fusion of RSSI and LQI to smooth the measured RSSI values. For this fusion filtering we use the LQI filtering in case of sudden peaks and shaded signals. In this fusion filter we decided to measure the difference between present RSSI value and previous RSSI value. If the difference of present and previous RSSI value is smaller than RSSI threshold value or if the LQI value is smaller than LQI threshold value then the signal will be filtered by RSSI filter otherwise it will use LQI filter. To determine the LQI threshold value we use the defined LQI threshold value 105. But for determining RSSI threshold value we did three kinds of experiments. Firstly we decided to use the smallest peak value (SPV) as an RSSI threshold. Secondly, we averaged the minimum and maximum RSSI values (AMM). And finally we averaged each distance difference of all RSSI values (ADD) and we determined that, by using ADD (average distance difference)

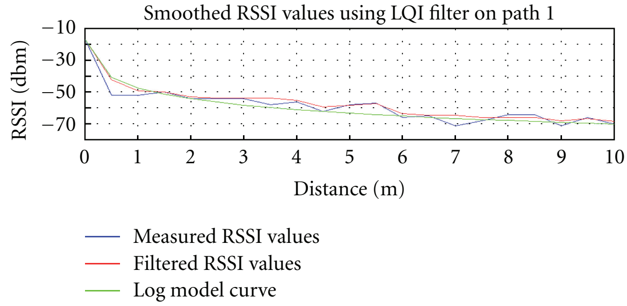

FIGURE 10: Smoothed RSSI values using LQI filter for path 1.

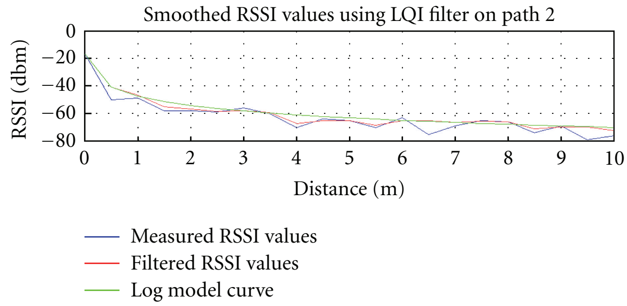

FIGURE 11: Smoothed RSSI values using LQI filter for path 2.

value as an RSSI threshold, filtering is happening more smoothly than the other two values:

$$\begin{aligned}&\text{if}(\text{abs}\,(\text{RSSI}_t - \text{RSSI}_{t-1}) < \text{RSSI}_{\text{Threshold}})\\&\qquad \mid (\text{LQIt} < \text{LQI}_{\text{Threshold}})\\&\qquad\qquad \text{RSSI filter}\\&\text{else}\\&\qquad\qquad \text{LQI filter}\\&\text{smooth\_RSSI}_{(\text{Fusion})} = a * \text{RSSI}_t + (1-a) * \text{RSSI}_{t-1}.\end{aligned} \tag{16}$$

Figures 13, 14, and 15 show the results for 3 paths by using the fusion filter. Figures 13, 14, and 15 are showing three types of RSSI measurement—raw RSSI, RSSI filtered RSSI, and fusion filtered RSSI values. Figure 13 shows that after the distance of 7.5 m in fully indoor environment the fusion filter smoothed well the raw RSSI than RSSI filter. In case of half-indoor environment in the distance from 3 m to 7.3 m fusion filter's performance is better than the existing RSSI filter. In open-spaced indoor environment fusion filter gives better performance from 0 m to 5.8 m (Figure 15).

After applying the filter, the program analyses the behavior of the filtered signal strengths over distance.

4.3. BOTH Filter. Our last proposed filtering scheme is BOTH filter. For this filtering process, we used the same condition as fusion filter but changed the filtering method. In this experiment, if the difference of present RSSI and previous RSSI values is smaller than RSSI threshold value or if the LQI value is smaller than LQI threshold value then

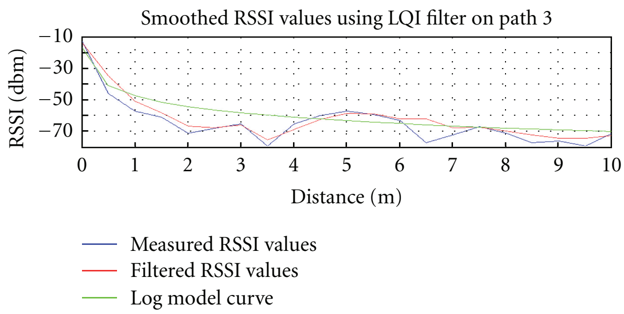

FIGURE 12: Smoothed RSSI values using LQI filter for path 3.

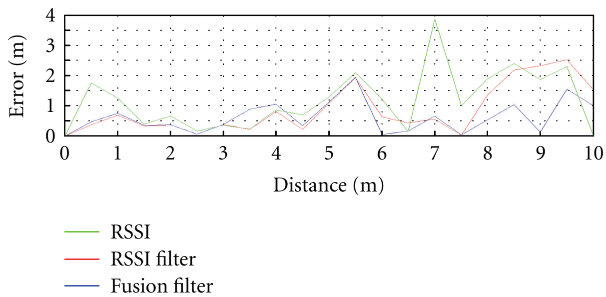

FIGURE 13: Distance error measurement of RSSI filter and fusion filter for path 1.

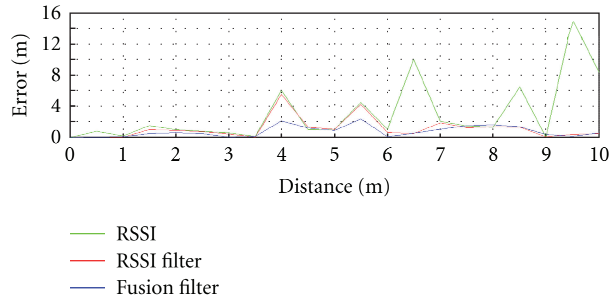

FIGURE 14: Distance error measurement of RSSI filter and fusion filter for path 2.

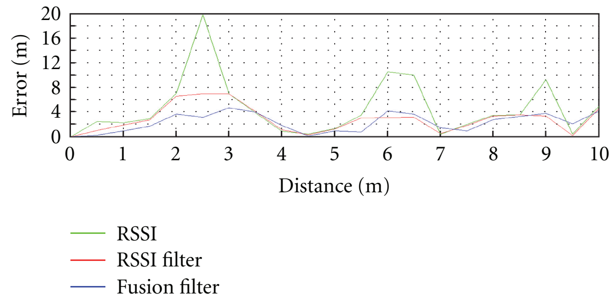

FIGURE 15: Distance error measurement of RSSI filter and fusion filter for path 3.

firstly the measured RSSI signal will be filtered by LQI filter. Secondly we used the RSSI filter to smooth the filtered RSSI by using RSSI filter. The following algorithm has been used to filter both RSSI and LQI values:

$$\begin{aligned}
&\text{RSSI} \longrightarrow [\text{LQI filter}] \longrightarrow [\text{RSSI filter}] \\
&\qquad \longrightarrow \text{smooth_RSSI}_{t(\text{Both})} \\
&\text{smooth_RSSI}_{(\text{BOTH})} = a * \text{RSSI}_t + (1-a) * \text{RSSI}_{(t-1)} \\
&\text{if } (\text{abs}(\text{RSSI}_t - \text{RSSI}_{t-1}) < \text{RSSI}_{\text{Threshold}}) \\
&\qquad \mid (\text{LQI}_{\text{t}} \ < \ \text{LQI}_{\text{Threshold}}) \\
&\qquad \text{LQI Filter} \\
&\text{smooth_RSSI}_1 = \text{LQI Filter} \\
&\qquad \text{RSSI Filter} \\
&\text{smooth_RSSI}_2 = \text{RSSI Filter} \\
&\text{smooth_RSSI}_{t(\text{BOTH})} = \text{smooth_RSSI}_2.
\end{aligned} \tag{17}$$

After applying the filter, the program analyses the behavior of the filtered signal strengths over distance. These figures are showing the distance error measurement of RSSI filter and fusion filter for 3 different environments. Figure 16 shows that the BOTH filtering smoothed all the sudden peaks and shaded signals from 4 m to 10 m well then the proposed LQI filter and existing RSSI filter. In Figure 17 also BOTH filter gave better performance from 1m to 7.3 m than LQI filter and RSSI filter. From Figure 18 we can see that again BOTH filter performed better than the LQI and RSSI filter in whole measured distance.

Based on this analysis, this system decides that LQI values perform better than RSSI values over distance in a fully indoor environment. But on the other two environments, RSSI values perform better than LQI values. The best performance happened when the RSSI values were smoothed by BOTH filtering. Figures 16–18 provided the results. So, from the above analyses, we can determine that BOTH filters perform better than the existing RSSI filter [18], fusion filter [13], and our proposed LQI filter.

5. Experimental Performance

From the above findings, we can say that the proposed BOTH filtering algorithm could reduce more average error and maximum error distance than other existing algorithm [8, 13, 18, 19]. The average reduction of distance error deduced by using the proposed BOTH filtering is 56% and 68% average error and maximum error, respectively, than the existing RSSI filtering [18] and fusion filtering [13]. As a result, our proposed method can perform well over other existing algorithm.

Table 2 shows the experimental results of our proposed filtering algorithm. From adaptive adjustment we found that this process could reduce a high number of errors without filter measured signal. So, we can draw the conclusion that our new enhancement technique gives a significantly improved performance over other existing techniques.

Table 2: Error reduction comparison of RSSI filter, fusion filter, proposed LQI filter, and BOTH filter.

Path	Filter name	Av. error	Max. error	RSSI filter		LQI filter		Fusion filter		BOTH filter	
1	Nonfilter	1.2750	4.0577								
	RSSI filter	1.0911	3.1117								
	LQI filter	1.0962	2.7127								
	Fusion filter	1.2807	3.0742								
	BOTH filter	1.0959	2.6453								
2	Non filter	3.0142	15.183								
	RSSI filter	1.0943	5.4847								
	LQI filter	1.0040	3.4574	Av. RDC. of Av. Error 33%	Av. RDC. of Max. Error 50%	Av. RDC. of Av. Error 41%	Av. RDC. of Max. Error 49%	Av. RDC. of Av. Error 49%	Av. RDC. of Max. Error 62%	Av. RDC. of Av. Error 56%	Av. RDC. of Max. Error 68%
	Fusion filter	0.8408	3.3281								
	BOTH filter	0.6495	1.8214								
3	Non filter	5.3016	21.183								
	RSSI filter	2.3972	7.2861								
	LQI filter	3.0213	13.609								
	Fusion filter	1.3088	3.1259								
	BOTH filter	1.3174	3.8351								

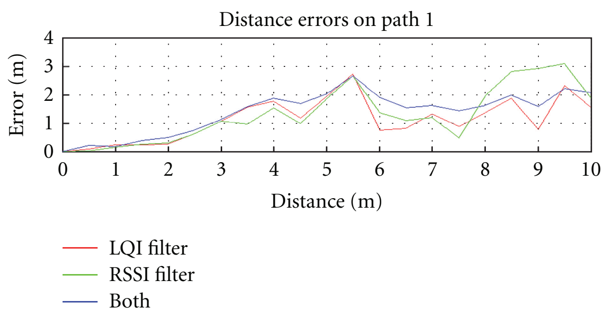

Figure 16: Smoothed RSSI values using LQI, RSSI, and BOTH filter for path 1.

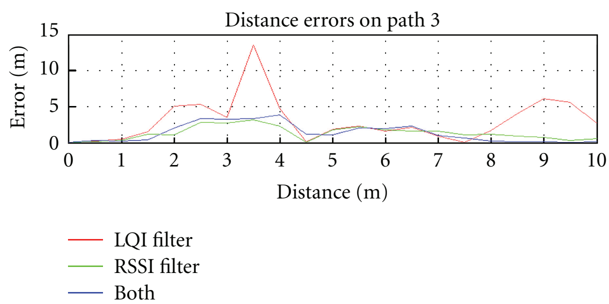

Figure 18: Smoothed RSSI values using LQI, RSSI, and BOTH filter for path 3.

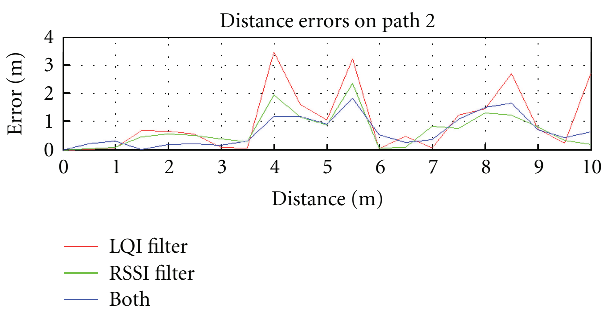

Figure 17: Smoothed RSSI values using LQI, RSSI and BOTH filter for path 2.

6. Conclusion

The technology is developing faster and faster; the expansion of the internet makes people connected. There have been many forms of connections in cyberspace, that is, wired connection, wireless network, structured network, Ad hoc network, and so forth. Life will be rather different without any form of such communication. Certainly the security will be a great concern in such beneficial technology. The security measures to provide confidentiality and integrity have been taken into account in the design of such technology. This paper investigates the use of RF location systems for indoor domestic applications. Based on the assumption, low cost and minimal infrastructure are important for consumers; the concept of RF location system for Integrated Indoor Location Using RSSI and LQI provided by ZigBee module is introduced.

This paper addresses the problem of tracking an object and discusses how to overcome the problems in the existing methods calculating the distance in indoor environment. In this paper, a new mathematical method is presented for reducing the error in the location identification due to interference within the infrastructure-based sensor network. The proposed mathematical method calculates the distance using LQI and RSSI predicted based on the previously measured values. The calculated distance corrects the error induced by interference. The experimental results show that the proposed mathematical method can reduce the average error around 25%, and it is always better than the other existing interference avoidance algorithms. This technique has been found to work well in instances modeled on real world usage and thereby minimizing the effect of the error and hope that the findings of this paper will be helpful for design and implementation of object tracking system in indoor environment.

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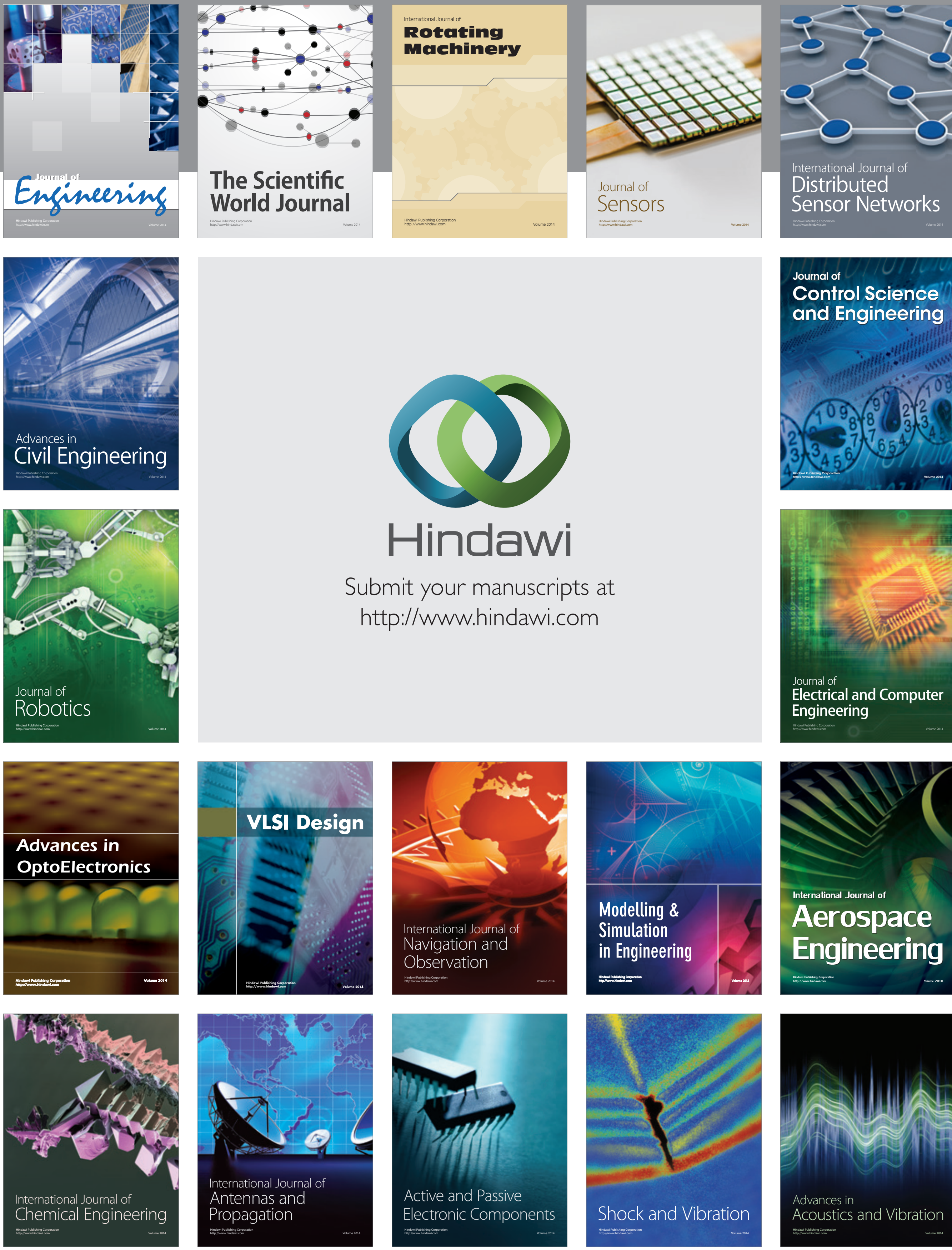

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