RF-based Monitoring, Sensing and Localization of Mobile Wireless Nodes

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Abstract. Spectrum sensing and characterization play a very important role in the implementation of cognitive radios and adaptive mobile wireless networks. Most practical mobile network deployments require some level of sensing and adaptation to allow individual nodes to learn and reconfigure based on observations from their own environment. Spectrum sensing can be used for detection of a transmitter in a specific band, which can help cognitive radios to detect spectrum holes for secondary users and to determine the presence of a transmitter in a given area. In addition to determining the existence of a transmitter, information obtained from spectrum sensing can be used to localize a transmitter. In this paper, we focus in oner particular aspect o that problem: the distributed and collaborative sensing, characterization and location of emitters in an open environment. Thus, we propose a software defined radio (SDR)-based spectrum sensing and localization method. The proposed approach uses energy detection for spectrum sensing and fingerprinting techniques for estimating the location of the transmitter. A Universal Software Radio Peripheral (USRP) managed via a small, low-cost computer is used for spectrum sensing. Results obtained from an indoor experimental setup and the K-nearest neighbor algorithm for the fingerprinting based localization are presented in this paper.

1 Introduction

Spectrum sensing in cognitive radios is becoming a widely researched area these days for two reasons. First, spectrum is a limited resource and is even becoming scarce. Wireless service providers buy a chunk of spectrum for various purposes and at times they use all their resource, while other times it remains underutilized [1]. Cognitive radios alleviate this problem by being able to sense the environment and exploit information to find if a user is present in a specific spectrum [2]. This allows secondary users, with lower propriety than primary users, to use the band that is not used by primary licensed networks. Second, spectrum sensing can be used in cognitive networks to detect, indicate and localize a target or an intruder in a given area [3]. For this work, we will use spectrum sensing to determine a presence of a transmitter in a given indoor environment,

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and then determine the location. Various approaches have been proposed for spectrum sensing in literature such as, matched filter detection, and cyclostationary feature detection, energy detection [4–6]. Energy detection method is chosen for this work due to its less implementation complexity and due to the assumption that there is no prior knowledge of the transmitted signal. Once a presence of a transmitter is determined, the location can be estimated using signal measurements obtained from receivers. In this research, we use fingerprinting based localization technique to estimate location of a transmitter. This technique is chosen because we are dealing with indoor environment, and its model free nature makes it efficient to be implemented in highly multipath environment.

The goal of this work is to show that a transmitter operating in a given frequency band, can be detected and be localized using n receivers. Software defined radios are a good candidate to implement these features. In this work we use a set of small computers (Banana PIs) to serve as hosts to software defined radios. These computers will perform spectrum sensing after receiving streams of data from the radios. Using these computers to control SDRs is cost effective and provides portability. A central controller connected to the Pis will perform the localization. We use USRPs, Ettus researches SDRs, together with the UHD C++ API to implement the sensing and localization of a transmitter in an indoor environment.

This paper is organized as follows. Section 2 presents background on software defined radios, and UHD C++ API package. In addition, Sect. 2 also discusses available sensing and localization schemes in the literature. In Sect. 3, experimental setup of our work is presented. Our results are presented in Sects. 4 and 5 concludes the paper.

2 Background

2.1 Software Defined Radio (SDR)

SDR is a reconfigurable radio system where its components are implemented by means of software on embedded devices. Its reconfigurability allows easier implementations of various radio functions instead of redesigning radio hardware for the same purpose. Its flexibility and cost has made it very popular in current wireless researches. For this work we use the Universal Software Radio Periferal (USRP).

USRP. The Universal Software Radio Peripheral (USRP) is a low-cost hardware platform developed by Ettus Research that enables users to design and implement a broad range of research, academic, industrial and defense applications [7]. The radio has a modular architecture that includes a motherboard and a set of optional daughterboards to provide different configuration and operational capabilities.

The USRP motherboard provides basic components for signal processing, such as clock generation, synchronization, ADCs, DACs, FGPA, host processor interface (USB 2.0 or Ethernet), and power regulation. The daughterboards are the modular front-ends used for up/down-conversion and filtering, and are selected based on the application requirements for frequency coverage, bandwidth, number of channels.

The USRP can be controlled by a host computer through the use of the USRP Hardware Driver (UHD) software package, also developed by Ettus Research. UHD provides a host driver and API for standalone or third-party applications, such as GNU Radio, Simulink, etc.

UHD API. The UHD API is a C++ set of libraries that provides basic peripheral configuration functions and enables applications access to the USRP hardware. Its purpose is to ease the configuration of the radio front-end as well as transfer of data between the host application and the USRP. It can be used on Linux, Windows and Mac OS. It implements a full network stack, which makes the UHD routable and requires no custom driver.

2.2 Spectrum Sensing

For spectrum sensing, primarily the following three techniques are proposed in literature:

Cyclostationary feature detection: This technique exploits the cyclostationarity of modulated signals to differentiate between random signal with particular modulation type in a background of noise and modulated signals [6]. Cyclostationarity features can be used to distinguish a signal from noise and other modulated signals.
Matched filter detection: Matched filter is a filter designed to maximize the SNR of a given signal. Matched filter detection performs coherent detection where a received signal is convolved with a filter whose impulse response is the time shifted version of the reference signal. This technique requires a prior knowledge of the received signal.
Energy detection: This type of detection is done by comparing the energy of a received signal with a predetermined threshold [8]. If the energy of a signal in a specific frequency band is greater than the threshold, then there is a signal present in the environment in that band. Otherwise, a signal is not present. It can be implemented in both time domain and frequency domain as shown in Figs. 1 and 2. It is less complex and requires no prior knowledge of the signal. Due to that, it is the most popular sensing technique used.

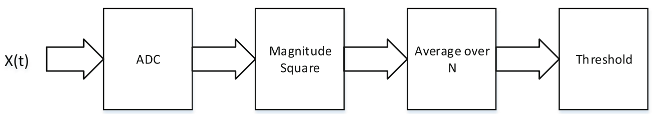

Fig. 1. Energy detection in time domain

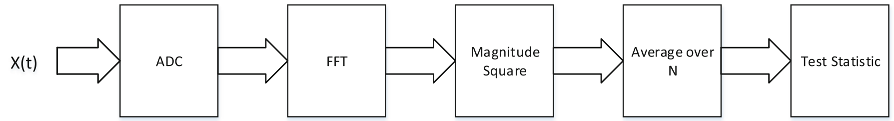

Fig. 2. Energy detection in frequency domain

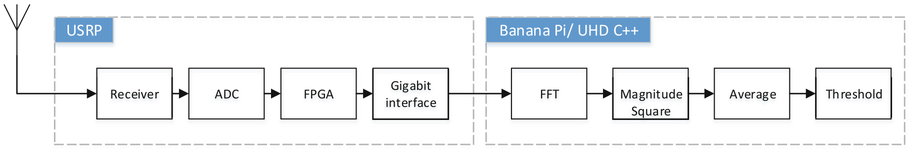

Fig. 3. Energy detection at the receiver

2.3 Indoor Localization

Most localization and tracking systems use GPS information to determine a location of a user. However, GPS information is only reliable when there is direct line of sight communication between the user and satellites in space which makes it impossible to use for indoors [9–11]. Examples of the localization techniques that can be used for indoor environments are TOA, TDOA, AOA, and fingerprinting appcoachers. In ToA, the emitter transmits time stamped signals so that the receivers calculate the distance between the emitter and themselves from the transmission delay. This requires synchronization of the transmitter with the receivers and it is not a viable choice when transmit signal is not time stamped. Instead of measuring time measurements at receivers, Time Difference of Arrival (TDOA) techniques use relative time measurements. Hence, only receivers require time synchronization [12]. Other systems use the angle of arrival (AoA) of a transmitter signal to determine location [13]. This technique's accuracy is negatively affected by the existence of multipath and non light of sight propagation of signals in the indoor environment. Localization and positioning in indoor environment using the aforementioned is a challenging task mainly because the propagation of wireless signal is highly affected by multipath components created from the environment. For that reason, it is difficult to mathematically model the wireless propagation in indoor setting. Therefore, fingerprinting localization approach is considered. When using this approach, a radio map of a given area is created based on signal strength measurements from several access points for a given location [14–16]. A mobile user at an unknown location then infers its location through comparing signal strength measurements to the map to estimate the location. Most indoor localization techniques are concerned with the user finding its own location based on received power it collects from a number of stationary access points. In those techniques, the user first trains itself by building an RSSI map. Then it uses the map to find a

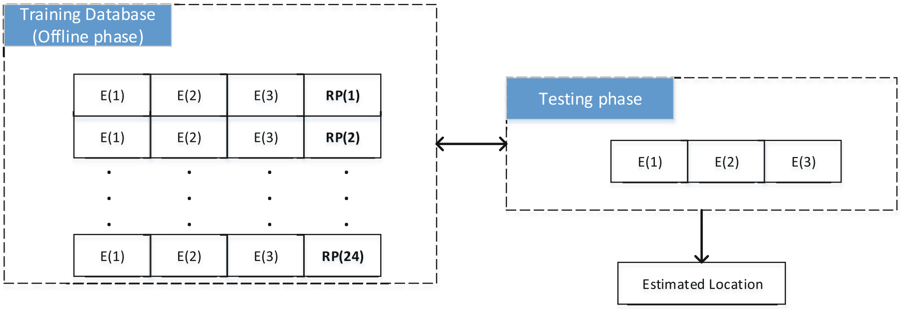

Fig. 4. Fingerprinting method

current location. In this work, however, the stationary access points operating in different spectrum collect received energy from a transmitter and estimate the location of the transmitter.

3 Experimental Setup

The experiment was designed to evaluate spectrum sensing and localization of a single transmitter using energy detection techniques. We used three USRPs acting as energy detectors and a USRP acting as the transmitter to be localized. The four USRPs were deployed in a medium-size conference room of the Harris Institute for Assured Information at the Florida Institute of Technology in Melbourne, FL (Fig. 7).

Each of the USRPs is connected to a host Banana Pi, which is a credit card-sized and low-power single-board computer that includes a 1 GHz ARM Cortex-A7 dual-core processor, 1 GB DDR SDRAM, SATA 2.0 and Gigabit Ethernet. The Banana Pi can run the Android, Ubuntu and Debian operating systems. It was chosen as the host computers for the USRPs because it is low cost, portable, and provides the required Gigabit Ethernet port to interface with the USRPs.

Each Banana Pi is connected to a central controller through a switch. We used SBX daughterboards for this experiment, which can cover frequencies from 400 to 4400 MHz. Each receiver senses presence of a transmitter in a specified frequency band and a bandwidth set to 5 MHz. The transmitter USRP is also configured to use a bandwidth of 5 MHz. The transmit frequency is set to 910 MHz. Figure 5 illustrates the configuration of the test network, including the four Banana Pi/USRP units and the controller computer that performs the localization of the transmitter based on energy measurements reported by three sensors.

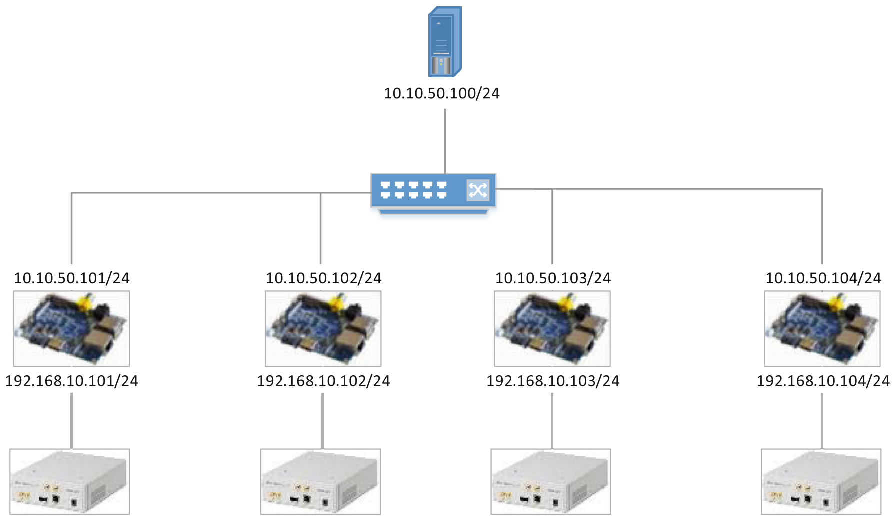

Fig. 5. Experimental setup

Energy detection technique was used for the spectrum sensing part. This kind of technique does not require prior knowledge of other users signals. The energy of a received signal is compared to a threshold to determine the presence of a signal in a band. Energy detection is based on two hypotheses:

$$H_0 : y(n)\& = w(n) H_1 : y(n)\& = w(n) + x(n), n = 1, 2, 3, ...N \qquad (1)$$

where $y(n)$ represents the received signal, $w(n)$ represents noise signal, and $x(n)$ represents a transmitted signal. Hypothesis H_0 defines that there is no transmitter present in a specified frequency band, and H_1 defines there is a transmitter in the band. The goal of the energy detection algorithm is to compute a test statistic T and compare it with a given threshold γ. The hypothesis selection can be determined by comparing the decision statistic T as follows:

$$T < \gamma \rightarrow H_0 T \geq \gamma \rightarrow H_1 \qquad (2)$$

Figure 3 represents a block diagram of a receiver that uses energy detector in this study. The USRP receiver captures analog signal and first converts it to digital signal then passes it to the computer through a gigabit interface. The FFT coefficient values were then calculated and squared. The squared FFT coefficients are averaged over observation interval. The final output is used to make decision on whether a signal is present or not by comparing it with a threshold γ.

After the presence of a transmitter is confirmed, the next step is to localize the transmitter. Each Pi connected to the USRP receivers send their measured energy value to the central controller using UDP sockets. The central controller receives energy measurements to perform the localization. The localization method used in this work is RF fingerprinting approach. There are two phases in location fingerprinting technique, offline phase also known as training phase, and online phase also known as localization phase. In the offline phase, the goal is to create a database for each reference or known locations from the energy of a signal captured by each stationary receiver. In the online or localization phase, the training database is used to determine the location of a transmitter with a given energy from the captured signal. The layout for the location fingerprinting technique used in this work is shown in Fig. 4.

As shown in the figure, in the offline phase, the signal energy fingerprints $E(1), E(2), and\, E(3)$ from the receivers are associated to their corresponding reference positions $RP(i)$ to create a training database.

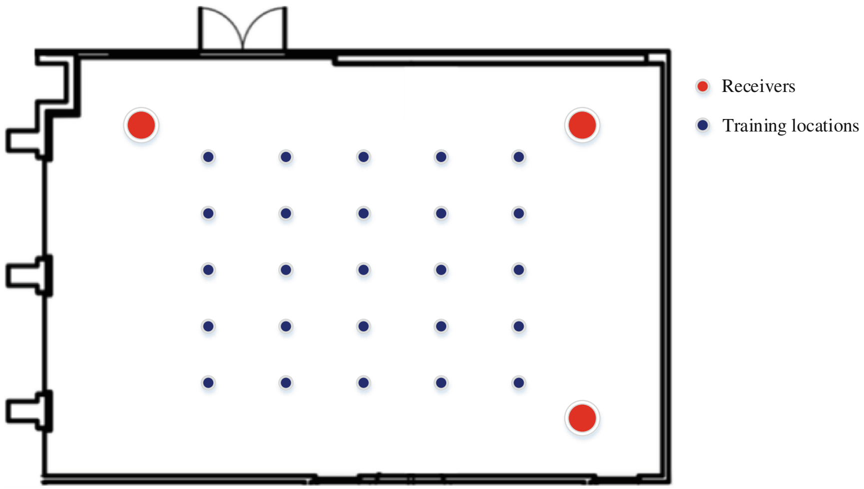

Fig. 6. Training locations with receivers positions

Figure 6 shows a layout of the training locations or reference points used in this work. For building the energy map, the area was divided into grids of 50 in. between them. They are denoted by the blue circles in the figure. Energy of a signal from each of the 25 reference positions is obtained from three receivers. For each position, we collected 50 energy measurements at 5 different times. Therefore, we will have a total of 250 energy measurements for each position from the three receivers. The difference of measurements from each receiver for each sets of samples is calculated. This is because energy received at different times might change. However, the difference of the measurement from each of the receivers is assumed to stay relatively constant. Each of the 5 sets of measurements, are averaged. The average of the averages of the difference in measured energy is used to construct our training data set. Therefore we have 25 samples corresponding to the reference points.

In the online phase, energy values at an unknown location measured by the three receivers is compared with the training database by measuring the

Fig. 7. Receivers and transmitter placement in the room

Euclidean distance from each reference point, and location of the transmitter is estimated. Euclidean distance in energy between energy vector E of an unknown position U and energy vector of reference point RP is given as:

$$E = \sqrt{\sum_{i=1}^{3} (U_i - RP_i)^2} \tag{3}$$

Then the weighted k-nearest neighbor algorithm is used to find the unknown location of the transmitter. K smallest Euclidean distances which correspond to k-nearest reference points are evaluated. To find the coordinates of the estimated location of the unknown signal point, each of the k-distances are given weights as follows:

$$w_k = \frac{\frac{1}{E_k}}{\sum_{i=1}^{k} \frac{1}{E_i}} \tag{4}$$

The estimated coordinates are then calculated using the weighted k-NN as:

$$(x, y) = \sum_{i=1}^{k} w_i (x_i, y_i) \tag{5}$$

4 Results

The measurement taken from the sensing and localization system built were analyzed and the results are presented here. The training data is composed of reference points (reference locations), where reference point has signal energy level from each of the stationary receivers. From the test data, distance from each reference point to test point is calculated to find the nearest neighbor. Here, by distance we mean signal distance. Then, k reference points which have minimum distance are selected to estimate location. As mentioned in the previous section, we averaged the energy over the samples to obtain a row vector for both the training and testing phases. That is because there could be variations in energy measurement that can be corrected when averaged over a period or sample number.

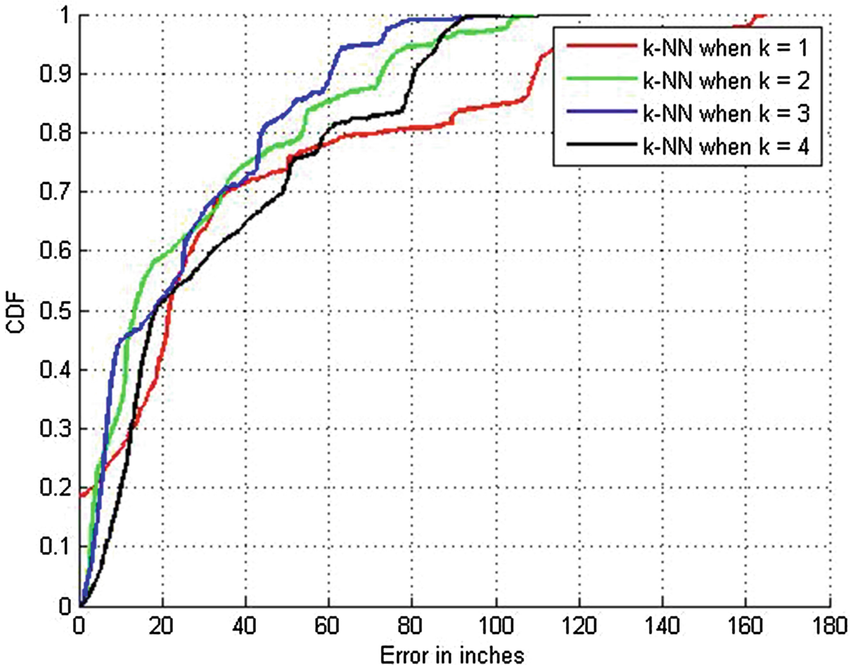

Fig. 8. CDF of estimation error

The results of the experiments using weighted k nearest neighbor algorithm are presented in Fig. 8. As a measure of performance, the Euclidean distance error was used, which represents the distance between the estimated location and true location of the transmitter. The cumulative distribution function (CDF) describes the estimation characteristics. Figure 9 shows the CDF of error depending of k-nearest neighbors used to estimate the location. From the figure, we can see that 90th-percentile error distance for k = 3 is 60 in.. That means about 90% of the time, the error was below 60 in.. The average of the error distance is 24.7 in., and the standard deviation is 22.5. For the 90-th percentile error distance, the average of the error distance is 20.86 in. and the standard deviation is 18.37. For the 90-th percentile, the 95% confidence interval (min, max) is (19.82 in, 21.9 in) with margin of error (ME) of 1.04 in.

5 Conclusion

In this paper we presented a SDR-based spectrum sensing and localization method using energy detection techniques for spectrum sensing and Euclidean distance-based nearest neighbor method for localization. We demonstrated our approach using a set of USRP radios, each of them connected to a small, low-cost computer to act as sensors for energy detection. A central controller was used to receive energy measurements from these sensors and perform the localization of a single USRP transmitter. Fingerprinting method was used to map the energy received at reference points for training, then to test using unknown locations. Test results has shown that the weighted 3-NN method for localization provides the best estimation distance error.

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