UWB Gesture Detection for Visually Impaired Remote Control

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***Abstract*-Recently, RSS based gesture detection using Wi-Fi signal has attracted considerable attention. UWB technology offers more features for gesture detection in indoor environments, which can be applied to medical applications to enhance its accuracy, agility and functionality. In this paper, we compare the gesture detection using Wi-Fi signal RSS and gesture detection using various characteristics of UWB signals, including time of arrival, first peak power, total power and the RMS delay spread.**

Keyword- gesture detection, Ultra wideband (UWB) signal, medical application, time of arrival (TOA), received signal strength (RSS)

I. INTRODUCTION

Gestures can be used to control the distribution of resources in hospitals, interact with medical instrumentation, control visualization displays and help handicapped users as part of their rehabilitation therapy. [1][2] Some of these concepts have been exploited to improve medical procedures and systems， like the automotive field and the medical sector. The first application of hand-gesture control we review—medical systems and assistive technologies—provides the user sterility needed to help avoid the spread of infection. As a result, gesture detection systems are becoming increasingly competitive in some special application areas, [3][4]

Gestures enable a whole new set of interaction technologies for always-available computing embedded in the environment. For example, with the sensor attached to the hand, visually impaired people can control the volume of the radio and change the channel.

Our contribution of this paper is we introduce a new method of gesture detection using UWB signals and compare the gesture detection using Wi-Fi signal RSS. We use four parameters of UWB signals, time of arrival, first peak power, total power and the RMS delay spread, and built a database by performing 500 candidate measurements on each gesture. This method can be applied to medical applications to improve its accuracy, agility and function.

This paper is organized as follows: Section II introduces two classes of gesture detection and two classes of RF signals. Section Ⅲ describes the scenario and measurement system for both the RSS based and UWB based gesture detection. In section IV, the results and performance differences are demonstrated between the two methods. Finally, we show our conclusions in Section V.

II. BACKGROUND

A. Two classes of gesture detection

There are two kinds of gesture detection, one is the active way using a mounted device, and another is the passive way using existing infrastructure.

There are some examples for the active approach for the device based gesture recognition: (1) in Wii from Nintendo, an accelerometer in the controller is responsible to measure acceleration along three axis; (2) a data glove is a glove-like input device often used for virtual reality environments. It is equipped with various technologies such as a system for detection of bending of fingers.

The passive approach compared with traditional activity recognition methods, radio based methods utilize wireless transceivers in environments as infrastructure, exploit radio communication characters to achieve high recognition accuracy, reduce energy cost and preserve users' privacy. We divide radio-based methods into four categories: Zig-Bee radio based activity recognition, Wi-Fi radio based activity recognition, RFID radio based activity recognition, and other radio based activity recognition. [5][6]

B. Two classes of RF signals

Two kinds of RF signals will be introduced in this part. The first one is narrow-band signal using RSS (received signal strength) as a parameter to analyze; the second one is the wide-band signal using ultra wide-band (UWB) features.

Received signal strength indicator is a measurement of the power present in a received radio signal. Theoretically, the RSSI should be stayed in the one value. RSS measurement is a packet-level estimator and represents the signal power over a packet as single amplitude. With the collected amplitude information, the

structure of magnitude changes and the timing information are combined to classify different gestures.
However, due to the multi-path reflection, diffraction and shadow fading, the RSSI varies a lot. Especially when some gestures are made between the transmitter and receiver, RSSI fluctuates more. [7][8]

UWB technology has been recognized as an ideal candidate for gesture detection in indoor environments, in which the traditional services are usually not available, unreliable or inaccurate. It offers a vast unlicensed frequency band, which also allows novel uncoordinated ways of access to spectrum resources. By using UWB signal, we can have more parameters to do the analysis, such as time of arrival (TOA), first peak power, total power and the RMS delay spread.

III. SCENARIO AND MEASUREMENT

A. *Scenario using Wi-Fi signal*

In order to implement the gesture detection mechanism, several challenges have to be addresses. First of all, we need to obtain RSSIs from the Wi-Fi environment, and then extract the movements from RSSI values. Then, we need to map those RSSI characteristics to different gestures. The experiment environment includes one wireless router, which works on 5Ghz. A laptop running Ubuntu 15.04 is placed 1.5 meters away from it in line of sight. The figure shows the preliminary experiment environment. A Wi-Fi card with omnidirectional antenna is attached to the laptop.

In Linux, you could check the Wi-Fi card information by typing *iwconfig*. Each time when you type *iwconifg*, the system will request RSSI from Wi-Fi card. Therefore, I wrote a short script in Bash, which could request RSSI automatically. The sample rate could reach up to 200Hz. We should move hand between them and using the laptop to collect the data of RSS. Two basic gestures are measured in this system, which are moving hand up down and left right.

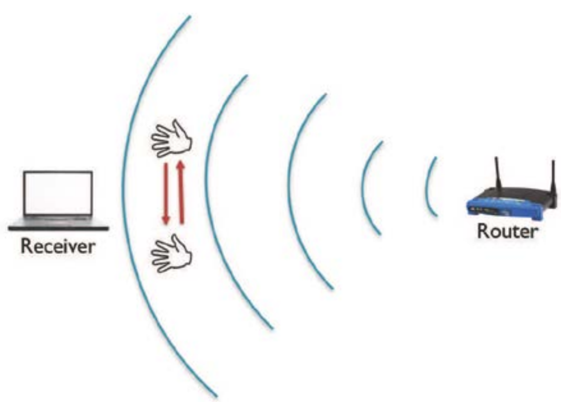


Fig.1 Measurement system for Using Wi-Fi signals

B. *Scenario using UWB signal*

Two possible scenarios as well as gestures have been introduced in our measurement. The first one is LOS condition where the receiving antenna attached to the hand has a direct line of site to the transmitter on the shelf. The second case is the OLOS condition where the user turns over the hand or obstructs the LOS by putting hand behind the body.

To measure the behavior of target node and base stations, a vector network analyzer has been employed in our measurement system. The measurements were carried out in the Atwater Kent Laboratory of Worcester Polytechnic Institute, using two UWB directional antennas, which have been connected to both transmit and receive port of the network analyzer through low loss RF cables. Moreover, a power amplifier has been added at the transmitter (TX) port of network analyzer to achieve better signal to noise ratio (SNR) at the receiver (RX) side. We use two UWB directional antennas that have been connected to both transmit and receive port of the network analyzer through low loss RF cables as shown in Figure 2. The vary frequency of operation of the network analyzer is from 3 GHz to 8GHz.

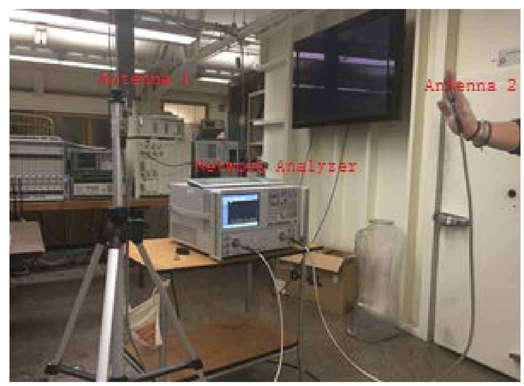
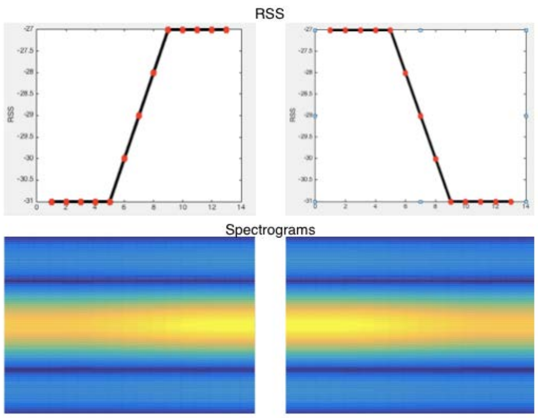


Fig.2 Measurement system for Using UWB signals

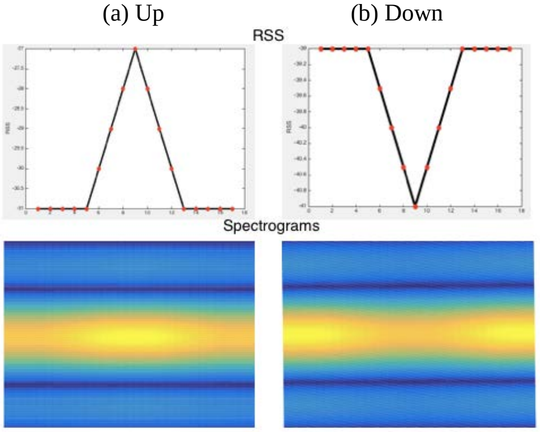
IV. RESULTS AND DISSCUSSION

In the gesture detection using Wi-Fi signal, we can have the statistics of RSS and use their spectrograms to detect different gesture, up-down and right-left. From Figure 3(a) and 3(b), we can see that the RSS separately in up and down, it increases from -31dB to -27dB in Up and opposites in Down. In Figure 3(c), the RSS first raise then decline when in the gesture up-down, but the gap is just 4dB; and in (d), the RSS first increase sand then decreases in the gesture right-left, the gap is only 2dB.

Due to Figure 3, we can see the difference between each gesture is not very clear. However, so there is a major challenge for accurate positioning due to the dynamic and unpredictable nature of radio channel, such as shadowing, multipath, orientation of the wireless device. [9]



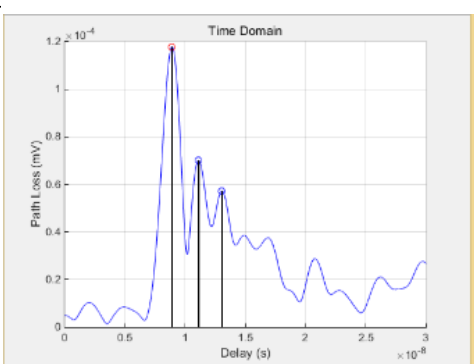
(a) Up (b) Down



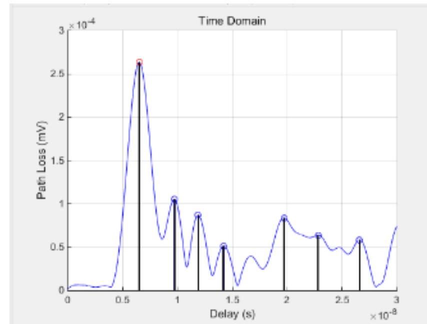
(c) Up-Down (d) Right-Left

Fig.3 Different hand gestures' RSS and spectrograms.

For the gesture detection using UWB signals, we have totally four parameters: time of arrival, first peak power, total power and the RMS delay spread [10]. We will discuss them one by one. When blind people wave his hand, the distance between the two sensors will change, which will directly affect the TOA. Figure 4 shows two profiles when the distance changes. In Position 1, the time of arrival is about 8.5ns; in Position 2, the time of arrival is about 6.5ns. Since the TOA changes can easily be detected, the changes in distance are obviously shown.



(a) Postion 1



(b) Postion 2

Fig.4 Profile Distrubitions of two different positions

` Besides, if visually impaired want to change the channel of radio or music player, he can just turnover or put his hand behind his body, to be an OLOS condition, then this geature can be detected. We use τ_{rms} (the root mean square delay spread) to as TOA detection of hand gesture change. τ_{rms} is a value generated from multipath environment [11], which can be express as

$$\tau_{rms} = \sqrt{\overline{\tau^2} - (\bar{\tau})^2} \quad (1)$$

$$\overline{\tau^n} = \frac{\sum_{i=1}^{L} \tau_i{}^n |\beta_i|^2}{\sum_{i=1}^{L} |\beta_i|^2} \quad n=1,\,2 \quad (2)$$

In these functions, τ_i is the time delay in different transmitting paths, and $|\beta_i|^2$is the corresponding peak power of each τ_i, n is the number of all paths in the measurement environment.

From Figure 5, we can find the mean of τ_{rms} separated in two clusters of LOS and OLOS. The expression of TOA method can be expressed as

$$\tau_{rms}(\mathrm{LOS}) = \tau_{rms}(\mathrm{OLOS}) + \tau_{\mathrm{gap}} \quad (3)$$

Where τ_{rms} (LOS) is the root mean square of delay spread of LOS, τ_{rms} (OLOS) is the root mean square of delay spread of OLOS, and τ_{gap} is the time gap from LOS to OLOS, $\tau_{\mathrm{gap}} \in$ (0.5ns, 1ns).

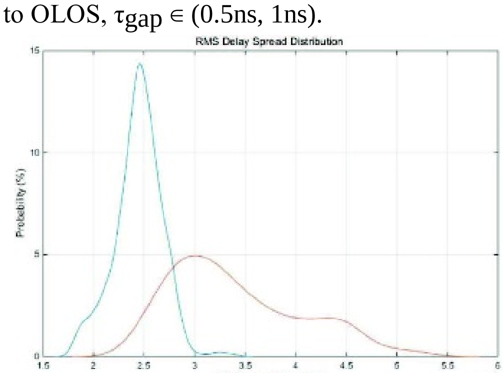


Fig.5 Mean of τ_{rms} and received in LOS and OLOS

Using UWB signals, we can also do the detection by according to the first peak power. Figure 6 shows the channel profile of both LOS and OLOS conditions, there is a huge decrease of the first peak power from LOS to OLOS. The power in LOS is about three times larger than it is in OLOS.

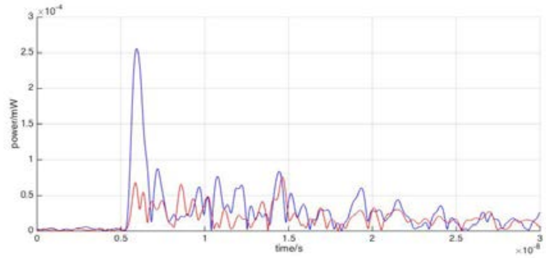


Fig.6 Firest peak power in LOS and OLOS

Moreover, the difference of power does not only occurs in the first peak, but also in the total power. The total power is the sum of power of peaks over given threshold. The value of total power shows the signal strength received by receiver. From the waveform of two scenarios in Figure 7, we can see that the total power of OLOS is dramatically smaller than LOS condition. From the measurement data, we find out that there is a statistical mean of power drop from LOS to OLOS. The relation can be expressed as

$$m_{power}(LOS) = m_{power}(OLOS) + P_{gap} \quad (4)$$

Where $m_{power}(LOS)$ is the mean of total power of LOS, $m_{power}(OLOS)$ is the mean of total power of OLOS, and P_{gap} is the power gap from LOS to OLOS. Note that $P_{gap} \in (6mW, 12mW)$.

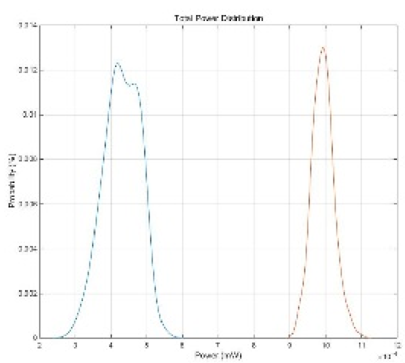


Fig.7 Total power in LOS and OLOS

By determining all the parameters shown in front, we can detect gestures and movements. Identifying little movement like hand turnover or put hand behind the body, which is very common in our daily life, but it will improve the quality of visually impaired life and even the medical applications using gesture detection.

V. CONCLUSION

In this paper, we compare the gesture detection using Wi-Fi signal RSS and gesture detection using various characteristics of UWB signals, which is more accurate and reliable than others before. We use four parameters, time of arrival, first peak power, total power and the RMS delay spread, and built a database by performing 500 measurements on each gesture.

Using the result of UWB gesture detection will help the visually impaired have a more convenient life and can also help the development of medical applications.

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