Driver Authentication for Smart Car Using Wireless Sensing

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***Abstract*—In the present evolving world, automobiles have become an intelligent electronic machine and are no longer a mere transport medium. In this article, we attempt to make them smarter by introducing the idea of in-car driver authentication using wireless sensing and develop a system that can recognize drivers automatically. The proposed system can recognize human identity by identifying the unique radio biometric information recorded in the channel state information (CSI) through multipath propagation. However, since the environmental information is also captured in the CSI, the performance of radio biometric recognition may be degraded by the changing environment. In this article, we first address the problem of "in-car changing environments" where the existing wireless sensing-based human identification system fails. We build a long-term driver radio biometric database consisting of radio biometrics of seven people collected over a period of two months. We leverage this database to create machine learning models that make the proposed system adaptive to new in-car environments. Second, we study the performance of the in-car driver authentication system with increasing effective bandwidth. We realize an effective bandwidth of 960 MHz by exploiting the multiantenna and frequency diversities in commercial WiFi devices. The performance of the proposed system is shown to improve with increasing effective bandwidth and the long-term experiments demonstrate the feasibility and accuracy of the proposed system. The accuracy achieved in the two-driver scenario is up to 99.13% for the best case.**

***Index Terms*—Driver authentication, human identification, radio biometrics, radio shot, smart car, wireless sensing.**

I. Introduction

THE FIELD of the Internet of Things (IoT) continues to extend its capabilities and engulfs many interesting applications within. With the deployment of tremendous smart devices that can sense, exchange, and analyze information, the IoT has enabled evolutionary changes in everyday lives. Smart environments and smart vehicles are among the many interesting applications in the IoT [1]. Using different sensors, smart vehicles can predict traffic patterns, automate driving, and optimize fuel consumption [2]. While these works focused more on automating the driving patterns, there are a plethora of other works on driver monitoring and activity recognition. Ohn-Bar *et al.* [3] and Jain *et al.* [4] used vision-based techniques to detect head, eye, and hand movements to predict driver behavior for accident prevention, although cameras, in general, introduce privacy concerns.

On the other hand, wireless sensing is an innovative modality to achieve security and privacy at the same time and has been widely used in many IoT applications because of the ubiquitous deployment of WiFi devices. High accuracy indoor localization has been achieved using WiFi fingerprinting [5]–[7]. By extracting statistics and identifying other features in the channel state information (CSI), multiple research teams investigated the detection of indoor motion or dynamics [8]–[10]. Recently, researchers have been working on using wireless sensing to enable indoor vital sign estimation by extracting the periodic components in the CSI [11], [12]. Other applications such as keystroke recognition [13], movement speed estimation [14], gesture [15], and gait recognition [16], have also been explored through wireless sensing. In the study on smart vehicles using wireless sensing, researchers have investigated driver activity recognition where driving actions have been estimated using received signal strength information (RSSI) and CSI amplitudes in a simulated environment [17]. However, not much research has been done on driver authentication based on wireless sensing.

The driver authentication system improves security and can automatically make in-car driver-specific adjustments, such as temperature and seat and mirror positions. Nowadays, human authentication is either done by using password-based methods, such as encryption keys, PINs, key cards, or by using biometrics. The term biometrics refers to a measurement of biological data. Any biological measurement that is potentially unique to a person is considered as a biometric. Biometric-based methods are gaining popularity due to their inherent uniqueness and convenience, compared to passwords and keys which may be easily forged or forgotten. Biometrics can be broadly classified into two categories: 1) physical characteristics comprising fingerprints, face, iris, and handprint and 2) behavioral characteristics, such as gait, keystroke dynamics, specific gestures, etc. Physical characteristics are more reliable and some may not change significantly with time, while behavioral traits can change over time or be changed intentionally [18].

In this article, we use a new type of physical biometrics, radio biometrics, to achieve reliable in-car driver

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authentication [19]. Radio biometrics is the pattern of a human body introduced to the wireless propagation environment. Researchers have studied the electromagnetic wave propagation through a human body [20], [21] and the dielectric properties [22]–[24]. Alongside these studies, the work in [25] showed that the electromagnetic propagation in and around a human body is influenced by such factors as the height, weight, body water volume, surface area, tissue density, and more. A combination of these features could be potentially unique to a person and serve as a biometric [19]. In an indoor environment, the wireless signal undergoes many reflections and scattering that generates multipath. At the receiver, the result of all the multipath can be recorded in the form of a CSI. Human radio biometrics can be recorded within the CSI and is determined by the unique biological characteristics of each individual. The captured CSI can be considered as a radio signature and the process of recording a radio signature is termed as a *radio shot*.

The first wireless sensing-based human recognition system [19] used CSI as the feature for individual physical characteristics and utilized the time-reversal technique to compare the similarity of radio biometrics. However, this prior art assumed that the indoor environment remains static throughout the period of the experiment. In reality, this is not the case and even a small change in the indoor environment will introduce a significant change into the multipath CSI. Different from the existing work, we do not make any such assumptions in this article. Instead, we build machine learning (ML) models which can adapt to the changing in-car environment.

ML techniques require data to learn patterns, draw inferences and generalize to new unseen references [26]. They perform an automated feature selection from the training data. ML and deep learning have achieved great success in the field of computer vision because they have large amounts of data to train on, while the performance of deep learning in other fields is largely limited by the availability of the training data. In this article, we build the first radio biometric database consisting of radio biometrics of seven people collected over a period of two months. Driver authentication is achieved by building ML models using this database.

Previous works have shown that the pattern of radio propagation through a human body is frequency-dependent [22]. Based on that, in this article, we try to obtain radio biometrics from several channels. One way to implement this idea is to use frequency hopping. Frequency hopping rapidly switches channels to transmit wireless signals. For example, Vasisht *et al.* [27] used frequency hopping to achieve a sub-nano-level time of flight (ToF) and Chen *et al.* [7] achieved high accuracy indoor localization by using augmented CSI fingerprint from several channels. In this article, we implement the frequency hopping on portable commercial WiFi devices that can be fixed in a car. Furthermore, we exploit the multiantenna diversity in the MIMO systems to obtain more differentiating features. We have evaluated the performance of the proposed system in a long-term experiment for two months and have studied the impact of different factors on the performance of the proposed driver authentication system. For two-driver authentication, an accuracy of 99.13% has been achieved in the best scenario while an accuracy of 72.12% has been achieved for the most difficult scenario.

The main contributions of this article can be summarized as follows.

1) We propose the first in-car driver authentication system using the human radio biometrics recorded in the wireless CSI.
2) We address the problem of in-car environmental changes. We build the first multiple-driver radio biometric database consisting of radio biometrics of seven people collected over a period of two months. To our knowledge, this is the first long-term study conducted for human radio biometric recognition. With the help of this database, we integrate ML techniques to make the proposed driver authentication system adaptive to different in-car environments.
3) We study the impact of multiantenna diversity and the frequency diversity on the accuracy of the proposed driver authentication system. For experimental evaluation, we have implemented frequency hopping on portable commercial WiFi devices that can be fixed in a car for the long term.
4) We perform an extensive analysis of the dependence of the classification accuracy on different factors, including the size of the training set, the similarity of radio shots, the time gap between training and testing days, the number of MIMO links, and the number of channels.

In the proposed in-car driver authentication system, we focus on cases in which there is only a single driver present in the car with no passengers. The more practical scenario where one or more passengers are present in the car will be studied in future work. Also, the radio biometrics of the driver should have been present in the radio biometric database of the car. In the case of a temporary driver, keys or passwords should be used. Here are some practical applications.

1) The proposed system can be used by parents preventing a car driven by kids or an unauthorized driver who might cause accidents. A physical key is easy to access whereas the radio biometric system can be used to differentiate kids from adults.
2) In a typical home, there are usually 2-3 daily drivers for a car (e.g., the wife and the husband). In such cases, our proposed system is very useful in both security enhancement and personalization. Also, in the case of recognizing the husband and the wife, the difference in attributes is usually higher and the proposed system performs better.

This article is organized as follows. Section II describes the challenges in the proposed in-car driver authentication system. Section III discusses the dataset preparation, preprocessing, and frequency hopping techniques. Section IV presents different methodologies to achieve in-car driver authentication and the experimental results are discussed in Section V. In-depth analysis of the classification accuracy is studied in Section VI. Limitations and future work are discussed in Section VII and finally, Section VIII presents the conclusions.

II. Challenges

The similarity of two CSIs can be defined by the time-reversal resonating strength (TRRS). For two channel frequency responses (CFRs) h_1 and h_2, the TRRS in the frequency domain is given by [19]

$$\mathrm{TRRS}(\mathbf{h}_1, \mathbf{h}_2) = \frac{\max_\phi \left| \sum_{k=0}^{L-1} h_1[k] h_2[k]^* e^{jk\phi} \right|^2}{\left(\sum_{l=0}^{L-1} |h_1[l]|^2 \right) \left(\sum_{l=0}^{L-1} |h_2[l]|^2 \right)} \tag{1}$$

where L is the number of subcarriers. The higher the TRRS is, the more similar the two CFRs are, and thus the more similar the two radio biometric samples are. There are two main challenges in the proposed in-car driver authentication system.

A. Change of In-Car Environment

The human radio biometrics are highly correlated with the environmental information in the CSI. Hence, when the in-car environment is altered, the CSI containing the driver radio biometrics is also changed. To measure the degree of changes in an in-car environment, we record the CSI of the empty car every day. The similarity between the CSI of an empty car captured on different days and the CSI of an empty car captured on day 1 is calculated by the TRRS. Fig. 1 shows the change of in-car environment with time measured in terms of TRRS. Overall, we can observe that the TRRS decreases as more changes accumulate in the in-car environment over time. The in-car environment is similar to the indoor wireless propagation environment with multipath created by numerous scatterers. The received CSI is a composition of such multipath signals. When one scatterer Sa is displaced, all the multipath which involved Sa in their paths are altered and this causes a change in the received CSI. Let the original CSI be CSIo and the CSI after displacing Sa be CSIa. Let another scatterer Sb be displaced and the corresponding CSI be CSIb. The difference between CSIa and CSIo is due to the multipath that involved Sa only whereas the difference between CSIo and CSIb is due to the multipath which involved Sa only, Sb only, and both Sa and Sb. Therefore, as an increasing number of scatterers are displaced with time, more multipath signals are altered and the CSI becomes more and more distinct from the original CSI. Since the displacement of scatterers in the car is random and there are many multipath signals involving each scatterer, it is highly unlikely to recreate the exact multipath profile by reversing the displacement of scatterers or by a new combination of scatterer locations. Therefore, on an average, we see that the TRRS decreases with time as more changes accumulate inside the car.

An existing WiFi-based human identification system used TRRS matching to identify humans [19]. During the training phase, the human radio biometrics which are embedded in the indoor CSIs are recorded and stored as a database. In the testing phase, the CSIs are compared with those in the training database using the TRRS similarity metric. The identity of the human is determined by the class of the highest matching CSI from the training database provided that the highest TRRS is greater than a predefined threshold (0.7). With the given degree of changes in the in-car environment, the TRRS matching technique can no longer be applied. For example, consider the CSIs of two drivers H1 and H2, collected on two different days A and B. As shown in Fig. 2, the TRRS between CSI of H2 on day A and CSI of H1 on day B is 0.81 while TRRS between CSIs of H2 on different days is 0.63 resulting in a misclassification. In this article, we overcome this challenge by adopting ML techniques to make the system adaptive to new environments.

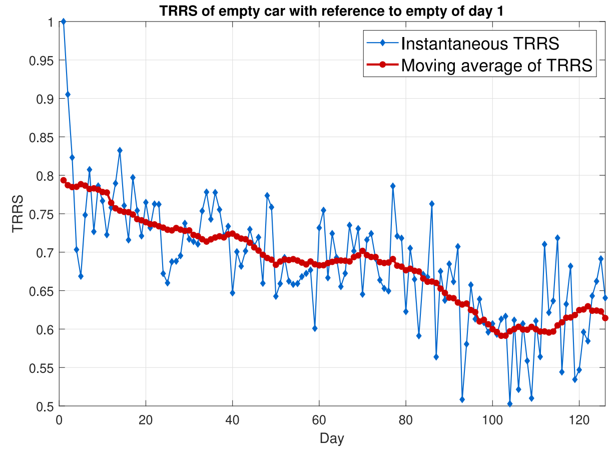

Fig. 1. Change of in-car environment with time measured in terms of TRRS. The blue curve shows the TRRS of each day with reference to day 1 and the red curve shows the moving average of the blue curve.

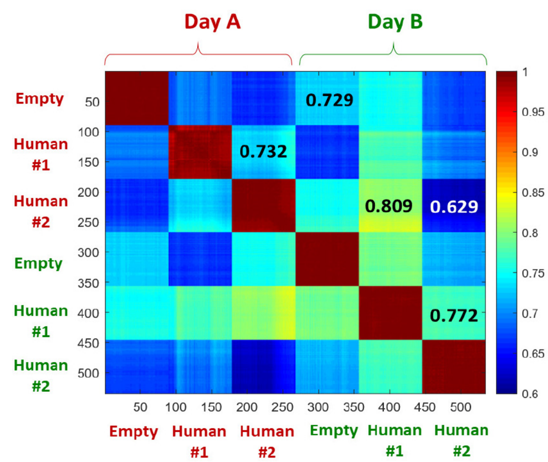

Fig. 2. TRRS heatmap between different radio biometrics captured on different days.

B. Low Resolution of Multipath

Second, the CSI recorded at each time instant is a collection of channel information on multipath signals that have different path lengths. To resolve the multipath with a higher resolution, a larger bandwidth is required. Since the bandwidth (40 MHz) is fixed for a channel in commercial WiFi devices, in this article, we achieve higher effective bandwidths by exploiting the diversity in multiple MIMO links as well as different frequency channels. The details are discussed in Section III.

1) Impacts of External Environment: The influence of the external environment on the in-car CSI has been studied. Fig. 3

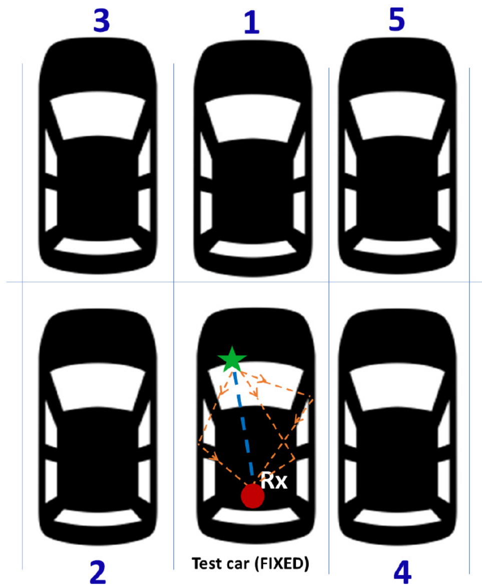

Fig. 3. Experimental setup to study the impact of external environment on the in-car CSI.

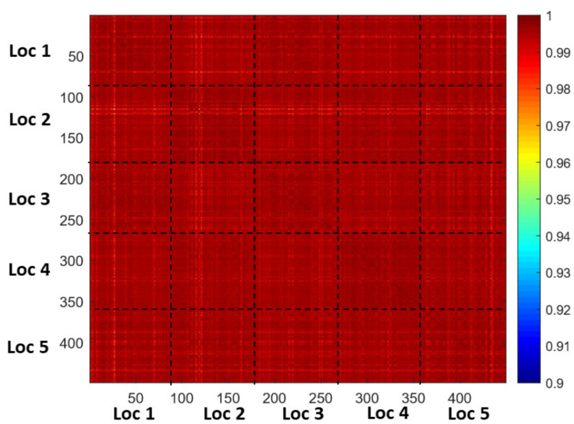

Fig. 4. TRRS matrix for in-car CSIs for different external environments.

shows the experimental set up where the test car is fixed and another car is parked in different locations (1–5) around the test car, in a public parking lot. In-car CSIs are recorded for each of the five scenarios. To quantitatively measure the degree of change of an in-car wireless propagation environment, we have calculated the TRRS matrix for all the recorded CSIs which is shown in Fig. 4. We can observe that the CSIs are highly correlated and the TRRS values are all nearly equal to 1. The car acts as a metal cage and only a few of the multipath signals escape to the external environment through the glass windows and only a smaller fraction of them are reflected by external objects. Such multipath signals which are reflected back into the car through the windows are severely attenuated and almost negligible. We can safely assume that the effect of the external environment is insignificant, and in this article, we focus only on the in-car environment changes.

III. In-Car Driver Authentication System

The proposed in-car driver authentication system uses commercial WiFi devices as transceivers that are placed in the car. The location of transceivers plays an important role in the performance of the proposed system. The location of the receiver is chosen at the back of the car at the typical location of an in-car RF antenna. The best location for the transmitter would be in front of the driver as we can capture more differentiating features including the face of the driver in a ray-tracing perspective. From our experience, the recorded human radio biometrics were more distinct for different people when the transmitter was placed in front of the driver. This is because the multipath channel is affected the most when the driver intercepts the LOS path between the transmitter and the receiver. Also, a greater number of multipath signals passing through the driver helps to capture more driver-specific radio biometric features. Fig. 5 shows two possible transceiver locations and the multipath propagation inside the car. The blue line shows the LOS path which is intercepted when the driver is present in the car. The orange-colored lines show the NLOS paths which are received by the receiver after several reflections inside the car. The transmitter is located at the back of the steering wheel in Fig. 5(a), while it is placed near the audio system in Fig. 5(b). The slight differences in the locations are because of the space limitation during experiments. The performance for other possible sets of transceiver locations is left for future work. In the following, we will describe the frequency hopping mechanism designed in the proposed system, data collection procedure, and the preprocessing technique.

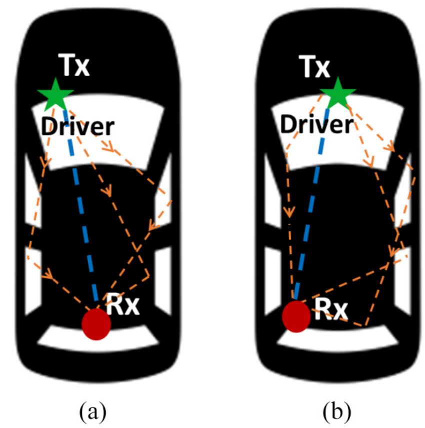

Fig. 5. Location of transceivers in the car. (a) Transmitter near the speedometer at the back of the steering wheel. (b) Transmitter is at the audio system.

A. Frequency Hopping on Commercial WiFi Devices

Frequency hopping refers to changing channels according to a prespecified schedule/pattern and enables utilization of frequency diversity. Using frequency hopping, we can record CSIs on different channels sequentially. In this article, to increase the number of features for in-car driver radio biometrics, we record CSIs on four channels in the 5.2-GHz band, during a radio shot. By doing so, we achieve a larger effective bandwidth as explained in a later section.

The frequency hopping algorithm that we used is explained in Algorithms 1 and 2. The transmitter and receiver function

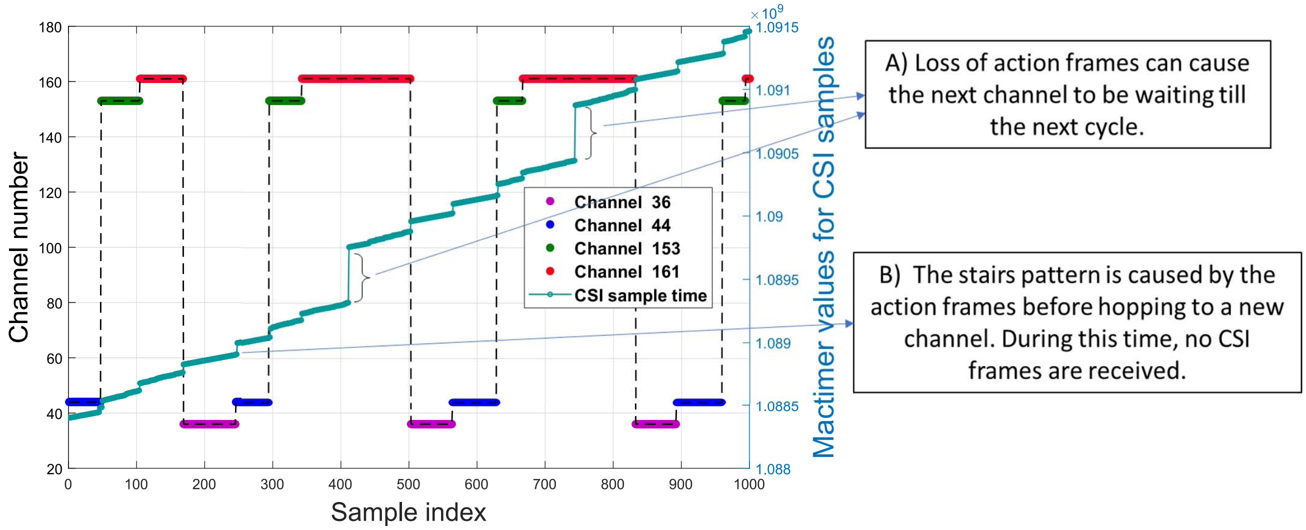

Fig. 6. Demonstration of channel hopping at the receiver with time.

Algorithm 1 Frequency Hopping Algorithm: Transmitter

channel-list ← {36, 44, 153, 161}
ch ← 0
while (1) **do**
  Set channel to *channel-list*(*ch*)
  Send CSI frames as channel probing signals on channel *channel-list*(*ch*) for dwell time (μ)
  Determine the next channel index $ch \leftarrow (ch + 1) \bmod 4$
  Next channel is *channel-list*(*ch*)
  Construct and send k action frames with new channel index information
end while

Algorithm 2 Frequency Hopping Algorithm: Receiver

channel-list ← {36, 44, 153, 161}
Set channel to *channel-list*(0)
while (1) **do**
  if CSI frame is received **then**
    receive CSI
  else if action frame is received **then**
    $ch^{'}$ ←next channel extracted from action frame
    Set channel to $ch^{'}$
  end if
end while

in parallel. The channel index is taken as *ch*. The transmitter sends the channel information to the receiver in specially designed frames called action frames. These are sent at regular intervals of time and the duration of each channel is specified by the user as dwell time (μ). In this article, we use μ = 125 ms. Fig. 6 demonstrates the mechanism of hopping channels at the receiver. It also shows the absolute time of arrival of the CSI frames at the receiver. The stairs-like pattern is caused by the action frames before setting to a new channel during which no CSI samples are recorded. Sometimes, due to channel congestion/packet loss, all of the k action frames might be lost and the receiver continues to stay in the same channel as in regions (*B*). In such cases, the next channel is not set until the receiver receives action frames on the existing channel in the next cycle. In Section VI, we evaluate the performance of the proposed driver authentication system for a different number of channels.

B. Dataset Preparation

In our experiments, during the radio shot, the driver sits in the driver's seat of a car and the wireless propagation environment is captured in the CSI. This CSI is used as the radio biometric for that particular driver. For every radio shot of the driver, we also record the CSI of the corresponding in-car environment without the driver.

The in-car driver authentication database was built by collecting radio shots of seven people over two months. On each day, for each test subject, four radio shots were taken in the morning and evening, in a car parked at different locations in a public parking lot. By doing so, a total of 60 different environments have been considered. Multiple recordings of the radio shots help us improve the classification accuracy using the grouping technique which is explained in Section IV.

The prototype of the proposed in-car driver authentication system was built using the commercial off-the-shelf WiFi chips with no additional hardware. The CSIs were recorded using a 2×3 MIMO system. The system operated in the 5.2-GHz band over four channels with 114 accessible subcarriers in each channel. Also, multiple CSIs were recorded using a sounding rate of 30 Hz to perform phase cleaning and remove outliers as discussed later in this section. So, for each radio shot, each CSI sample is a $2 \times 3 \times 456$-D complex-valued matrix.

C. Data Preprocessing

Timing and frequency synchronization errors in the Wi-Fi systems introduce phase offsets in the recorded CSI. The multiple CSIs recorded for each radio shot are highly correlated to each other and thus can be used for phase compensation and outlier removal. In data preprocessing, we compensate for the linear and the initial phase offsets.

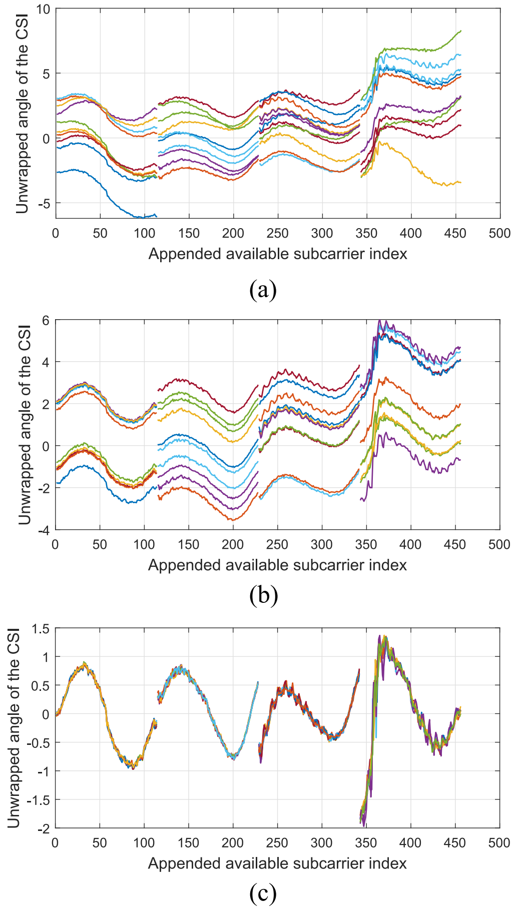

Fig. 7. Demonstration of linear and initial phase compensation. Figure shows the phase (a) of raw CSI, (b) after linear phase compensation, and (c) after initial phase compensation.

Let $\hat{h}_i^k$ be the received CFR of the ith sample on the kth subcarrier. Let h_i^k be the CFR without phase distortions. Then, h_i^k is given by the following [7]:

$$\hat{h}_i^k = \text{sinc}(\pi(\Delta\epsilon + \Delta\eta k))h_i^k e^{j2\pi(\beta_i k+\alpha_i)} \tag{2}$$

where $\Delta\epsilon$ and $\Delta\eta$ are the residual errors of channel frequency offset and sampling frequency offset, respectively, and β_i and α_i are termed as the linear and initial phase. Assuming the argument of the sinc function is small, the linear phase can be aligned with a reference CFR [19].

Consider two CFRs $\hat{h}_1^k$, $\hat{h}_2^k$, and $\hat{h}_1^k$ be the reference. Then, we have the following equations:

$$\hat{h}_1^k = h_1^k e^{j2\pi(\beta_1 k+\alpha_1)} \tag{3}$$

$$\hat{h}_2^k = h_2^k e^{j2\pi(\beta_2 k+\alpha_2)} \tag{4}$$

$$\delta\beta = \arg\max_{\phi} \left| \Sigma_k \hat{h}_1^k \hat{h}_2^{k*} e^{j2\pi k\phi} \right|. \tag{5}$$

The aligned linear phase is obtained by $\hat{h}_2^{k'} = \hat{h}_2^k e^{-j2\pi k\delta\beta}$. The initial phase is equal to the phase of the first subcarrier on each CFR sample. It is compensated as $h_{\text{align}} = \angle\hat{h}[0]'$.

An example is shown in Fig. 7 where the linear and initial phases are compensated for CSIs collected using four channels. In this case, the phase compensation should be done independently for each channel as the phase offsets are different for different carrier frequencies. Fig. 7(a) shows the phase of raw CSI for four channels. The first 114 subcarriers correspond to channel 1, the next 114 to channel 2, and so on. Fig. 7(b) shows the phase after linear phase compensation and Fig. 7(c) shows the resultant phase after linear and initial phase compensation. The CSIs are then appended to form the feature vector for the in-car driver authentication system.

After the phase alignment, the combined CSI from the four channels results in a $2\times3\times456$ (i.e., 114 subcarriers per channel) dimensional complex-valued vector which can be flattened to a 5472-D real-valued vector. With such a high dimension of features, the number of parameters that need to be learned in ML models is large and usually, the models require a lot of data to train. Unlike computer vision techniques, obtaining a large amount of data in our case is expensive. Hence, we perform dimensional reduction using principal component analysis (PCA) to reduce the number of parameters. PCA transforms the original features into a new feature space based on the degree of variance. In this article, we consider the number of features that contribute to 99% of the total variance in the data. For instance, the dimension reduced from 5472 to 270 for the data using all the four channels and 2×3 MIMO links.

IV. Learning Methodologies

In this section, we introduce the ML techniques and methods that we adopt in the proposed driver authentication system.

A. K-Nearest Neighbors

We know that the radio biometrics are embedded inside the CSI of the environment and are highly correlated. In the proposed in-car driver authentication system, a new in-car environment is presented on a new day. This can be seen as a new instance of the problem and one baseline approach would be to use instance-based learning methods [28]. The K-nearest neighbor approach is the simplest of these methods and often used as a baseline for classification algorithms. In this approach, for a new test sample, we select K nearest neighbors from the existing database and assign the majority label to the test sample. We measure the similarity using the Euclidean distance.

The value of K is a hyperparameter and can be chosen by conducting several experiments and finding the best value of K that gives the maximum average performance. For example, consider radio biometric data of two drivers collected for 40 days. Fig. 8 shows the 40-fold cross-validation accuracy with varying number of nearest neighbors (K). The maximum accuracy is achieved for a value of 3. Therefore, for the classification of these drivers, we use 3-nearest neighbors.

B. Support Vector Machine

The support vector machine (SVM) is the most popular approach for classification algorithms in ML [29]. The aim of linear-SVM is to find a hyperplane that divides the classes

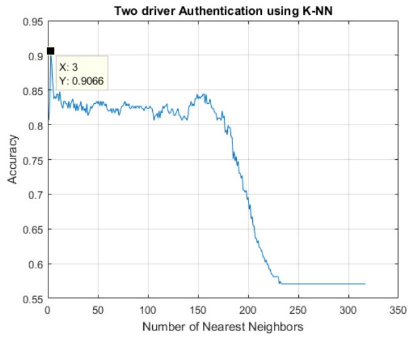

Fig. 8. Average K-NN accuracy for varying value of K.

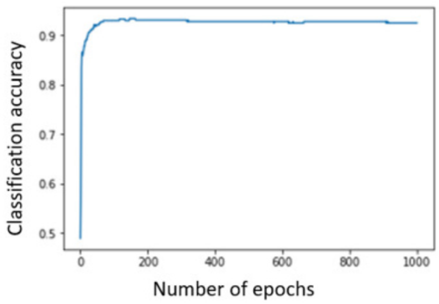

Fig. 9. Average classification accuracy with number of epochs in a neural network.

with maximum margin where the margin is defined as the minimum distance of the hyperplane to points from either class. When the data is not linearly separable which is often the case, the "kernel-trick" is used to project the data to higher dimensions where it is linearly separable [30]. In this article, we use linear and RBF kernels to evaluate the proposed system with the regularization parameter $C = 1.0$. Also, we use the cross-validation technique to report classification accuracy.

C. Neural Network

As the in-car environment changes with time, we would want the system to be more adaptive and learn human radio biometrics for different environments. Therefore, we refer to neural networks (NNs) which have been used in ML and deep learning to learn more nonlinear and complex decision boundaries for classification problems.

1) Architecture: The hyperparameters in the NN are tuned using the K-fold validation technique. Consider, for example, the number of training epochs. We find the classification accuracy for all the K experiments for 1000 epochs. It is observed that the model is overfitted much before 1000 epochs. We then calculate the average performance for every epoch. Fig. 9 shows the average classification accuracy obtained for the pair $A - D$ with the number of epochs. The maximum value is reported as the final accuracy. Here, the maximum is achieved near epoch 160 with an accuracy of 93.33%. The number of hidden layers and hidden nodes are determined by cross-validation. As we further increased the number of hidden layers or the hidden nodes, the capacity of the network increased and it began to overfit. The NN architecture that we use is shown in Fig. 10. The network consists of an input layer with the number of input nodes equal to the input features, two hidden layers, and an output layer which gives the class probabilities for a data point. In this article, we adopt the ReLU activation function and cross-entropy loss with Adam optimizer.

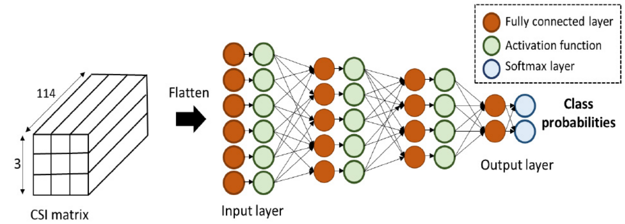

Fig. 10. NN architecture.

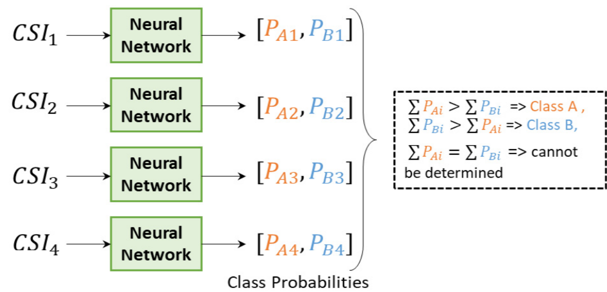

Fig. 11. Grouping technique.

2) Data: We have used about 40 days of data for evaluating the performance using K_v-fold validation. The number of samples per day is 8 and the total data available per class is nearly 320 samples. The data are partitioned by date and in total, we have 40 partitions. The 40-fold validation accuracy is used as the evaluation metric in Section V.

D. Grouping

During the process of radio shots, slight variations in the seating positions of the driver can cause a change in the CSI and might sometimes lead to a misclassification. To capture and compensate these small variations, we collect multiple radio shots for the same in-car environment and take a combined decision. We call it the grouping technique which is explained in Fig. 11. During the testing phase, for each test subject, assume the four radio shots are indexed as i; $i = 1, 2, 3, 4$. Let P_{Ai} and P_{Bi} represent the predicted class probability of the ith radio shot for class A and class B, respectively. Then the identity of the test subject is determined as class A, if $\Sigma P_{Ai} < \Sigma P_{Bi}$ and *vice versa*. If $\Sigma P_{Ai} = \Sigma P_{Bi}$, the test subject cannot be determined and we considered such samples as incorrectly classified in our accuracy calculations. We used four radio shots since, for our test subjects, more than four radio shots led to repetitions of the CSI. This can be easily extended to more radio shots based on the consistency of seating postures of the test subjects.

V. Experimental Results

We evaluate the performance of the proposed in-car driver authentication system using the ML models discussed in the

TABLE I
INFORMATION ABOUT THE TESTERS

Name	Gender	Age	Ht (cm)	Wt (kg)
A	F	25	163	56.2
B	F	28	165	58.5
C	M	30	168	82.5
D	M	23	172	85
E	M	25	180	73

TABLE II
CLASSIFICATION ACCURACY: COMPARISON BETWEEN THE LEARNING-BASED AND TRRS-BASED APPROACH FOR TWO-DRIVER AUTHENTICATION

Classes	TRRS-based(%)	Learning-based(%)
A-B	76.51	96.55
A-C	83.09	98.27
A-D	87.73	99.13
A-E	82.18	93.10
B-C	80.88	96.55
B-D	81.58	93.67
B-E	76.13	87.06
C-D	64.93	72.12
C-E	74.60	91.37
D-E	73.41	90.22

TABLE III
PERFORMANCE ON TWO DRIVER AUTHENTICATION

Classes	K-NN(%)	Linear SVM(%)	SVM-RBF(%)	NN(%)
A-B	88.93	92.52	90.22	96.55
A-C	91.88	90.87	93.03	98.27
A-D	90.37	94.39	93.10	**99.13**
A-E	88.50	94.39	90.44	93.10
B-C	89.79	89.15	90.51	96.55
B-D	85.70	88.93	90.08	93.67
B-E	75.71	84.69	85.48	87.06
C-D	65.80	70.83	72.12	60.63
C-E	83.11	86.99	85.77	91.37
D-E	82.68	86.99	88.36	90.22

previous section. First, we discuss the special case of two driver authentication which can serve a similar purpose as the existing memory seating facilities in cars alongside providing authentication. Later, we evaluate the performance of the proposed system in the multidriver scenario.

One of the main challenges in evaluating the in-car driver authentication system is the availability of data. The study of the trend of radio biometric data with the time required that the testers be available throughout the experiment duration which is two months. Since the amount of data is limited, the accuracy values obtained are dependent on the split of the train and test data. This is because the selected train data may or may not be able to generalize well to the test data. To overcome this, cross-validation techniques are used in ML models [31]. In the simplest cross-validation technique, the entire data set is divided into K_v parts and K_v experiments are performed with each part as testing data and the remaining $K_v - 1$ parts as the training data. In this article, the value of K_v is taken as the number of days of available data, i.e., we treat the data corresponding to each day as a partition. By doing so, we make sure that the same instance of the in-car environment is not present in both training and testing data. Throughout this article, the reported accuracies are calculated using the K_v-fold validation and the value of K_v is taken as the total number of days of data available.

A. Two-Driver Authentication

In this scenario, we classify a driver into one of the two known drivers, i.e., a two-class problem. We consider five test subjects denoted by A, B, C, D, and E. More information about the testers is shown in Table I.

The accuracy of the proposed system with different ML techniques is evaluated using 40-fold validation with CSI from one channel and with the proposed grouping technique. Table II shows the classification accuracy for different sets of drivers from the in-car driver radio biometric database. The performance of the k-nearest neighbors (K-NN) in the first column can be taken as the baseline performance. On an average, the NN approach gave about a 7% increase in accuracy. The highest accuracy achieved is 99.13% for the pair $A - D$.

1) Comparison With State-of-the-Art Approach: To our best knowledge, there is only one prior work which uses radio biometrics embedded in the CSI of wireless signals for human recognition [19]. However, as discussed in Section II, the performance of the previous work will be compromised by the in-car environment changes because it heavily relied on TRRS to compare the similarity between different radio biometrics embedded in the CSI. Table III demonstrates the improvement delivered by the proposed learning-based approach. In all the cases, the learning-based approach outperforms the state-of-the-art TRRS-based approach by at least 7% and up to 20%.

B. Multiple Driver Authentication

We also evaluate the performance of the proposed system in identifying more than two drivers. Fig. 12 shows the confusion matrices for multiple driver classification using the NN approach. The average detection rate for an individual among three drivers is 84.33% while among seven drivers is 53.85%. This is much greater than the accuracy achieved by random guessing of identities among seven people, i.e., 14.28%. The performance decreases with an increasing number of drivers. The increasing off-diagonal elements from confusion matrices between three to seven people also indicate an increasing false alarm. The average false alarm increased from 15.33% in the three driver case to 46.14% in the seven driver case.

VI. DISCUSSION

The performance of a human radio biometric-based system is dependent on many factors, such as the physical characteristics of the people, the number of channels used to obtain CSI, the environment, the amount of training data present, the number of classes present, etc. In this section, we analyze and evaluate the impact of the various factors on the in-car driver authentication system using the NN approach. The hyperparameters are tuned using the K_v-fold validation technique.

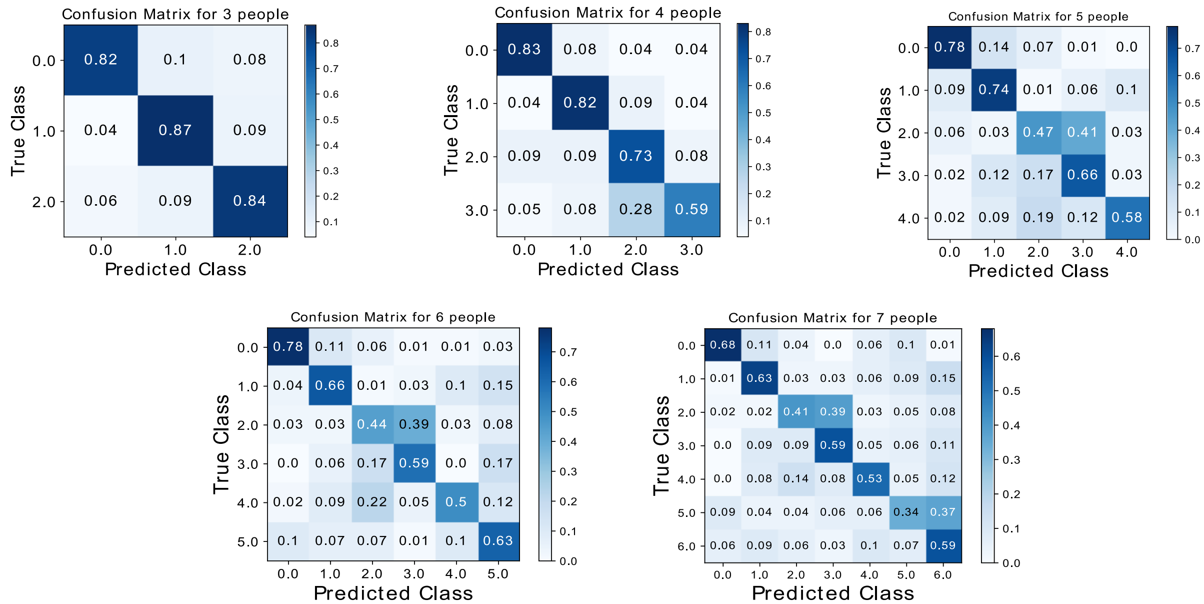

Fig. 12. Confusion matrices for different number of people.

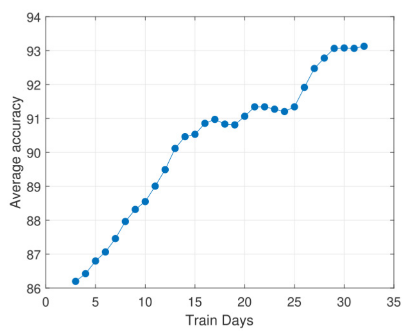

Fig. 13. Accuracy averaged over several pairs of people with the amount of training data.

A. Size of the Training Set

We evaluate the performance of the proposed system as the size of the training set increases. Fig. 13 shows the performance of the system averaged over several pairs of people. As the amount of training data increases, the classification accuracy improves. When a new user is added, the performance will improve as the proposed adaptive NN continues learning and generalizing the distinctiveness between his/her and others radio biometrics. From Fig. 13, we can see that the accuracy improves drastically and reaches about 90% in 15 days. As the user continues to use the car, the proposed system can capture more radio biometric information of him/her and then improve the recognition accuracy.

B. Similarity of Radio Shots

We can observe from the previous experiments that the classification performance largely depends on the set of people that we aim to differentiate. This is because some people can have more similar radio biometrics compared to others. Classification of such people might be more challenging than others.

TABLE IV
SIMILARITY OF RADIO SHOTS AND CLASSIFICATION ACCURACY

Classes	Average TRRS	Classification accuracy
A-D	0.7094	99.36%
C-D	0.7773	84.19%

To support our observation, we have calculated the similarity of radio biometrics in the same environment for different sets of people, where similarity is measured in terms of TRRS as defined in (1). In Table IV, we show the TRRS calculated for the pairs with maximum $(A-D)$ and minimum accuracy $(C-D)$ averaged over all days. We can say that the similarity of CSIs is one of the many factors affecting the classification accuracy. The accuracy is lower for the pair with more similar CSIs. However, many other factors can influence the classification accuracy in addition to the similarity of radio biometrics. A few of them are listed as follows.

1) *Consistency of Seating Position:* If the seating position of a tester is consistent and similar during the training and testing period, the classification accuracy is improved. On the other hand, if the tester tends to sit in different seating postures or positions every time, it might lead to a decreased classification accuracy but can get mitigated with an adaptive training data set which keeps refreshing with newly added radio biometrics samples.
2) *The Difference in the In-Car Environment:* As the human radio biometrics are highly correlated with the in-car environment, if the difference in the in-car environments (measured quantitatively by the TRRS) during the training and the testing period is significant, the classification accuracy tends to decrease.
3) *The Difference in the Training and Testing Data:* For example, if a tester wears a thick jacket during the training phase and no jacket during the testing phase, the classification accuracy might decrease.

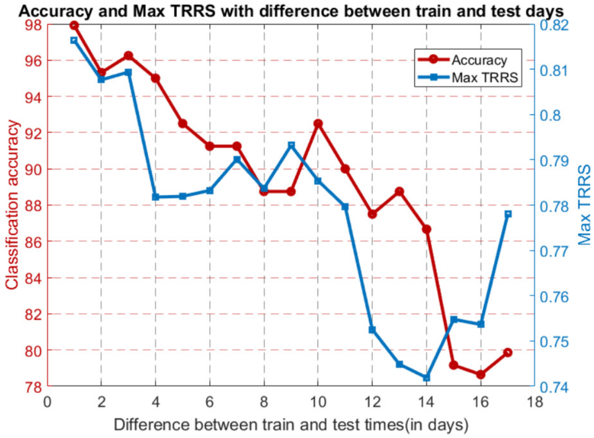

Fig. 14. Accuracy and maximum TRRS with difference between train and test days. Red line shows an accuracy with increasing gap between the training and testing days. The blue line shows the TRRS which is the best match of the empty in-car environment from the training database.

C. Performance With Increasing Gap Between Training and Testing Data

As discussed in Section II, with time, the changes in the in-car environment accumulate and the TRRS with reference to day 1 continues to decrease. This causes a decrease in classification accuracy. Fig. 14 shows the classification accuracy with an increasing gap between the training and testing data. The maximum TRRS achieved by the test sample with the samples from the training database is shown in blue. The red line shows the average accuracy achieved in the case of two-driver authentication. We can see that with increasing difference between train and test times (days), the maximum matching TRRS and the classification accuracy have a decreasing trend. The classification accuracy does not monotonically decrease since it also depends on other factors, such as variation in the seating positions, type of clothing, etc. From this observation, the best performance of the system can be achieved when it is used regularly and by constantly updating the database. The more regular and longer this system is used, the better is the performance.

D. Effect of Grouping

Grouping technique (Section IV-D) uses multiple radio shots to determine the driver identity. In Table V, we show the classification accuracy with and without grouping for one channel using the NN approach. We observe that in most cases, the grouping technique can significantly improve the classification accuracy and hence using multiple radio shots to predict the identity is more reliable. Few exceptions in the case of KNN could be due to a large variation in the seating position for each radio shot.

E. Effect of the Number of Links

Through exploiting the antenna diversity provided by multiple links of the MIMO system, we can explore different multipath signals in the environment and there is a potential increase in the number of independent features. Fig. 15 shows the classification accuracy with an increasing number of links for two driver authentication. Overall, we can see that the performance, increases with the number of links.

TABLE V
PERFORMANCE WITH AND WITHOUT GROUPING

Classes	KNN	KNN(G)	NN	NN(G)
A-B	88.93	90.22	88.93	96.55
A-C	91.88	94.25	92.81	98.27
A-D	90.37	90.51	94.18	99.13
A-E	88.50	90.80	87.42	93.10
B-C	89.79	91.09	90.22	96.55
B-D	85.70	85.91	87.93	93.67
B-E	75.71	71.26	80.45	87.06
C-D	65.80	61.78	57.75	60.63
C-E	83.11	86.20	84.77	91.37
D-E	82.68	85.91	82.39	90.22

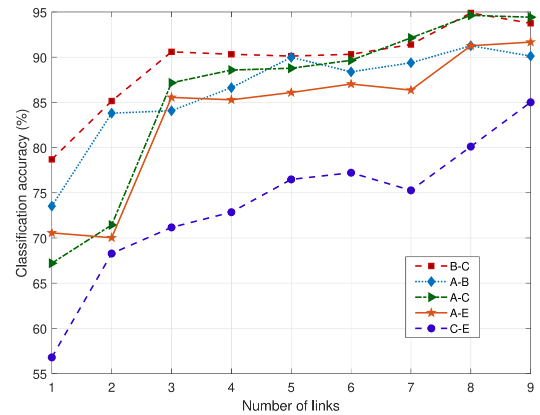

Fig. 15. Classification accuracy with an increasing number of links for different sets of people.

TABLE VI
PERFORMANCE WITH INCREASING EFFECTIVE BANDWIDTH USING THE NN APPROACH

Classes	1 ch	upto 2 ch	upto 3 ch	upto 4 ch
A-B	77.95	78.69	81.63	82.51
A-C	92.39	92.39	92.39	92.39
A-D	78.14	82.58	88.26	88.26
A-E	68.37	79.97	83.37	83.37
B-C	90.53	92.18	92.18	92.18
B-D	83.64	83.64	83.64	83.64
B-E	**64.13**	**73.80**	**79.04**	**80.65**
C-D	73.65	76.06	76.06	76.06
C-E	88.97	88.97	88.97	88.97
D-E	77.90	83.50	83.50	83.50

F. Effect of the Number of Channels

The effective bandwidth has been defined as $We = D \times W \times N$, where W is the bandwidth per channel per link which is 40 MHz in the proposed system, D is the number of channels, and N is the number of links [7], [32], [33]. The radio shots are taken on a single channel at a time, according to the proposed frequency hopping mechanism. In this article, we use a maximum of four channels and achieved the largest effective bandwidth of $2 \times 3 \times 40 \times 4$, i.e., 960 MHz. Table VI shows the performance using the NN approach with a training data of 12 days for a different number of channels. While in a few cases, there is a marginal difference in the accuracy, in other cases such as B–E, a significant increase in the classification accuracy is observed from 64.13% to 80.65%. The effective bandwidth that we achieve here is different from the physical bandwidth. Although we increase the number of channels using frequency hopping, the system uses only one channel at a time which cannot improve the resolution of multipath. However, using different channels and thus different carrier frequencies, more features can be extracted. The variation in the performance improvement for different pairs of people with the number of channels is yet to be analyzed by involving more number of subjects in the study.

VII. Future Work

The proposed driver authentication system is the first generation of such an effort where we focused on key enabling issues and carried out a proof-of-concept development. Several limitations and issues deserve additional attention, which can be addressed in our on-going work and future plan.

1) A small change in the environment can alter the multipath channel and the CSI. All the techniques based on the exact value of CSI are sensitive to these changes. In this article, we attempted to address the problem of "changing in-car environments" using learning methods for a restricted environment such as a car. For more general environments such as indoor, more advanced techniques will be necessary. Also, environment independent radio biometrics cannot be obtained by direct subtraction of the CSI of an empty environment. As a future work, we will study the pattern of the indoor multipath channel change and the dependence of human radio biometrics on the multipath channel.
2) We have used a simple NN in this article. Other NNs with a more complicated architecture involve a larger number of learnable parameters and thus require a much larger number of samples for training. Gathering more radio biometric data for different people in different environments can enable the usage of a more complex NN architecture and provides a better understanding of human radio biometrics. Although this increases the complexity, with the available level of computational ability in the recently manufactured cars used for auto pilot mode, adaptive cruise mode, and even face recognition, we believe that the future cars will be well equipped to carry out the task of model updating in an NN. An alternate approach can be cloud computing, by sending gathered data to the cloud and fetching the recurrent training computed on the cloud.
3) In a practical scenario, there will be at most two or three authenticated drivers for a car. In such cases, the similarity in all the physical attributes is highly unlikely. As future work, more data need to be gathered to study the performance of the proposed system for people with similar physical characteristics like twins. The variability in the accuracy of different pairs of people can also be understood with more data and by including more testers.
4) This system cannot recognize a new temporary driver without learning the knowledge of his/her radio biometric information in advance. The radio biometrics of the driver should be present in the driver radio biometric database of the car. In case of a temporary driver, keys or passwords have to be used.

VIII. Conclusion

In this article, we introduced the idea of in-car driver authentication to make the automobiles smarter and more user-friendly. To evaluate the feasibility and performance of the proposed system, we conducted long-term experiments in a car. We built the first long-term driver radio biometric database for multiple persons and proposed to integrate ML techniques into the system. Furthermore, we have implemented frequency hopping and used MIMO systems to exploit the frequency and multiantenna diversities, respectively. The experimental results show that the proposed system is practically feasible with good accuracy for two or three driver authentication, which is a typical use case for a smart car.

References

[1] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Comput. Netw.*, vol. 54, no. 15, pp. 2787–2805, 2010.
[2] M. Keertikumar, M. Shubham, and R. M. Banakar, "Evolution of IoT in smart vehicles: An overview," in *Proc. Int. Conf. Green Comput. Internet Things (ICGCIoT)*, 2015, pp. 804–809.
[3] E. Ohn-Bar, S. Martin, A. Tawari, and M. M. Trivedi, "Head, eye, and hand patterns for driver activity recognition," in *Proc. 22nd Int. Conf. Pattern Recognit.*, Stockholm, Sweden, 2014, pp. 660–665.
[4] A. Jain, A. Singh, H. S. Koppula, S. Soh, and A. Saxena, "Recurrent neural networks for driver activity anticipation via sensory-fusion architecture," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Stockholm, Sweden, 2016, pp. 3118–3125.
[5] E. Martin, O. Vinyals, G. Friedland, and R. Bajcsy, "Precise indoor localization using smart phones," in *Proc. 18th ACM Int. Conf. Multimedia*, Florence, Italy, 2010, pp. 787–790.
[6] J. Xiao, K. Wu, Y. Yi, and L. M. Ni, "FIFS: Fine-grained indoor fingerprinting system," in *Proc. 21st Int. Conf. Comput. Commun. Netw. (ICCCN)*, Munich, Germany, 2012, pp. 1–7.
[7] C. Chen, Y. Chen, Y. Han, H.-Q. Lai, and K. J. R. Liu, "Achieving centimeter-accuracy indoor localization on wifi platforms: A frequency hopping approach," *IEEE Internet Things J.*, vol. 4, no. 1, pp. 111–121, Feb. 2017.
[8] Q. Xu, Z. Safar, Y. Han, B. Wang, and K. J. R. Liu, "Statistical learning over time-reversal space for indoor monitoring system," *IEEE Internet Things J.*, vol. 5, no. 2, pp. 970–983, Apr. 2018.
[9] A. E. Kosba, A. Saeed, and M. Youssef, "Robust WLAN device-free passive motion detection," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Shanghai, China, 2012, pp. 3284–3289.
[10] K. Muthukrishnan, M. Lijding, N. Meratnia, and P. Havinga, "Sensing motion using spectral and spatial analysis of WLAN RSSI," in *Proc. Eur. Conf. Smart Sens. Context*, 2007, pp. 62–76.
[11] J. Liu, Y. Wang, Y. Chen, J. Yang, X. Chen, and J. Cheng, "Tracking vital signs during sleep leveraging off-the-shelf WiFi," in *Proc. 16th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, Hangzhou, China, 2015, pp. 267–276.
[12] C. Chen *et al.*, "TR-BREATH: Time-reversal breathing rate estimation and detection," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 3, pp. 489–501, Mar. 2018.
[13] K. Ali, A. X. Liu, W. Wang, and M. Shahzad, "Keystroke recognition using WiFi signals," in *Proc. 21st Annu. Int. Conf. Mobile Comput. Netw.*, Paris, France, 2015, pp. 90–102.
[14] F. Zhang, C. Chen, B. Wang, and K. J. R. Liu, "WiSpeed: A statistical electromagnetic approach for device-free indoor speed estimation," *IEEE Internet Things J.*, vol. 5, no. 3, pp. 2163–2177, Jun. 2018.
[15] Q. Pu, S. Gupta, S. Gollakota, and S. Patel, "Whole-home gesture recognition using wireless signals," in *Proc. 19th Annu. Int. Conf. Mobile Comput. Netw.*, Miami, FL, USA, 2013, pp. 27–38.
[16] W. Wang, A. X. Liu, and M. Shahzad, "Gait recognition using WiFi signals," in *Proc. ACM Int. Joint Conf. Pervasive Ubiquitous Comput.*, Heidelberg, Germany, 2016, pp. 363–373.

[17] S. Duan, T. Yu, and J. He, "WiDriver: Driver activity recognition system based on WiFi CSI," *Int. J. Wireless Inf. Netw.*, vol. 25, no. 2, pp. 146–156, 2018.

[18] D. Bhattacharyya, R. Ranjan, F. Alisherov, and M. Choi, "Biometric authentication: A review," *Int. J. u-e- Service Sci. Technol.*, vol. 2, no. 3, pp. 13–28, 2009.

[19] Q. Xu, Y. Chen, B. Wang, and K. J. R. Liu, "Radio biometrics: Human recognition through a wall," *IEEE Trans. Inf. Forensics Security*, vol. 12, no. 5, pp. 1141–1155, May 2017.

[20] I. Dove, "Analysis of radio propagation inside the human body for in-body localization purposes," M.S. thesis, Faculty Elect. Eng., Math. Comput. Sci., Univ. Twente, Enschede, The Netherlands, 2014.

[21] A. Fort, J. Ryckaert, C. Desset, P. De Doncker, P. Wambacq, and L. Van Biesen, "Ultra-wideband channel model for communication around the human body," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 4, pp. 927–933, Apr. 2006.

[22] C. Gabriel, S. Gabriel, and Y. E. Corthout, "The dielectric properties of biological tissues: I. Literature survey," *Phys. Med. Biol.*, vol. 41, no. 11, p. 2231, 1996.

[23] S. Gabriel, R. W. Lau, and C. Gabriel, "The dielectric properties of biological tissues: II. Measurements in the frequency range 10 Hz to 20 GHz," *Phys. Med. Biol.*, vol. 41, no. 11, p. 2251, 1996.

[24] S. Gabriel, R.W. Lau, and C. Gabriel, "The dielectric properties of biological tissues: III. Parametric models for the dielectric spectrum of tissues," *Phys. Med. Biol.*, vol. 41, no. 11, p. 2271, 1996.

[25] G. Melia, "Electromagnetic absorption by the human body from 1–15 GHz," Ph.D. dissertation, Dept. Electron., Univ. York, York, U.K., 2013.

[26] A. L. Blum and P. Langley, "Selection of relevant features and examples in machine learning," *Artif. Intell.*, vol. 97, nos. 1–2, pp. 245–271, 1997.

[27] D. Vasisht, S. Kumar, and D. Katabi, "Decimeter-level localization with a single WiFi access point," in *Proc. 13th USENIX Symp. Netw. Syst. Design Implement. (NSDI)*, Santa Clara, CA, USA, 2016, pp. 165–178.

[28] D. W. Aha, D. Kibler, and M. K. Albert, "Instance-based learning algorithms," *Mach. Learn.*, vol. 6, no. 1, pp. 37–66, 1991.

[29] N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods*. Cambridge, U.K.: Cambridge Univ. Press, 2000.

[30] V. Vapnik, *Estimation of Dependences Based on Empirical Data*. New York, NY, USA: Springer, 2006.

[31] M. Stone, "Cross-validatory choice and assessment of statistical predictions," *J. Roy. Stat. Soc. B Methodol.*, vol. 36, no. 2, pp. 111–147, 1974.

[32] C. Chen, Y. Chen, Y. Han, H.-Q. Lai, F. Zhang, and K. J. R. Liu, "Achieving centimeter-accuracy indoor localization on WiFi platforms: A multi-antenna approach," *IEEE Internet Things J.*, vol. 4, no. 1, pp. 122–134, Feb. 2017.

[33] B. Wang, Q. Xu, C. Chen, F. Zhang, and K. J. R. Liu, "The promise of radio analytics: A future paradigm of wireless positioning, tracking, and sensing," *IEEE Signal Process. Mag.*, vol. 35, no. 3, pp. 59–80, May 2018.

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