Human Subject Identification via Passive Spectrum Monitoring

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Abstract—**Human subjects' identification including face recognition, fingerprint recognition, and gait recognition enhances biometric health and safety. However, existing methods have their limitations as it is difficult to identify humans when humans cannot touch devices or there is a dim environment. This paper proposes a novel human identification approach, which utilizes passive radio frequency (RF) signal as a biometrics modality to achieve human identification. The passive human subject identification with radio-frequency (PHSIR) approach is verifies that different human subjects could generate different spectrum signatures, and these spectrum characteristics can be distinguished by machine learning (ML) algorithms to achieve human subjects' classification. Software-defined radio (SDR) technology acquires passive RF in the frequency bands that are sensitive to human occupancy. The passive spectrums were collected in two environments. Four ML algorithms were used to classify the sample spectrums associated with different human subjects, including decision tree, support vector machines (SVM), k-nearest neighbors (KNN), and random forest. Experimental results from seven volunteers indicate the classification accuracy is higher than 94% for seven volunteers using KNN algorithms.**

Keywords—human subject identification, passive radio frequency, spectrums monitoring, human RF signatures

I. Introduction

Identity authentication is an important part of information security which relies on physiological recognition and human classification towards individual identification. Traditional authentication methods mainly rely on various certificates, pins, and passwords. However, certificates are easy to lose, and passwords are very liable to forget and crack [1]. Therefore, biometric identification is becoming more and more popular. Biometric identification is to use human biological characteristics for classification towards identity authentication. These technologies mainly utilize the inherent physiological or behavioral characteristics to verify personal identity. Physiological biometric technology utilizes the human body structure and shape, which includes fingerprint recognition, face recognition, and iris recognition [2][3][4]. The behavioral characteristics refer to behavior patterns of a human subject such as signature, voice, and gait [5][6][7]. Biometric identification is a reliable, convenient, and fast method to provide authentication.

Currently, identification (ID) technologies are based on fingerprint or face recognition widely applied in our daily life such as account login, online payments, and access control. These technologies have their own strengths and limitations. For example, fingerprint recognition can identify humans with high accuracy, but this technology requires the users to be close to the ID devices and cannot realize ID without touching the device. Face and iris recognition rely on camera to capture the biometrics, which can only work in a well-lit environment. In addition, some researchers utilized Electroencephalogram (EEG) to identify human subjects [8]. Although the ID accuracy of EEG is very high, it requires contact sensors using complex equipment to receive the signals. Hence, the EEG technology is relatively complicated and costly. Therefore, it is important to develop a user friendly and low-cost solution to overcome these limitations.

Passive Radio Frequency (P-RF) signals are available almost anywhere except in extreme environments. P-RF signals have multiple benefits such as less contamination of spectrum, low interception, and reduced power requirement. In previous research, human occupancy can alter the passive spectrum and humans at different locations can generate different spectral signatures [9][10]. According to these characteristics, P-RF signals can be utilized to detect the human presence and achieve accurate human indoor positioning. Based on the previous research, we propose a new hypothesis, which is that different human subjects could generate different spectral signatures, and a system of human ID can be developed for P-RF spectral monitoring. The method neither requires the touch of any device, nor depends on the lighting condition of the environment. Software-defined radio (SDR) acquires the P-RF spectrum in the frequency bands that are sensitive to human occupancy.

Statistical machine learning (ML) algorithms are widely used and can classify the sample spectrums associated with different human subjects, including decision tree, support vector machines (SVM), k-nearest neighbors (KNN), and random forest.

This paper presents the passive human subject identification with radio-frequency (PHSIR) classification approach to support a new biometric ID modality. The contributions of this research are as following. First, the hypothesis that different humans generate different P-RF spectral signatures is verified. Second, a novel user friendly and low-cost approach to identify human subjects by collecting P-RF wireless signals from surrounding environment is developed. Third, four ML algorithms classify the passive power spectral density to classify human subjects. The classification accuracy is over 94%, which can enrich the practical biometric ID methods for authentication.

The remaining sections of this paper are organized as follows. Section II reviews existing identification (or classification) techniques in the literature, focusing on several ML algorithms used in PHSIR, as well as explaining cognitive radio, to support human occupancy authentication. Section III presents the proposed PHSIR technique and the experimental design. Section IV shows the experimental results. Section V discusses the conclusions and future directions of our research.

II. Related Works

A. Exisiting Identification Technologies

The current human classification, recognition, and identification technologies mainly depend on the physiological characteristics, which include fingerprint, face, and iris recognition, and behavioral characteristics of movement based on signature, voice, and gait patterns. These technologies are discussed as follows.

Fingerprint recognition mainly includes two technologies, capacitive fingerprint recognition and optical fingerprint recognition. The principle of capacitive fingerprint recognition is to integrate pressure sensing, capacitive sensing, thermal sensing, and other sensors into an integrated chip. When the fingerprint is pressed on the surface of the chip, the internal capacitive sensor will generate peaks and valleys in the fingerprint. The charge or temperature difference is used to form a fingerprint image, which is matched with the fingerprint library to complete the fingerprint classification which is referred to as identification (ID) in the biometric literature [11]. The optical fingerprint recognition is when a finger touches the screen, the screen emits light to illuminate the finger area, and the reflected light that illuminates the fingerprint returns to the sensor on screen to achieve the ID [12]. The advantages of fingerprint recognition technology are low price, small size, and easy integration. However, the disadvantage is this method requires the user to touch the receiver. If the hand is injured or the glove is worn, the recognition cannot be reliably achieved.

Face recognition is a popular biometric technology. Face recognition technology first needs to find the position of the face in the picture. When a face is found in the picture, the facial features will be marked. Then feature points of the human face such as eyes, nose, and mouth are extracted. Finally, facial matching is realized by comparing the face features [3]. Facial recognition is used widely, but it cannot be used in dim light or when the face is obscured. For instance, currently wearing masks in public places due to COVD19 greatly restricts the efficacy of facial recognition.

Voice recognition is a technology that recognizes human subjects by analyzing the physical characteristics of the user's voice. Although voice recognition technology has been used in some products, they are not very convenient to use, because human voices are highly variable, and signatures require training [6]. In addition, compared to other biometrics, voice recognition is more complicated, and which is inconvenient in some conditions.

Gait recognition is to use the camera to collect the image sequences of a human walking (or other movements), extracts feature from the joints, and compares the dynamic feature patterns with the stored data for behavior classification. Human subjects can be recognized in long-distance or low video quality [13]. Some other research developed a method, which is to capture the gait information by using Wi-Fi signal [14]. However, the limitation of gait-based analysis needs to capture the dynamic information of the human subjects. If using a camera to capture the dynamic information, it will also depend on the quality of the imaging.

B. Software Defined Radio

RTL-SDR[1] is a software-defined radio (SDR) based on digital video broadcast technology (DVB-T) television (TV) tuners with RTL2832U chips. which is used to collect passive RF signals in the PHSIR method. SDR can realize many operations by developing software. For instance, an algorithm can be modified to make the SDR scan the specific frequency bands. There are many applications of SDR such as communications, spectrum monitoring, and RF transmitter identification [15]. SDR can be used for real-time communication [16]. SDR can be utilized to receive the animals' nerve signals [17]. The position of the mobile station can be estimated by using the signal strength received by the SDR [18]. SDR can be used to recognize gesture through Wi-Fi signals [19]. In our previous work, SDR was used to scan the RF signal spectrums to detect and estimate the human occupancy and the human occupying position in an indoor environment [10]. Moreover, the SDR devices used in our experiments are low cost, compact, and easy to deploy.

C. Machine Learning Algorithms

ML algorithms are divided into supervised, semi-supersede, and unsupervised learning. In the process of supervised learning training, the algorithm requires specific input and output, and a model is built from the training data set, and the result of the test set is derived a model. Decision tree, support vector machine (SVM), k-nearest neighbors (KNN), and random forest are common methods and have been utilized to identify the human subjects. A decision tree refines a feature set through analysis of meaning features based on the domain of interest, such as for human movements[20]. SVM is statistical method to align features to categories. For example, gender identification of human face has general features for normal categories SVM[21]. The KNN algorithm is a method based on local approximation and supports clustering. A KNN classifier shows promise for face classification and electrocardiogram (ECG) biometric [22]. The random forest can be regarded as a collection of decision trees. A gait recognition method can uniquely identify human based on the random forest [23].

[1] https://www.rtl-sdr.com

D. Discussion

Comparing available human classification technologies, there are some differences with the PHSIR method. PHISR uses passive signals to recognize and classify the human subjects, which is an efficient and friendly method. PSHSIR utilizes the signatures in the passive spectrum for different human subjects to realize the classification, so the new signal transmitters are not needed. It is beneficial for different environments, such as those crowded with various RF signals, which has electromagnetic pollution, and radiation of RF signals can be harmful to people's health. Therefore, passive sensing techniques are preferred overactive sensing techniques if they can achieve the high accuracies. In addition, PHSIR is not affected by factors such as environment, light, and temperature. The traditional methods are active sensing as human identification needs the user to touch on the device or using in an environment that sufficient light to achieve. However, PHSIR incorporates passive sensing not requiring user to touch a sensor, nor wear the receiving devices, but also can be used in a dark or low-light environment. Finally, experimentation research found that carrying a mobile phone will not affect the accuracy of PHSIR human recognition.

III. METHODOS

PHSIR assumes that different human subjects can generate different signatures as passive RF spectrums, because different people have different heartbeat, body temperature, or body shape, and the subtle variation can be detected by the ML classifiers. Based on these assumptions, utilizing passive RF signals can achieve human identification and disambiguation.

The proposed human subject's identification method includes three stages. The first stage is data acquisition, which applies multiple SDRs to collect passive RF spectrums in the frequency bands that are sensitive to human occupancy in two environments. The second stage is the data pre-processing, which converts the raw data to power spectrum. The third stage is the analysis of subject signature detection (person, animal, etc.), human recognition (e.g., gait), human classification (e.g., adult) which lead to identification from a known set of requirements (e.g., allowed student to enter a location. The power spectrums were classified by four ML algorithms to identify human subjects. The details about data acquisition, data pre-processing, and identification of different human subjects are described in the following subsections. The framework of human subject's identification system via passive spectrums is shown in Fig. 1.

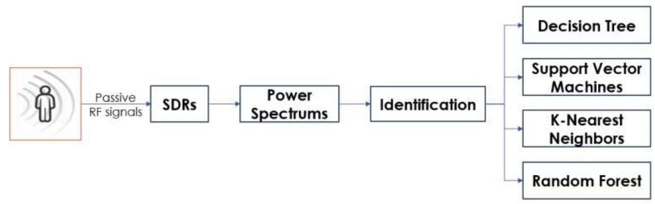

Fig. 1. The framework of human subjects identification system via passive spectrums.

A. Data Acquisition

In our experiments, five RTL2832U were applied to scan the selected frequency band to acquire the passive RF spectrum. In our previous work, the frequency bands sensitive to human occupancy are identified to be around 330MHz [10]. In this experiment, the frequency bands from 300MHz to 420MHz were scanned and the sample step size is 1.2MHz. We conducted the experiments in two different environments. One is the lobby in the Engineering Center building at Oakland University, while the other one is the living room of an apartment, which has more furniture compared to the lobby. Five SDR of the same model were placed around the human subject. Seven volunteers were asked to stand in the center in turn. Then seven known human subjects were numbered sequentially from 1 to 7. The locations of SDRs and human subject are shown in Fig. 2.

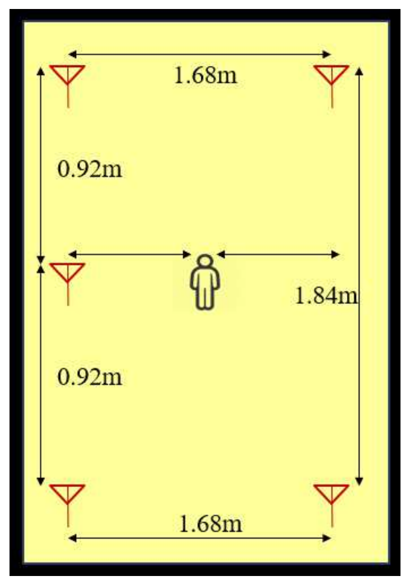

Fig. 2. The distributions of the devices and human occupying locations.

The data acquisition was performed with the human subjects occupying the same location in the same posture. A total of 100 frequency bands were scanned in one spectrum sample. Seven human subjects without any electrical devices were asked to stand in the center and then conduct movements. For each human subject,20 samples of RF data were collected in each environment of which some volunteers carried their cell phone. A total of 140 samples were collected in each environment. The information of the experiment setup is listed in TABLE I.

TABLE I. THE INFORMATION OF THE EXPERIMENT SETUP

Items	Description
Name of Devices	RTL-SDR
Number of Devices	5
Number of Humans	7
Experimental Site	Living Room Lobby
Frequency Range	300 MHz - 420 MHz
Number of Frequency Bands	100
Scanning Step	1.2 MHz
Sampling Rate	2.4 MHz
Duration	2 milliseconds per frequency band
Spectrum Samples per Human	20

B. Data Pre-processing

In our experiment, the input of the ML classifiers is the average power spectrum density, so the average power of each human sensitive frequency bands should be calculated as follow:

$$P(f) = 10 \cdot \frac{\log_{10} \sum_{i=1}^{N} \left(\frac{s_i}{127.5} - 1\right)^2}{N/2} \tag{1}$$

Where $P(f)$ is the average power of 100 frequency bands centered at f, $N$is the number of samples per frequency band, and s_i represents the value of raw data of the i-th received by each SDR devices. In our work, the sample rate is 2.4MHz and one collection duration of each frequency band is 2 milliseconds, so N is 4800. The power spectrum densities in lobby collected by the five SDRs for human subject 1 are shown in Fig. 3.

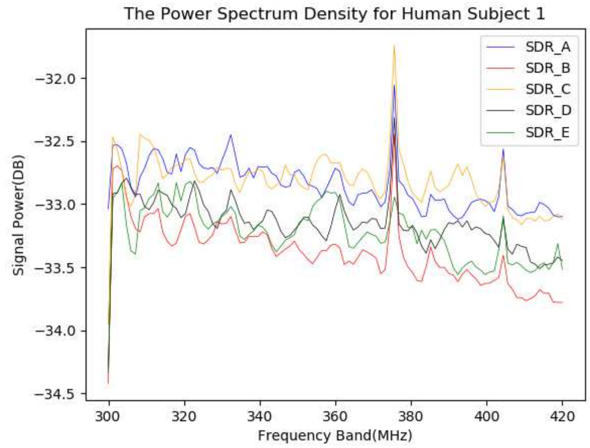

Fig. 3. The power spectrum density collected by the 5 SDRs for human subject 1.

C. Identification

In our experiment, four supervised ML algorithms were used to associate spectrum samples with different human subjects, including decision tree, SVM, KNN, and random forest. The input of the four ML classifiers is the power spectrum density, and the output is the index of the human subjects. A total of 140 samples of the power spectrum density were split into 75% training data set and 25% testing data set. For each experimental environment, four classifiers were trained. Finally, 35 spectrum samples were used to test the classifiers in each environment. As highlighted, since the subjects were known, the scenario represents the opportunity for human subject identification for authentication. Inherent in the analysis is that movement supports detection and recognition, and the ML classifies the subjects. With a known training signature of specific people, the spectrum can be used to not only classify a human subject, but as compared to a known signature, ID a specific person who has appropriate access (assuming they consented to the PRF collection to create their profile – as consistent with fingerprint access).

IV. RESULTS

This section presents the experiments to demonstrate the proposed human identification method and compares the identification accuracies using different ML algorithms in two environments. In addition, the impact of human subjects carrying a cell phone are provided as a sensitivity analysis. The details are described in the following subsections.

A. Evaluated Method

The F1 score is commonly used to evaluate the accuracy of the model [9][10] so in our experiment, the F1 score was calculated to obtain the identification accuracy. The function of the F1 score is as follows:

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (9)$$

$$precision = \frac{TP}{TP + FP} \quad (10)$$

$$recall = \frac{TP}{TP + FN} \quad (11)$$

$$F1 = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (12)$$

where TP is a true positive, FP is a false positive, FN is a false negative, and TN is a true negative. The F1 score ranged from 0 to 1. When the value of the F1 score is close to 1, the accuracy of the model is high, and the identification result is good.

B. *Identification Accurency*

We compared the human subjects' ID accuracy of different ML models in different environments. The results are shown in TABLE II.

TABLE II. HUMAN SUBJECTS' IDENTIFICATION ACCURACY FOR DIFFERENT MACHINE LEARNING MODELS IN DIFFERENT ENVIRONMENTS

	Decision tree	**SVM**	**KNN**	**Random forest**
Lobby	74.3%	62.8%	**94.3%**	74.3%
Living room	71.4%	82.8%	**94.3%**	74.3%

The results show that decision tree and random forest achieved the same ID accuracy in different environments, and the accuracy in the living room is higher than the accuracy in the lobby when using the SVM to identify human subjects. KNN got the highest accuracy in two different scenarios with 94.3%. These results not only verified different human subject can generate different signature on passive RF spectrums, but also demonstrated spectrum monitoring can be used to identify different human subjects. The signatures generated by different human subjects on the spectrum are more suitable to be distinguished by KNN.

In order to consider the impact of spectrum congestion, the subjects were asked to carry a cell phone. The data were collected in two environments, when human subjects carried their cell phone that can be compared without a phone. The identification results are show in TABLE III.

TABLE III. THE IDENTIFICATION OF HUMAN SUBJECTS CARRYING A CELL PHONE ACCURACY FOR DIFFERENT MACHINE LEARNING MODELS IN DIFFERENT ENVIRONMENTS

	Decision tree	**SVM**	**KNN**	**Random forest**
Lobby	68.5%	51.4%	**97.1%**	82.8%
Living room	88.5%	88.5%	**97.1%**	96.2%

In this table, using KNN achieved the highest ID accuracy - over 97%. This result means carrying the cell does not reduce the identification accuracy; and in fact, increased the performance. Compared to the accuracy in the lobby, all four ML methods have achieved higher accuracy in the living room. The considered reason is that the living room's area size is smaller than the lobby's area size, and there are more items in the living room, so the spectrum can be more sensitive to the human subject occupancy. The signatures generated by different human subjects can be more easily detected. Hence, these results demonstrate that the PHSIR method is suitable for identifying human subjects in a closed environment. More enhanced experiments will afford analysis for sensitivity and robustness of the technique.

V. CONCLUSIONS

In this paper, a passive method was developed from which results verify that different human occupancy can generate different signatures on the spectrum. In two different environments, the human subjects ID accuracy is 94%. Human subject carrying the cell phone does not reduce the ID accuracy and was shown to increase the accuracy is 97% in two different environments. PHSIR includes ML methods for classification and can be used as a good secondary identification method when known subject signatures are available. For example, PHSIR can be used in the environments that require certification to enter such as offices, laboratories, and meeting spaces. PHSIR scans the passive spectrum for the human subjects who have permission to enter and then the signatures on the spectrums for authorized human subjects are saved in the database. The human subjects who match the signature on the spectrums in the database can pass or enter through identification.

The future directions of development include how to locate and count the multiple human subjects in an indoor environment, to measure the speed and to track the movement of the human [24] as well as label and tracking the subject.

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