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Design of Software Defined Radios Based Platform for Activity Recognition

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ABSTRACT Recently, activity recognition and classification (ARC) of human activity opens new research area in the field health care, security, and privacy of human society. Specifically, the promise of device-free activity recognition platform attracts researchers to develop platform to ensure the correct detection of activity recognition. The technologies, such as Wi-Fi, GSM, and radars, do not require installing cameras or wearable sensors for activity monitoring and recognition. Therefore, this device-free technology has gain popularity in health care and safety measurement systems. Traditional ARC systems depend on wearable sensors such as magic rings and vision technology such as a Microsoft Kinect. In the future, researchers are striving to reduce such devices and targeting a promising device-free sensing system. In this paper, a software-defined radio platform was designed for the detection of human activity. The extensive experiments were performed in the laboratory environment by using two Universal Software Radio Peripheral (USRP) to extract the wireless channel state information (WCSI). The 64-Fast Fourier Transform (FFT) point's Orthogonal frequency division multiplexing (OFDM) signal was used to determine the WCSI. The design of the proposed system can be used for multiple applications due to scalability and flexibility of the software-defined hardware.

INDEX TERMS ARC, ARP, SDR, OFDM, USRP, WCSI.

I. INTRODUCTION

Human activity recognition has gained tremendous attention in recent years due to numerous applications. Its aim to monitor the movement and behavior of humans in indoor areas. Applications such as health care monitoring and fall detection for elderly people [1], contextual awareness, activity recognition for energy efficiency in smart homes [2] and many other Internet of Things (IoT) based applications [3]. Currently, various Wi-Fi-signal based human ARC systems have been proposed [2], [4], [5]. The main feature of these ARC systems are human body, which contains mostly water and can reflect Wi-Fi signals. Therefore, the change in received signal characteristics by the nearby Wi-Fi system indicates human activity. While studying the traditional human activity recognition systems, they use cameras monitoring [6] radars scanning [7] and wearable sensing devices [8], [9].

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The used of device free Wi-Fi signals based systems have given the following solutions over the traditional systems. First, Wi-Fi based solutions are device-free without placing any sensors equipment's on human body. The activity is analyze by the reflection of human body through wireless signals. Therefore, this will provide ease to patients especially for pregnant women, kids and aged people to equip with sensors. Second, Wi-Fi based solutions have increase coverage area than conventional cameras system. Wi-Fi signals have capability to see through walls and other obstacles, whereas on the other hand cameras have limited degree of viewing angles and need good lighting conditions. Also camera based solutions have privacy issues and dedicated person is required to monitor the activities. Third, the recently radar based solution proposed at 60 GHz frequency radar have limited coverage area of less than one meter due to the smaller wavelength [7]. Recently human Activity Recognition and Monitoring system (CARM) uses theoretical models of Wi-Fi signals [10]. This system uses the Wi-Fi link between Commercial Off-The-Shelf (COTS) devices to detect human activities. In this, when there are human's movements, the Wi-Fi signals reflected by the human body will affect the signals travelling through the direct path. The WCSI is measured at the receiver to recognize the human activity. WCSI-speed model and WCSI-activity model are used in CARM. Commercial Wi-Fi cards are normally low cost and they have various types of noises during WCSI measurements. Mostly the hardware devices are not calibrated properly so they introduces carrier frequency offset (CFO), which is the source of random variations in the phase of WCSI [11], [12]. The amplitude of the WCSI values also fluctuates due to the adjacent electromagnetic noises and the power adaptation phenomena of the Wi-Fi card. These fluctuations leads to higher amplitude than the small changes produced by human activity. Under these noisy circumstances it is very difficult to extract the actual activity during WCSI measurements. Another challenge during extraction of WCSI is to build a robust model that can extract the activity perform by the human. Usually different human perform same activity by their own ways. This requires a system which is more robust and it can still recognize the activity. To counter this challenge, Hidden Markov Model (HMM) was used for speed features of human activities. HMM model has capability to recognize the same activities but they performed in different manners. Environmental changes are also challenge for extraction of WCSI. Data fusion is used on multiple Wi-Fi links offers better robustness under different multipath fading environments. CARM system achieves 8% of improvement in recognition accuracy when data combine from three Wi-Fi links [10].

Although previous research work provide improvement in recognition accuracy but still they are Wi-Fi signal dependent. They are not scalable and flexible to determine activity in area where Wi-Fi signals are not available. Especially Wi-Fi signals are not suitable in flood, earthquakes and emergency situations where human health and safety measurement is necessary to cure. This requires flexible, adoptable and mobile solution for ARC. Software defined radio is one the promising solution for providing scalability and flexibility. In this research work we develop a software defined platform for extracting WCSI to determine human activity. The rest of the paper is organized as follow:

In section 2 information about the existing platform and related work in detecting the human ARC.

In section 3 Design of SDR based human ARC platform is presented.

In section 4 Methodology used to extract the WCSI for human ARC and experiment details are given.

In section 5 conclusion and future recommendation in developing SDR based human ARC.

II. RELATED WORK

Research used following four methods for human ARC: RSSI based system, Radar based system, CSI tool based system and SDR based system. RSSI Based: Received Signal Strength Indicator (RSSI) based human ARC systems mainly depend on the received signal strength variation caused by human activities performed [13]–[15]. However, In RSSI system has limited accuracy and detection capability. Although using SDR it improve the recognition accuracy up to 72% to capture RSSI with a higher resolution [14]. The accuracy and coverage area of RSSI based systems are still less than CARM in absence frequency diversity which is presence in CSI tool based system. Radar Based Systems (RBS): RBS was also used for human activity recognition having much higher bandwidth [16]–[18]. Frequency Modulated Carrier Wave (FMCW) radar can used bandwidth up to 1.79 GHz band [16] whereas Wi-Fi only uses bandwidth 20 MHz. RBS is use for extraction of micro-Doppler information [18] and having higher distance resolution of about 20 cm [16], [17]. However, RBS based systems require specific hardware and processing unit. CSI Based: Recently, CSI feature extraction by Wi-Fi network interface cards (NICs) [19], [18] are widely used for human activity recognition [20], [21]. Researchers paid attention in developing CSI based applications, which includes fall detection of kids and elder people [1], presence detection of human [12], indoor localization [4], [22], and human gathering counting [23]. Literature provide information about CSI is also able to detect and recognize small movements of body lip movements [25], keystrokes [14], and heartbeats [23]. SDR based system: SDR based platform or specially designed hardware can used in human ARC signal measurements [26]–[28]. For example, Wi-See uses USRP to measure the Doppler shift in wireless signals and attain an activity recognition accuracy up-to 95% [2]. All-see introduces a short range (less than 2.5 feet) detection method for gesture recognition using specialize circuit hardware. While considering Wi-Fi signal for the extraction of WCSI without upgradation and modification of hardware only solution is to used SDR platform.

FIGURE 1. System model of Project.

III. SYSTEM MODEL

In this section project design is discussed which consists of two USRPs of bus series. Each USRP is connected to Personal computer (PC) via USB port and are equip with single antenna. One USRP with PC is used for transmitter operation and other perform receiver operation. The real time wireless channel in lab environment is use to extract the WCSI for human activity as shown in Fig. 1.

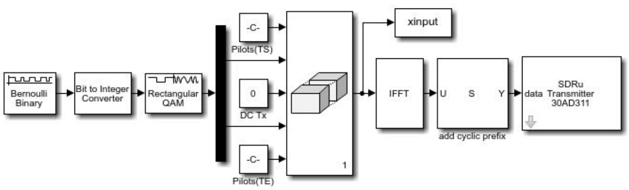

FIGURE 2. Transmitter simulink model.

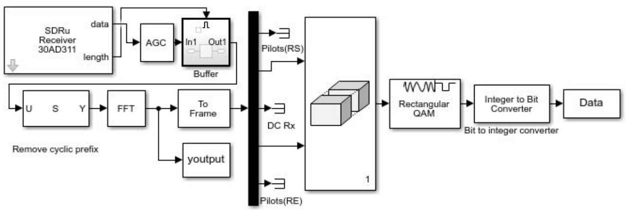

FIGURE 3. Receiver simulink model.

A. TRANSMITTER OPERATION

In transmitter operation data is generated and processed in MATLAB/Simulink and transmitted wirelessly using USRP. Random data bits are generated using Bernoulli source block with probability of 0.5. Then these bits are converted into symbols and mapping using any modulation scheme due to the software flexibility to constitute symbols of source data. These source data symbols are in complex domain. They contain modulation constellation points. These symbols will link to single subcarrier system. Then, they are transferred to serial to parallel converter to perform Inverse Fast Fourier Transform (IFFT). In the frequency domain, each multiple adjacent tones or sub-carriers are independently modulated with complex data. IFFT is performed on sub-carriers to produce the OFDM symbol in the time-domain. Then in the time domain, guard intervals are inserted between each of the symbols to prevent inter-symbol interference at the receiver caused by multi-path delay spread in the radio channel. Multiple symbols can be concatenated to create the final OFDM signal. Then OFDM signal is up-converted and digital to analogue conversion (DAC) using USRP hardware. The software defined operation of the transmitted signal is shown in Fig. 2 using Simulink model.

B. CHANNEL

Additive white Gaussian noise (AWGN) was consider for simulated environment whereas wireless indoor lab environment was used for capturing the WCSI.

C. RECEIVER OPERATION

In receiver operation OFDM signal was received using another USRP as shown in Fig. 3. Firstly USRP hardware perform analogue to digital conversion (DAC) and then down conversion. Automatic gain controller block (AGC) is used because this block adoptively adjust its gain to achieve a constant signal level at the output. OFDM can retrieves signal efficiently by following three conditions given below.

- Timing and frequency offset does not exist.
- Offsets should be estimated correctly.
- Length of CP should always be greater than maximum value delay spread.

In this process, real-valued passband waveform is mixed with the carrier tone that is generated locally, after that low pass filter was used to generate I/Q baseband waveform that is carried out in USRP Hardware. Fast Fourier transform (FFT) is one of the technique for converting time domain signal into frequency domain, this process is implemented at the receiver end. Inserted zero padding at the transmitted end is also removed during recovering of the original signal. The receiver operation is opposite to transmitter as shown in the Fig. 3.

IV. METHODOLOGY

Following three phases were used to design a software defined radio platform for activity recognition.

Phase 1: In this phase software part was design and implemented in Simulink. Firstly system was tested by measuring bit error rate (BER) for reliable communication. The multiple parameter values are tested due to the software flexibility that can be used for multiple applications and wireless standards as shown in table 1. AWGN channel was used to test the software part.

TABLE 1. Software parameters.

Parameter	Values
Input data (Random bits)	100000
Bits per Symbols (M)	2, 4, 8, 16, 32 and 64
Modulation type	BSPK, QPSK, 8PSK, 4QAM, 16QAM, 64QAM
OFDM subcarriers	64, 128, 256, 512, 1024 and 2048
Data subcarriers	48, 96, 192, 384, 768, and 1536
Pilot subcarriers	4, 12, 8, 42, 82 and 166
Null subcarriers	12, 20, 56, 86, 174 and 346
Used subcarriers	52, 108, 200, 426, 850 and 1702
NFFT points	64, 128, 256, 512, 1024 and 2048
Cyclic prefix	NFFT - Data subcarriers
Samples per frames	Used subcarriers*log2(M)

Phase 2: In this channel amplitude and phase response was measured by using IFFT block at the transmitter and FFT block at the receiver. Equation (1) shown channel response measurement.

$$H\left(f\right) = \frac{Y(f)}{X(f)} \tag{1}$$

In (1)$X(f)$ is the frequency response of the transmitted signal, $Y(f)$ is the frequency response of the received signal and $H(f)$ is the channel response of the system.

Phase 3: In this phase USRP is interface with the MATLAB/Simulink to implement the system in real time lab environment. Configure the hardware transmitter and receiver parameters as shown in table 2 with PC. Calibrate both USRPs to find the frequency offset because these devices

TABLE 2. Hardware configuration parameters.

Platform	B210
Channel Mapping	1
Centre Frequency	900MHz, 2.45GHz
Local oscillator offset	-2.34345
PPS Source	Internal
Clock Source	Internal
Master Clock Rate	32MHz
Transport data type	int16
Enable Burst mode	false
Interpolation Factor	500
Decimation Factor	500
Output data type	Same as transport data type
Transmitter serial number	30AD311
Receiver serial number	30AD2FE

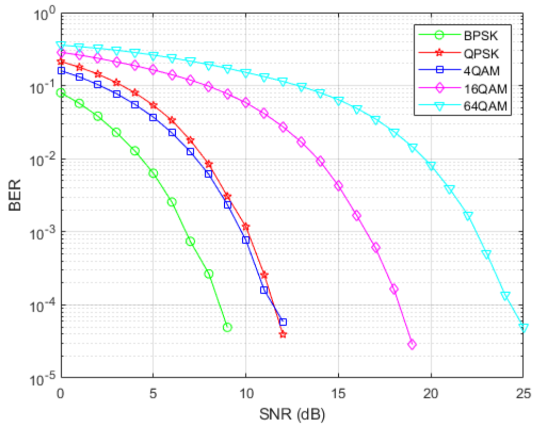

FIGURE 4. Simulated BER analysis of OFDM system.

are un-calibrated. After calibrating hardware platform is test by running basic example of QPSK transmitter and receiver example to ensure that hardware is working properly. Finally applied our own software defined Simulink model to capture the WCSI with and without human activity.

V. RESULTS AND DISCUSSION

Following results are discuss to evaluate the design of the system.

A. SIMULATED BIT ERROR RATE (BER) OF THE SYSTEM

BER is the most important parameter to analyze the performance of the system of any reliable communication. In Fig. 4. shows the BER performance analysis of the system by using different digital modulation schemes. AWGN channel was considered for simulated results. In Fig. 4. shows water fall curve for BER analysis of different modulation schemes. The results shows increasing the value of SNR the performance of BER improves. Higher order modulation 64-QAM has high BER than lower order BPSK. This trend verified our system design.

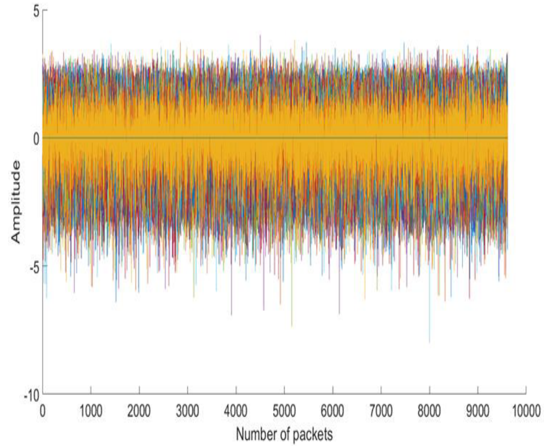

FIGURE 5. Simulated frequency response of AWGN.

B. SIMULATED FREQUENCY RESPONSE OF THE SYSTEM

Simulated frequency response of the system is measure using (1) to analyze the system using AWGN. 64-subcarrier are used and 9616 packets are send and receive by the system in 10 seconds. The sample rate is 64 kHz is used. WCSI of the AWGN shows results in Fig. 5. that amplitudes changes are observe but no prominent change indicate any unusual behavior of the channel. The frequency distribution remain same for all the sub-carriers. These results verified the frequency channel response of the AWGN system which is normally distributed over the entire frequency range. This also verified the AWGN characteristics and ensure software model design is working properly. Analyzing the result shown by our system can be used for extracting WCSI to facilitate human ARC.

C. REAL TIME CHANNEL RESPONSE OF THE SYSTEM

USRP based hardware platform is used to captured the WCSI for activity recognition. Real time experiment is perform for two cases: when no human activity is perform in between the transmitter and receiver and when human activity is performed. We consider human waving hand activity and pendulum movement for our activity recognition experiments. While using hardware platform a lot of factors are involves in real time experiments either by evaluating any human activity recognition or analyzing wireless communication systems. Environment effects always changes the characteristic of the received information which may lead to the false detection of the activity. Hardware testing is also necessary while performing experiments because there may be human error or device configuration and calibration error. To ensure the activity detection extensive experiments are perform to acknowledge activities. Before performing the actual experiment we send ''Hello word'' text message form one USRP to another USRP to ensure that message is receive by the hardware setup. Firstly the experiment is perform for no activity to analyze the WCSI of the system

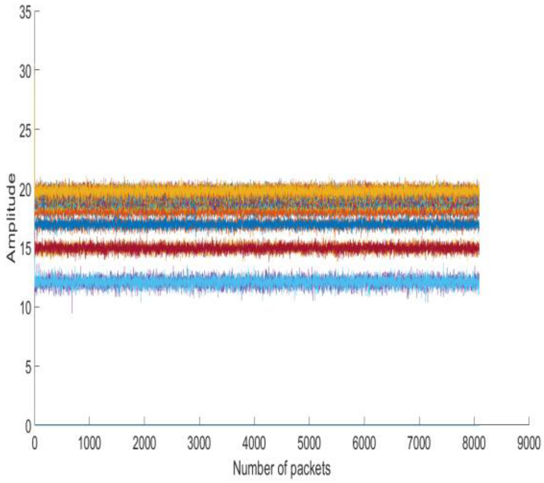

FIGURE 6. WCSI when no activity is performed.

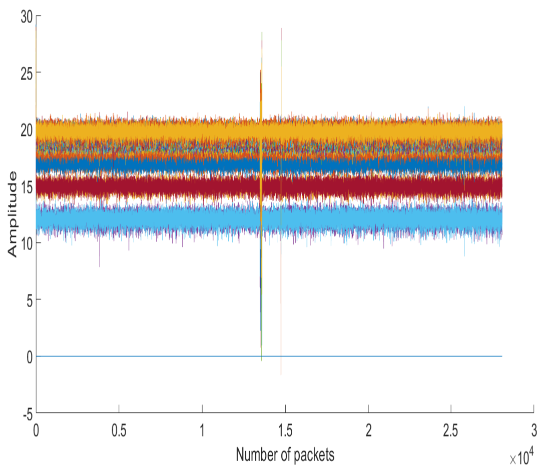

FIGURE 7. WCSI when activity is performed.

in quite lab environment. Amplitude variations are observe but no prominent changes occurs in amplitude during the experiment. The experiment was repeated for ten times and same results achieved as shown in Fig. 6. 8088 packets were received out of 10001 in 10 seconds. Every time we perform this experiment for 10 seconds in the same environment and received same number of packets. While considering the case when activity is perform by human waving hand and pendulum motion in between the transmitter and receiver. We increase time from 10 seconds to 30 seconds. It's good to have more time to observe the amplitude changes while considering the activity is perform in between the transmitter and the receiver. While increasing time it was observed that it required more time to process the real-time data for more number of packets. For this reason we selected only 30 seconds to monitor the activity. We transmit 30001 packets and receive 27880 packets in 30 seconds. In Fig. 7. Shows the results of when activity is perform. In this case amplitude changes are observe for the waving hand. We perform this experiments ten times and every time we receives some prominent amplitude changes when activity is perform in lab environment. These amplitude changes is the information for the human activity and ensuring that some activity is going on in between the transmitter and receiver. These results shows our system design is key for other human activities and in future if we applied machine learning algorithms (MLA) or deep learning algorithms (DLA) we can determine variety of activities like sitting, walking, running, eating and many vital sign to enhance the human care system.

VI. CONCLUSION

Software defined radio based human ARC system provides flexibility and scalability to facilities number of applications. Accurate human activity is always a daunting task for engineer and researchers. In this work system was first tested for reliable commination in term of BER by applying different modulation schemes. Channel response of the system using AWGN channel was used to ensure the system design and response. Finally USRP based platform was set by transmitting and receiving OFDM signal to extract the WCSI for human ARC. In future this extracted WCSI is used for human ARC by applying MLA and DLA. This platform can used in health care monitoring system, security and emergency condition to serve humanity with flexible software modifications.

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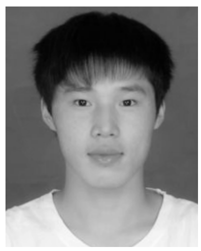

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