Indoor Anti-Collision Alarm System Based on Wearable Internet of Things for Smart Healthcare

Fu Xiao, Qianwen Miao, Xiaohui Xie, Lijuan Sun, and Ruchuan Wang

The authors present IAAS, a smart indoor anti-collision system based on RFID, which identifies and tracks passive RFID tags by analyzing the received backscatter signals. They extract RSSI based on the LWLR algorithm and phase profiles as fingerprints to guide the user away from obstacles without observations of eyes.

Abstract

Smart healthcare, instead of traditional healthcare, has attracted tremendous attention all over the world, and calls for integrated design bringing together interdisciplinary technological approaches and solutions with the aim of supporting affordable and high-quality patient care. With the increasing number of visually impaired people, including the blind, the elderly, and patients with eye diseases, it is vital to help them explore their outside environment with the assistance of smart technologies so that they can adapt to the environment more easily. The smart indoor anti-collision system is one typical application. Previous works normally use video monitors or deployed sensors to provide outside environment information for visually impaired people. However, these methods suffer from privacy disclosure and inconvenience. In this article, we present IAAS, a smart indoor anti-collision system based on RFID, which identifies and tracks passive RFID tags by analyzing the received backscatter signals. We extract RSSI based on the LWLR algorithm and phase profiles as fingerprints to help the user guide from obstacles without observations of eyes. Experiments are conducted to verify our system, and results show that IAAS could achieve high accuracy of 94 percent in obstacle avoidance.

Introduction

Researchers have been making advances in the study of next-generation information technologies such as fifth generation (5G) wireless networks, the Internet of Things (IoT), and cloud radio access networks (C-RANs) for the purpose of improving people's quality of life, popularizing the concept of smart healthcare, which aims to address societal and economic challenges like limited resources, population aging, and globalization. Smart healthcare has the potential to revolutionize many aspects of our society, especially for the disabled. The anti-collision system for visually impaired people, as a typical examples, is now attracting tremendous attention from large amounts of people with poor eyesight all over the world, including the blind, the elderly, and patients with eye diseases.

Previous works normally use video monitors or deployed sensors [1, 2] to provide outside environment information for visually impaired people and send alarms when risks of obstacles are sensed. However, video cameras require unobstructed line of sight to maintain good accuracy, which may violate privacy in some cases. In addition, it is less comfortable for visually impaired people to carry sensors than to simply attach a tag to clothes, even the sensors can be powered in indoor environments.

Another application in our daily life relies on a traditional anti-collision guide rod to avoid obstructions outside. However, this method is not suitable for indoor scenarios because of limited space and denser obstructions, so insufficient information is provided to help visually impaired people sense the outside environment. Eyeronman [3], a smart vest with sensors installed, takes full advantage of laser radar, ultrasonic sensors, and infrared sensors to protect visually impaired patients from the risks of some pre-deployed dangerous areas, but it suffers from high costs and the incidental inconvenience to the daily life of people.

With the development of wearable IoT, many technologies are applied into people's daily lives, bringing more solutions to smart healthcare. Traditional wearable devices are mainly based on sensors, which suffer from a high-cost data transmission support system and poor user experience. In this article, we introduce RFID as an alternative to sensor-based wearable devices and present an anti-collision system for visually impaired people by analyzing reflected backscatter signals of passive RFID tags that are attached to their clothes and raise an alarm when they deviate from the normal path or closely approach obstructions. We conduct a series of empirical studies and identify that both phase and received signal strength indicator (RSSI) fingerprints can act as indicators of the distance between RFID tags and antennas. However, there are three major challenges. First, RSSI suffers from severe multipath fading and temporal dynamics, causing fluctuation of RSSI fingerprints. Second, wrapped phases we measured from commercial RFID devices cannot be directly used, which increases the position ambiguity. Third, RFID antennas are not omnidirectional but can only sense limited fan areas in front of

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A UHF RFID system typically operates on frequency band between 902MHz and 928MHz using a backscatter radio link. An RFID antenna communicates with the passive tags in full-duplex mode, in other words, it must supply continuous wave for the tag to backscatter while listening to the response at the same time.

them, beyond which the backscatter signals of tags are too weak to ensure system accuracy.

To address these challenges, we process original RSSI values to degrade effects of time dynamics. We extract RSSI fingerprints based on the Locally Weighted Linear Regression (LWLR) algorithm to identify the distance between the user and obstacles. As for the wrapping phenomenon of phase, we do not directly use phase values for anti-collision detection but guide the walking track of users by utilizing the rate of unwrapped phase change.

In summary, our main contributions can be concluded as follows:

- To the best of our knowledge, the indoor anti-collision alarm system (IAAS) is the first attempt to design an anti-collision system for visually impaired people based on RFID information available from commercial off-the-shelf (COTS) RFID devices. Our system can protect users from indoor obstacles during walking and guide the user to the door without eye observations.
- The LWLR algorithm is used for RSSI fingerprint extraction to identify the distance between the RFID tag and antenna while unwrapped phases are used for indicating the degree to which the user is straying off the normal path.
- Statistical analyses of RF information are extensively conducted, including the phase and RSSI values, making our system much more feasible.
- A prototype is established and extensive experiments are conducted using RFID devices. Results show that our system can achieve high accuracy of 94 percent on obstacle avoidance.

The remainder of this article is organized as follows. We first present the background and related works, and then detail our methodology and system design, respectively. Afterward, system implementation and evaluation are also interpreted. Finally, we conclude this article.

Background and Related Work

Background

A UHF RFID system typically operates on frequency band between 902 MHz and 928 MHz using a backscatter radio link. An RFID antenna communicates with passive tags in full-duplex mode; in other words, it must supply continuous wave for the tag to backscatter while listening to the response at the same time. Present COTS RFID readers such as Impinj [4] can provide rich signal information such as signal phase, RSSI, and Doppler frequency shifts, which provide potential for environment sensing. In this article, we mainly use RSSI fingerprints combined with phase profiles to realize a sophisticated anti-collision system for visually impaired people.

Received signal strength: The received signal strength (RSS) is a measurement of the power of received radio signals. In RFID systems, RSS is one of the reader outputs, reflecting the power of received backscattered signal. The longer the transmission distance of signals, the weaker the RSS according to the path loss model, which enables RSS as a characteristic to reflect the distance between the tag and the antenna.

Phase: The phase value of an RF signal describes the degree to which the received signal is offset from the sent signal. Let d be the distance from the antenna to tag; as the signal transmits in a backscatter way, a round-trip ($2d$) is traveled in every communication. More than the RF phase rotation over distance, the reader's transmit circuits, the tag's reflection characteristics, and the reader's receiver circuits will also introduce some additional phase rotation, termed as θ_T, θ_{TAG}, and θ_R [5], Hence, the measured phase can be expressed as

$$\theta = \left(2\pi\frac{2d}{\lambda} + \theta_T + \theta_{TAG} + \theta_R\right) \bmod 2\pi$$

where d is the distance between the transmitter and receiver and $\lambda = c/f$ is the wavelength of signal at frequency f (in Hz).

Related Work

WiFi-Based Sensing Technology: Recently, wireless sensing technologies have attracted intensive research interest. Most of them are based on WiFi or RFID because of the advantages of non-intrusiveness and pervasiveness. Wang *et al.* [6] quantitatively build the correlation between channel state information (CSI) dynamics and specific human activities, while Liu *et al.* [7] exploit the fine-grained channel information to capture the minute movements caused by breathing and heartbeats. Zhu *et al.* [8] extract the first-order difference of eigenvector of CSI across different subcarriers for TTW human detection. Wu *et al.* [9] extract CSI phases of multiple antennas for real-time LOS identification. However, WiFi works in a relatively short range and is highly position-dependent, which limit its application. RFID is a promising alternative technology for wireless sensing, including object tracking, activity monitoring, access control and so on.

RFID-Based Indoor Localization: Many schemes for object localization using RFID tags have been proposed [10, 11]. LANDMARC [12] is a pioneering positioning system leveraging multiple reference tags to calculate the absolute location with RSSI, which could suffer from severe multipath effects. BackPos [13] uses RF phase values and the hyperbolic positioning technique to calculate the absolute location of a tag in two-dimensional regions without need to deploy any infrastructure in advance. RF-HMS [14] extracts phase shifts to detect the absence or presence of any moving persons and further derives the reflections off a single moving person to identify his/her forward or backward motion direction. However, these works mostly focus on absolute object localization and require special hardware or multiple antennas and anchors. Consequently, our work is different from all of these above. We concentrate on the relative distance and deviation angle between the mobile tag and obstacles rather than acquiring the absolute location.

Methodology

In this section, we first discuss the challenges in our initial attempts to directly use the information available from commercial RFID devices to realize a well-performing anti-collision system for visually impaired people. Then we introduce our solutions and show our system designs in detail.

Initial Attempts

We start out with a consideration that radio signals are transmitted through invisible electromagnetic waves from the sender to the receiver in mobile communications. In typical indoor scenarios, a transmitted signal propagates to the receiver through multiple paths, including reflection, scattering, diffraction, and so on. Hence, radio signals can convey the information about the environment through which they pass, which makes RFID-based detection possible.

Typically, an RFID system consists of a reader, an antenna, and multiple tags. Tags are battery-free and modulate their information on the backscattered signals emitted from the reader. As the RFID antenna sweeps over a set of tags and keeps querying them, the reader can obtain rich information that can be impacted by the changes in the spatial relationship between the tags and the antenna: RSSI and the received phase value most commonly, which can be extracted from commercial RFID devices easily. We attempt to utilize these two fingerprints for anti-collision detection.

Challenges and Solutions

RSSI is widely adopted due to its easy accessibility, which characterizes the attenuation of signals during propagation and hence is inversely proportional to the distance between the tag and the antenna. As a person carrying a RFID tag moves close to the antenna and then away from (across an obstacle), the RSSI values measured by the antenna should increase and then decrease because the distance between the tag and the antenna first decreases and then increases. Unfortunately, this works only in theory because of the multipath effect. In addition, RSSI suffers from coarse features and poor stability of time due to multipath fading and temporal dynamics, which makes it impossible to identify the distance between the tag and antenna simply through the measured RSSI value.

To address these challenges of RSSI, we make anti-collision decisions not only by analyzing the current measured RSSI value, but also historical RSSI values. To solve the multipath fading and temporal dynamics problems of RSSI, we introduce LWLR, a machine learning algorithm which predicts the data value by regression of adjacent data series, to extract a more robust RSSI fingerprint for system design.

RF phase is a basic attribute of a signal along with amplitude and frequency. The phase value of an RF signal describes the degree at which the received signal is offset from the sent signal. However, the phase we measured is wrapped, which is a periodic function, ranging from 0 to 2π. Hence, we cannot use phase to identify relative tag locations.

To address these challenges, we first unwrap phase profiles by detecting the jump point and make phase values continuous. However, unwrapped phase values still could not be used for identifying the distance between the tag and antenna and thus for anti-collision monitoring as the unwrapping process can only eliminate the abrupt change of phases, but the phase value of starting position is still wrapped, which means the phase value of a tag after unwrapping in the same position will be different when we start from a different location. Thus, we do not directly use phase values for anti-collision detection, but guide the walking path of users by utilizing the rate of unwrapped phase change. The guiding system is necessary as a supplement of our anti-collision system to prevent users walking toward a severe slanting direction before entering the obstacle monitoring area.

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System Design

In this section, we present the details of IAAS to help visually impaired people safely walk indoors. RSSI characterizes the attenuation of signals and is mapped into the distance between the tag and antenna by the prevalent log-normal distance pass loss (LDPL) model. Hence, we attempt to use the measured RSSI values to identify the distance between visually impaired people and obstacles in the indoor environment. However, as a superposition of multipath components, RSSI not only varies over distance on the order of the signal wavelength, but also fluctuates over time, which hampers the localization based on RSSI.

Fortunately, our purpose is not to achieve a high-precision localization but give a warning in advance when the monitored visually impaired person approaches obstacles. Our system is appropriate for directional walks that aim to guide people to the door. Giving the physical truth of visually impaired people with mobility difficulties, we do not consider the case in which they walk randomly indoors.

RFID Antenna Settlement

From prior knowledge, RFID antennas are not omnidirectional, but can only sense limited fan areas in front of them. Thus, the first step of designing our system is to determine the sensing areas of the RFID antenna we use. We keep RFID devices working and make a person with a tag circle around the antenna, and we record the boundary beyond which the antenna cannot sense the tag. After repeated tests, we settle the maximum sensing angle of the antenna to 60°.

Then we determine the settlement of RFID antennas. We put an antenna behind every indoor obstacle and identify the distance from the person with a tag to the obstacle by analyzing the measured RSSI values. We must put the antenna in the appropriate position, ensuring that the whole obstacle can be sensed by the reader. One antenna is enough when an obstacle is small, and two antennas should be deployed when it is large, which can avoid blockage of the human body. Since multiple tags will interact with each other, which may directly increase the difficulty in data processing, we only use one tag to conduct experiments. Indeed, we can achieve high reliability by leveraging only one tag. In this article, we only consider the first case and use only one antenna.

Characteristic Extraction Based on a Forecasting Model

Considering the multipath fluctuations and temporal dynamics of RSSI, we introduce the LWLR algorithm [15] to extract more robust RSSI fingerprints for system design. LWLR is an improvement of a linear regression algorithm to solve the

In the training part, we collect RSSI values when a person stands at different distances from the obstacle. We divide the entire monitoring area into safety zone, warning zone, and danger zone according to the distance to the obstacle and determine the RSSI thresholds to identify the area in which the person is currently.

problem of underfitting, which gives a certain weight to each point near the prediction point, and the normal regression is performed on this subset based on the minimum mean square error (MMSE). LWLR uses a kernel function to give a higher weight to adjacent points, and we choose the most commonly used Gaussian kernel function in our system. Corresponding weights are as follows:

$$\omega(i,i) = \exp\left(\frac{\left|x^i - x\right|^2}{-2k^2}\right)$$

where x is the RSSI value of the predicted point, x^i is the RSSI value of an adjacent point, and k represents the wavelength parameter, which controls the rate at which the weight decreases with distance.

In this way, we construct a weight matrix **w** with diagonal elements only, and the closer the point is to the predicted point, the greater the weight is assigned. Then we can extract RSSI fingerprints based on LWLR.

Anti-Collision System Based on RSSI

To realize an anti-collision application for visually impaired people, IAAS needs to identify the distance from the person to obstacles, and give alarms when approaching the obstacles to a certain extent. We settle an antenna near the obstacle and attach a tag on people's clothes; then we use RSSI values for distance identification. Our system consists of two steps: training and monitoring.

In the training part, we collect RSSI values when a person stands at different distances from the obstacle. We divide the entire monitoring area into safety zone, warning zone, and danger zone according to the distance to the obstacle and determine the RSSI thresholds to identify the area in which the person is currently.

In the monitoring part, we collect the RSSI value in real time, extract RSSI fingerprints with LWLR, and keep comparing the current RSSI fingerprint with the threshold. A warning is alerted when the person enters the warning zone; hence, our system can prevent the person entering the danger zone and protect visually impaired people from the obstacle.

Extensions of IAAS

To make IAAS more robust, we consider how a visually impaired person walks before entering the monitoring area. If the person walks directly toward a severe slanting direction, the monitoring area may not be reached, and thus the person may hit a wall or be trapped, unable to walk out. To solve this problem, we use phase profiles, which describe the degree that the received signal is offset from the sent signal, to guide the directions in which the person walks.

We unwrap collected phase profiles by detecting the jump point of 2Π to make phase values be continuous. Then the intensity of phases' variations is used for identifying the direction in which the person walks, and a threshold is set to help guide the person's walking tracks. It is worth mentioning that we do not choose RSSI for guiding because of its coarse features, including instability and fluctuation, which may hamper the detection accuracy.

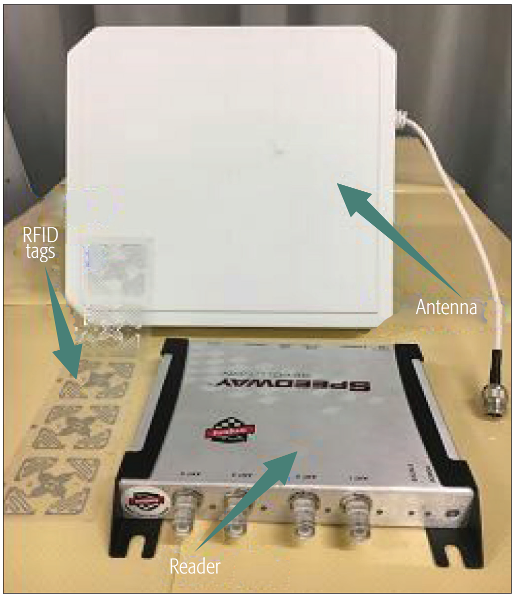

Figure 1. Experimental equipment.

System Implementation and Evaluation

In this section, we present the implementation and conduct performance evaluation of our system.

System Implementation

Hardware: We implement our scenarios using COTS UHF RFID devices, including an Impinj R420 RFID reader, several 8 dBi directional antennas, and Impinj H47 RFID tags, as shown in Fig. 1. The whole RFID system operates at the frequency of 920.625 MHz.

Software: The software part running on a personal computer is implemented using C# language. The software is integrated with the Octane SDK, an extension of the LLRP Toolkit, which supports reporting of RFID information, such as signal phase and RSSI.

Deployment: Since the beam range of the RFID antenna is about 60°, it may not cover the obstacle completely when the obstacle is too big. To solve this problem, we deploy multiple antennas, and the number of antennas could be determined by the size of the obstacle.

Fingerprints Extraction Based Lwlr

As a real-time monitoring system, the performance greatly depends on the accuracy and stability of measured data, and hence, original RSSI values suffering from multipath fluctuations and temporal dynamics could not be used directly as fingerprints for identification. To solve this problem, we introduce LWLR, an algorithm that predicts the current RSSI value through adjacent historical RSSI values, to help us extract more robust RSSI fingerprints.

Figure 2 demonstrates the result of LWLR processing. The red scatters are original RSSI values, while the blue line is the regression result after LWLR, when a user carrying a tag walks toward the antenna and then away. Obvious observations can be seen from the figure that LWLR can greatly degrade the fluctuation of original RSSI values without losing the inherent characteristics.

LWLR uses a Gaussian kernel function to give a higher weight to adjacent points, where kernel parameter k controls the rate at which the weight decreases with distance. To further analyze the effects of k, we choose different values of k, as shown in Fig. 2: k = 1, 40, 100, respectively. It is obvious that when k = 1, the over-fitting phenomenon happens, which means too much noise is contained in the fitting curve, and under-fitting happens when k = 100. In comparison, k = 40 is the most appropriate with a fitting coefficient of 0.88, retaining the inherent characteristics of RSSI, and is chosen in this article.

In order to transform the boundary division of different zones to corresponding RSSI levels, we let a person keep moving in the danger zone and warning zone, respectively, and record the measured RSSI values, shown in Fig. 4. We choose the minimum value of each RSSI profile as the threshold for area division after removal of outliers, that is, −36.5 dbm for danger zone and −52.5 dbm for warning zone, respectively.

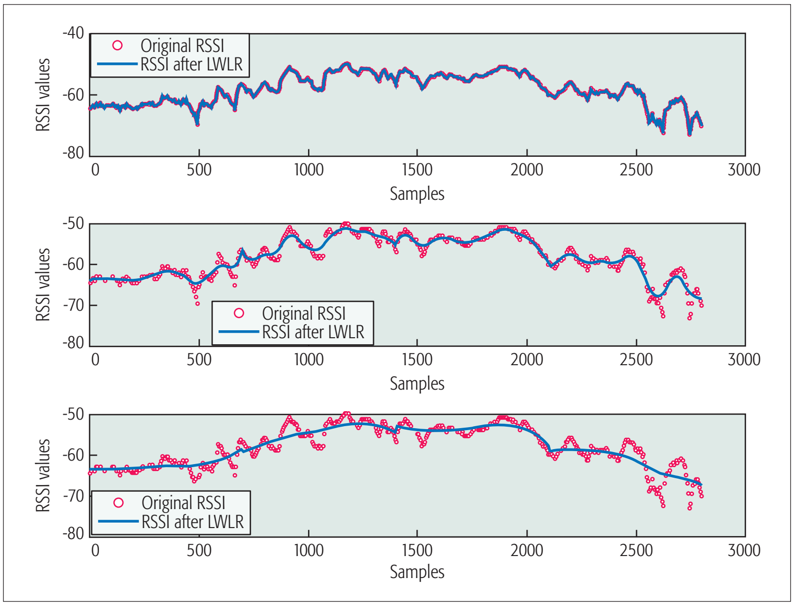

Figure 2. Results of LWLR processing a) k = 1; b) k = 40; c) k = 100.

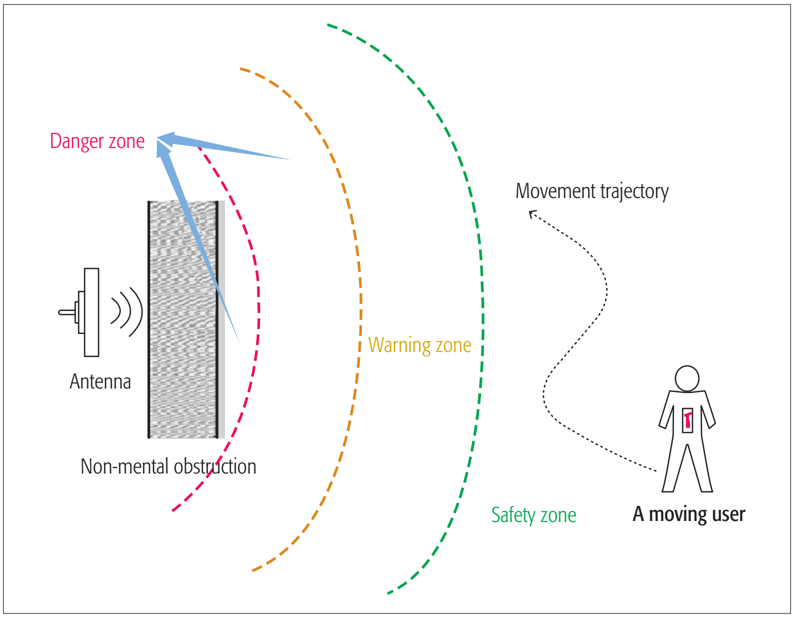

Figure 3. Zone division scenario.

Anti-Collision System

In this section, we evaluate the performance of our system. Our purpose is to give the correct alarms when the user enters the warning zone or even the danger zone. We mainly focus on the following metrics to evaluate our scheme:

1. Negative alarm rate P_{NA}: The number of cases where the receiver misses sending the alarms when the user enters the warning zone or even the danger zone
2. False alarm rate P_{FA}: The number of cases where the receiver gives a wrong alarm when the user is in the safety zone

Overall Performance: To verify our system, we let a person walk normally (away from the warning and danger zones), walk through the warning zone, and walk through the danger zone, respectively. The result is shown in Fig. 5. Three background areas filled by three different colors correspond to the danger zone, warning zone, and safety zone determined by the two division thresholds mentioned above. As depicted in Fig. 5, three different tracks can be distinguished clearly through analysis as to whether the user enters the warning zone or danger zone, which verifies the feasibility of our system. Results show that our system could achieve promising performance in obstacle avoidance. To further depict the accuracy of our system, we repeat the experiments 50 times at random intervals and count the error times of our system.

Results show that only two negative alarms (P_{NA} = 2) and one false alarm (P_{FA} = 1) happen throughout the experiments, probably caused by the fluctuation of RFID signals.

Response Time of System: Real time is an important measure for an anti-collision system. The time cost of our system mainly lies in the sampling rate of RFID devices and the time complexity of LWLR. To reduce the time delay and guarantee the real-time performance of our system, we take two measures. The first is that we put a tag array within the sensing range of the antenna to reduce the sampling frequency to the target tag and make the rate of computer processing synchronized with the actual rate of data access, thus guaranteeing the real-time performance of our system. The second is to improve the processing speed of LWLR. LWLR takes all the training data into consideration to predict each time, as a result, when the data size is relatively large, the amount of calculation is very large, and the learning efficiency is very low. To solve this problem, we introduce the concept of a time window, perform LWLR operations in each time window, and sequentially connect all of the time windows as a complete data fingerprint. After the processing of these two solutions, our system can be almost real time.

Extensions of IAAS

From prior knowledge, the phase value of an RF signal describes the degree to which the received signal is offset from the sent signal. To make our system more robust, we use the rate of phase

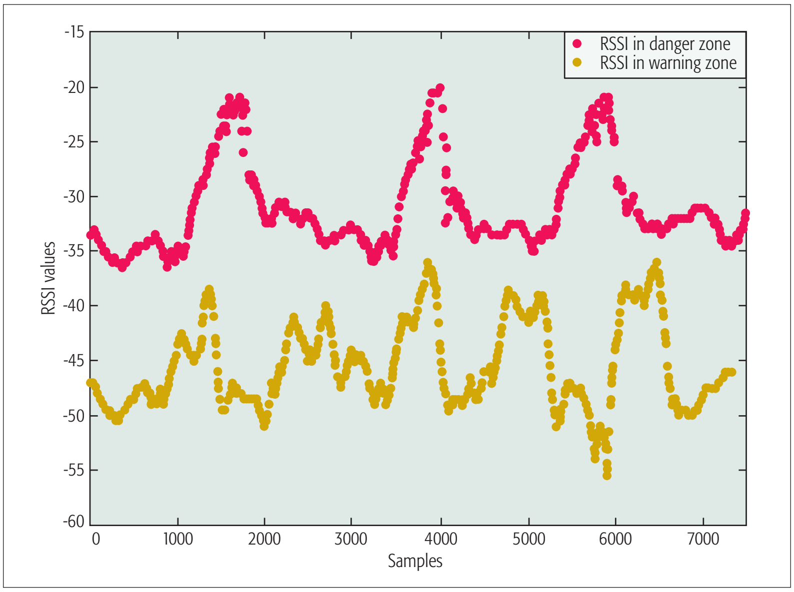

Figure 4. RSSIs in danger and warning zone.

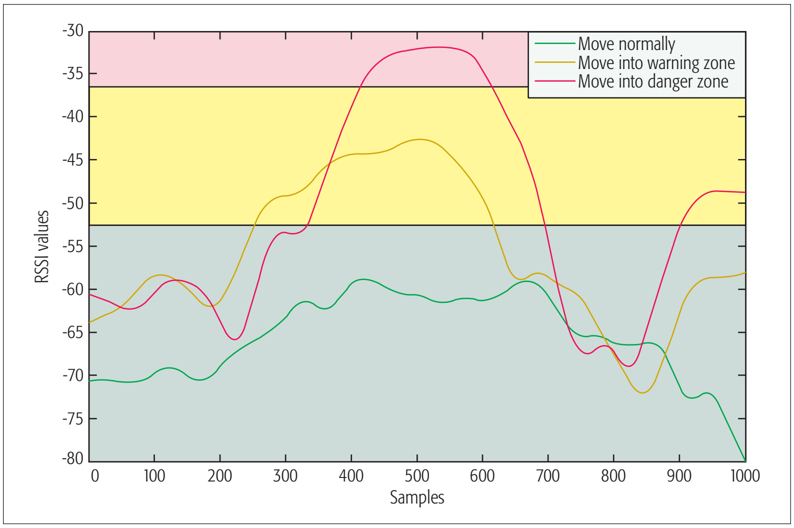

Figure 5. Results of three tracks: walk normally, walk through the warning zone, and walk through the danger zone, respectively.

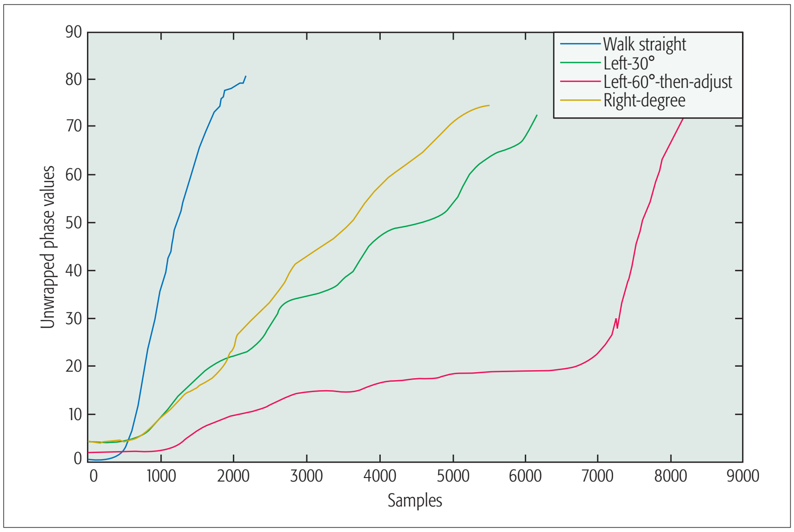

Figure 6. Phase profiles of four tracks simulating different angles the user strays off the normal path.

changes to guide the user's walking tracks as an extension of our system considering the case that the user may hit a wall or be trapped and unable to walk out before entering the monitoring area. Figure 6 shows the unwrapped phase profiles after Gaussian filtering of four different tracks. It is obvious that the smaller the rate of phase changes, the greater the degree of deviation, no matter whether it is to the left or right.

More specifically, take a close look at the red curve, which indicates the track the user walks in a slanting direction of 60° and then adjusts to the proper path. The change can be clearly observed from the curve, indicating that we can guide the user's walk in the proper paths through monitoring the rate of phase changes.

Conclusions

In this article, we present IAAS, an indoor anti-collision system for visually impaired people, which shows the potential to provide smart healthcare to solve the problems arising by the increasing number of visually impaired people, including the blind, the elderly, and patients with eye diseases. In our system, passive RFID tags are attached to users' clothes, RSSI fingerprints based on the LWLR algorithm are extracted to identify the distance between the user and obstacles, and the rate of unwrapped phase changes is utilized to guide the user's walk in the proper paths. Results from our evaluation show that our system can achieve high accuracy and efficiency in guiding visually impaired people away from obstacles. We envision this work as a new attempt in smart healthcare, which provides more potential for more intelligent applications in future.

Our future work will concentrate on taking more RF features into consideration, like Doppler frequency shift, and bringing more applications based on RFID devices to our daily life.

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