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WiFi-based Vehicle Security System for Future Intelligent Transportation Systems

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Research Article

Abstract

With the rapid maturation in automotive industry, intelligent sensing has been emerged as a vital research field for fast paced future intelligent transportation system. After the progressive integration of advanced driver assistance system and the rapid growth in next generation Internet of Vehicles (IoV), diver's identification constitutes an indispensable aspect for the authorization in next generation internet-connected smart vehicles. Real-time driver identification is crucial in next generation smart vehicles. The presented solution is based on channel state information (CSI) of WiFi signals. In this proposed framework, an innovative WiFi- based low cost driver identification system is proposed which can recognize driver with good accuracy and less computational burden. The core idea is based on analyzing the steering wheel maneuver, exploiting CSI of WiFi signal. In the era of advanced information and communication in intelligent transportation system, this driver identification system may incorporate various intelligent means that are beneficial in many applications including safety, security, fleet management, ride hailing, insurance telematics, and customized vehicles. The proposed framework can recognize the activities with an average accuracy of 92.5% and identification with an average accuracy of 91.8%.

Keywords: Channel state information; Driver identification; Next generation smart vehicles; Vehicle security s ystem; Wireless sensing

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1. Introduction

With the progressive development in auto industry, intelligent vehicles have been evolved that are integrated with advanced driver assistance systems using driving behavior analysis [1]. These sophisticated systems may lead to provide driver's fatigue and distraction monitoring for the safety and well-being. For the next generation smart transportation system, driver identification is also an important topic to be considered by auto developers and researchers in designing customized vehicles for better driving experience [2].

Driver identification can be commercially used to avoid using an unauthorized driver in freight transportation or intercity public transport system [3]. It may also be used in intelligent vehicles for quality driving by monitoring the amount of driving per day. The insurance companies can also use driver identification system to recognize the actual owner of vehicle and automatically detect car theft. Moreover, driver identification is an important aspect in connected vehicles and data- driven cars for the privacy sensitivity of in-vehicle apps and data. In shared vehicles, drivers can be differentiated by their unique driving behaviors. The unique driving behavior is also beneficial in recognizing young or old drivers for personalized vehicle environments, i.e. side mirror adjustment, height of the driving seat, in-vehicle temperature settings.

The primary goal of this automotive research topic is to identify drivers with minimal deployment or infrastructure needs. During the previous decades, many innovative techniques have been emerged to accurately recognize drivers by using finger print, voice and face recognition. Recently, sensor based methods have also been evolved to recognize in-vehicle drivers [4, 5]. However, all these methods have some limitation in quality and reliability. Similarly, the traditional biometric solutions are un-scalable and costly for practical application [6]. Therefore, the driver identification process needs to take place transparently and without involving conventional sensors for biometric measures. To this end, an autonomous driver identification system is still a crucial research problem for automotive developers.

Table 1. Different types of turns

Activity Performed	Activity Label
Turning left without stop event	TLW
Turning right without stop event	TRW
Turning left with stop event	TLS
Turning right with stop event	TRS
Change of left lane	CLL
Change of right lane	CRL

The presented novel technique exploits the variations in CSI-WiFi channel caused by driver's activities. The CSI of WiFi signal is physical layer information that works on the principle of MIMO with orthogonal frequency division multiplexing (OFDM), constitutes a MIMO-OFDM system that may lead to enormous applications for next generation vehicles. From the literature [7-11], the future vehicles will be equipped with pre-installed WiFi devices.

The core idea is based on analyzing driver's behavior on steering wheel including left or right turns and change of lane. Each driver has different habits on turns, starting from approaching a turn, completing a turn and then leaving a turn [12]. For example, each driver has its own preference to start rotating the steering wheel at very early stage of turn and rotate steering wheel very slowly. In our experimentation, turns are categorized according to the driving or traffic conditions, as shown in Table 1. The turns with regular stop conditions i.e. red traffic light, waiting for pedestrian, or stop sign are referred as the "turns with stop events". On the other hands, turns without any stop conditions are considered as the "turns without stop events".

We observed that the driver identification using turns is practical, because a driving session usually starts with leaving residential areas or taking the vehicle out of a parking lot. Therefore, a driver needs to perform different types of turns, which gives us the opportunity to utilize these turns for our driver identification solution.

Our driver identification system is based on data segmentation. The data segmentation is determined by the variations in channel state information (CSI) signal caused as a result of the driver slows down the vehicle, steering wheel is turned, turn is processed, and then the speed pedal is again pressed to speed up the vehicle. We observed alternating peak/valley due to large CSI variations, when the driver was performing turn event otherwise relatively smaller variations were observed. Therefore, our proposed model is based on peak/valley detection algorithm [13], where each peak represents the occurrence of turn event. Firstly, we segment the steering wheel turning data using peak/valley detection algorithm and then extract the time domain statistical features. Afterwards, we suggest frequency domain analysis and extract frequency domain features. Finally, we use one-class support vector machines (SVM) algorithms to identify the driver. The proposed method is tuned to improve specificity, sensitivity, and accuracy and by using the suitable and appropriate machine learning technique.

As far as authors know, this is the first step for wireless device-free WiFi-based driver's in-vehicle identification. Our remarkable contributions are four folds that are mentioned as:

• We propose a device-free wireless driver's identification system leveraging the CSI of WiFi signals. We provide a methodological framework to demonstrate the significance of activity recognition for driver identification.

• For activity recognition, we suggest to segment the steering wheel turning data using peak/valley detection algorithm.

• For driver identification, we propose to construct the one-class model for each authenticated driver in the users' profiles. We calculate a score (S) that compares the similarity index between the extracted features of testing samples and user's profile support vectors.

• Comprehensive experiments are conducted to validate the reliability of presented scheme and the performance is evaluated with existing state-of-the-art conventional schemes.

The organization of this research paper is stated as; Section-2 (Related Work) reviews the conventional existing solutions relevant to the proposed framework. Section-3 (System Overview) highlights the system architecture and WiFi CSI overview. Section-4 (Methodology) demonstrates the detailed implementation of presented framework. In Section-5 (Experimentation and Evaluation), experimentation settings and performance evaluation is carried out. In Section-6 (Results Analysis and Discussion), the prominent results are discussed along with some limitations. Finally, the conclusions with future suggestions are provided in conclusion.

2. Related Work

In this section, we review the existing systems relevant to our research work including conventional driver identification systems, CSI of WiFi for human activity and gesture recognition, and WiFi CSI for in-vehicle systems.

Driver identification has attracted many researchers as an active field of study [1]. The authors of [14] presented a deep learning based driver identification system exploiting a residual convolutional network (RCN). This novel mechanism outperforms the conventional state-of- the-art methods with less time for training. A supervised machine learning based method was introduced in [15] for driver detection in real-time. The authors of [16] investigated driver's natural style for identification. An innovative anti-theft vehicle tracking system was introduced in [17]. In this approach, a camera captures an image of the intruder, while a global positioning system (GPS) is employed to gather the vehicle's longitude and latitude coordinates. Another approach to identify the driver was introduced in [18] based on the driver's photo-plethysmo-graphic (PPG) signal. This approach is utilizing temporal convolutional neural network driver identification from

PPG signal. The authors of [19] presented a novel driver identification method utilizing deep learning.

The WiFi CSI-based recognition systems have been emerged in various fields [20, 21]. Wi-Run [22] is an intelligent step estimation system utilizing CSI of WiFi signals. The WiFi CSI based micro activity recognition method was introduced in [23]. The authors of [24] proposed the idea of robust intrusion detection exploiting WiFi-CSI. Similarly, Wi-Alarm [25] is a low cost intrusion detection method using CSI of WiFi. In this technique the cost of data pre-processing is omitted and the detection is based on SVM algorithm. The authors of [26] discussed the idea of writing in air with CSI of WiFi signals. WiFi Vision [27] focused on the survey of WiFi vision problems in device-free recognition, identification and detection. The authors of [28] worked on multi-variations activity based gait recognition observing the variations in CSI of WiFi signal. The authors of [29] explored deep learning based wide-band WiFi in- formation for robust activity recognition.

The concept of WiFi-based human activity recognition to mitigate the problem of small-size WiFi activity data was discussed in [30]. The authors of [31] presented a method for WiFi-based multi-user gesture recognition. WiReader [32] focused on handwriting recognition in air through the CSI of WiFi. WiAct [33] proposed a framework for passive activity recognition by exploring the correlation between CSI and human body movements to identify different activities. DeepSeg [34] is a deep learning based activity recognition system. Wihi [35] is a WiFi based human identity identification system using CSI. WiPass [36] is WiFi CSI based smart phones keystroke recognition system. Recently, Wi- COVID [37] has been evolved to detect the COVID-19 symptoms and patients monitoring using CSI of WiFi signals. DF-WiSLR [38] is a WiFi based method for sign language recognition.

In the recent years, the CSI of WiFi signal has been widely employed in automotive industry. In this context, WISDOM [39] presented a WiFi based system to improve the safety of autonomous driving systems by analyzing driver behavior. They leverage the benefits of random forest (RF) algorithm to identify the driver. The authors of [40] proposed a framework for human activity detection by characterization of WiFi CSI features in a smart public transportation system. Wi-Watch [41] explored the fine grained CSI data of WiFi signals to monitor and assess whether the ship officer is following safety protocols. The authors of [42] leverage the benefits of WiFi CSI and internet of things (IoT) to detect and classify the animal crossings on roads.

During the previous few years, WiFi CSI has been widely employed for in-vehicle activity and gesture recognition. The authors of [43, 44] presented driver's activity recognition with very good recognition performance at the less cost of computation. Similarly, Reference [45] focused on driver gesture recognition for in-vehicle infotainment system. WiDriver [46] has given the idea of driver actions recognition depending on driver's hand movements exploiting WiFi-CSI signals. WiFi-CSI based device-free technology has been evolved that can estimate vehicle speed accurately [47]. WiFind [48] utilized the CSI of WiFi signal for driver's fatigue detection. The presented system is based on one-class support vector machine (SVM). However, as per author's knowledge, the WiFi CSI-based in-vehicle driver identification has not been deeply examined yet in literature.

3. System Overview

This section demonstrates the important highlights of WiFi CSI and overview of proposed system architecture.

WiFi CSI Overview

The CSI of WiFi signal is physical layer fine grained information that works on the mechanism of orthogonal frequency division multiplexing (OFDM). Commercially available WiFi devices that support 802.11n/ac protocols usually obey multiple input multiple output (MIMO) mechanism. Hence, off-the-shelf conventional WiFi devices usually contain multiple transmitter (Tx) and receiver (Rx) antennas.

In this research work, an IEEE 802.11n enabled off- the-shelf WiFi router is used as a transmitter. The receiver is a laptop with Intel 5300 network interface card (NIC) to record the CSI data. The CSI data is acquired in the form of channel variations available on off-the-shelf IEEE 802.11n enabled WiFi devices [49]. Generally, the OFDM technique with Intel 5300 NIC supports 30 subcarriers to acquire and record the CSI obtained data for each and every Tx-Rx antenna pair.

For CSI received data, the narrow-band flat-fading channel exploiting OFDM and MIMO methods are formulated as:

$$Y_n = H_n X_n + N_n , n \in [1, N] \tag{1}$$

where X_n is transmitted signal while Y_n is the received signal for n packet. H_n represents the CSI channel matrix, N stands for the total number of received packets and N_i is the Gaussian noise vector.

Let us have N_{Tx} and N_{Rx} as the total number of transmitting and receiving antennas respectively. The CSI matrix for each stream consists of $N_{Tx} \times N_{Rx} \times 30$ complex values. The CSI matrix H for each Tx-Rx antenna pair is formulated as:

$$H_n = [p_1 , p_2 , \dots , p_{30}], n \in [1, N] \tag{2}$$

where p has both amplitude and phase measurements in the form of complex number; represented as:

$$p = |p| e^{j sin\{\angle p\}} \tag{3}$$

where $|p|$ and $\angle p$ are the amplitude and phase data respectively.

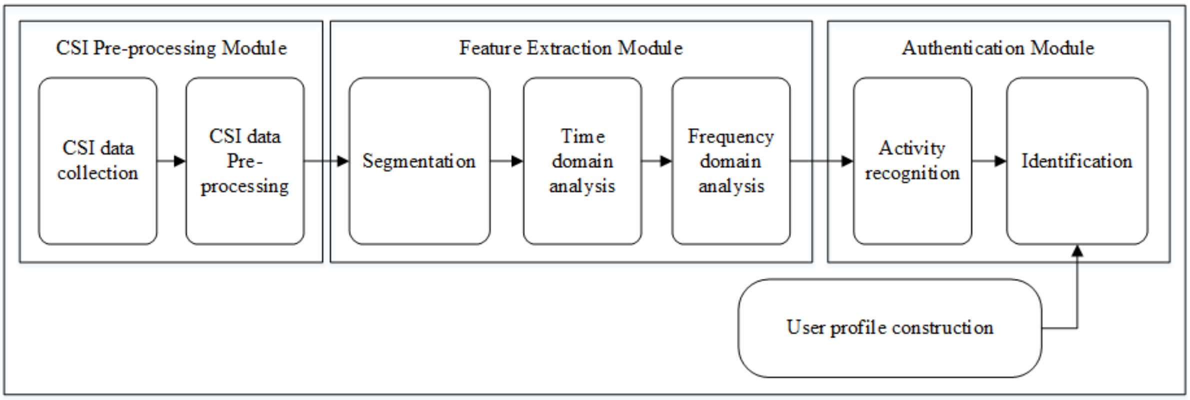


Fig. 1. System architecture.

4. System Architecture

The presented WiFi CSI-based driver's authentication framework comprises of three basic modules, i.e. (1) CSI pre-processing module, (2) feature extraction module, and (3) authentication module, as shown in Fig. 1.

CSI pre-processing module

This module consists of two sub-systems i.e. CSI data collection sub-systems and CSI data pre-processing sub- system. The CSI data collection sub-system gathers the required CSI data of WiFi signals from physical layer. Once CSI data is collected, it can be processed and analyzed to extract useful information about the wireless channel.

The acquired CSI data consists of useful information and unwanted noise which is further processed in CSI data pre-processing sub-system. In this sub-system, state-of-the-art filtering techniques are used to remove unwanted noises from received raw CSI data.

Feature extraction module

In this module, pre-processed CSI data is used and most relevant features are extracted. The feature extraction module perform three tasks i.e. segmentation, time domain analysis, and frequency domain analysis.

In segmentation, the pre-processed CSI data is segmented into small chunks of data. Each segment typically represents a short duration of time, during which the user performs a specific activity.

After segmentation, time domain analysis is performed. Time domain analysis examines the data directly in the time domain. It focuses on the amplitude or magnitude of the signal over time. Time domain analysis is computationally efficient and straightforward to implement. It provides insights into the temporal characteristics of activities and can capture short-term dynamics effectively. Frequency domain analysis allows for the examination of signal components at different frequencies. It can capture long-term patterns and repetitive motions that may not be apparent in the time domain.

Authentication module

The authentication module performs two main function i.e. activity recognition and driver identification.

Based on extracted features, activity recognition refers to the process of automatically detecting and categorizing specific activities or behaviors performed by driver. Similarly, the driver is identified based on particular instances or activities.

5. Methodology

The function of each processing block is explained in this section.

CSI Pre-processing

The CSI data acquired by the receiver consists of beneficial information as well as unwanted noises from the surroundings objects. Firstly, we filter the raw CSI data using state-of-the-art filtering method. From the literature review, it is concluded that the human activities generally have low frequencies as compared to the frequencies of noise [24]. Intuitively, we remove high frequency noise from the raw CSI data to get the actual data. In this context, we use a second order low pass Butterworth filter. Throughout the experiments we adjust the packets sampling rate (F_s) at 80 packets/second that is taken equal to the normalized cutoff frequency $w_n = 2\pi f / F_s = 0.025\pi\ rad/sec$. The received CSI data is normally influenced by some static path components. The CSI raw phase measurements exhibit high randomness due to un-synchronized clocks of the transmitter and receiver. To accurately extract the true phase and mitigate channel frequency offset, the process involves phase calibration and linear transformation. For phase calibration and amplitude information processing, we follow the same procedure as described in [43].

Phase calibration

For i^{th} subcarrier, we consider $\angle \mathrm{p}_i$ as true phase and $\angle \widehat{P}_i$ as measured phase. The relation between $\angle \mathrm{p}_i$ and $\angle \widehat{P}_i$ is:

$$\angle \widehat{P}_i = \angle \mathrm{p}_i + 2\pi \frac{N_i}{N} \Delta t + \beta + z \quad (4)$$

where n_i is the subcarrier index, N represents the FFT size, Δt denotes the time lag, β is the unknown phase offset, and z stands for the random noise.

We can formulate two parameters P_s and P_o for the slope of phase and the offset respectively.

$$P_s = \frac{\angle\widehat{p_k} - \angle\widehat{p_1}}{n_k - n_1} \quad (5)$$

$$P_o = \frac{1}{k}\sum_{j=1}^{k}\angle\widehat{p_j} \quad (6)$$

By subtracting a linear term $P_s n_i + P_o$ from raw phase $\angle\widehat{p_i} - P_s n_i$ to get the sanitized phase $\angle\widetilde{p_i}$ as:

$$\angle\widetilde{p_i} = \angle\widehat{p_i} - P_s n_i - P_o \quad (7)$$

After performing phase calibration, we performed amplitude information processing.

Amplitude information processing

For amplitude information processing, the Weighted Moving Average (WMA) is employed over the whole CSI streams. For the purpose, we consider a time interval t during which p_t is CSI value. We apply WMA as:

$$\acute{p_t} = \frac{[m\times p_m + (m-1)\times p_{(m-1)} + \cdots . + 1\times p_1]}{m + (m-1) + \cdots . + 1} \quad (8)$$

$\acute{p_t}$ is the newly obtained value which has the weight value of m.

Data Segmentation

In driver identification, we are interested to find the relevant segments containing steering wheel data of a turn. For the purpose, we find a time-series data of CSI signal and adopt peak/valley detection algorithm to extract the steering wheel turning data. The peak/valley algorithm rely on local minimum and maximum values of obtained CSI time-series information to estimate the start of the turn. Immediately after we have observed that a driver is performing a turn, we start determine the turn duration. We have also setup expected turn duration ranging from 0.5s to 4.5s. If we detect the turning event less than the specified duration, the algorithm will further include the next peak or valley.

Feature Extraction

The feature extraction relies on preliminary experiments performed on segmented data. Preliminary investigations are performed on 22 different time domain and frequency domain features, as demonstrated in Table 2. We specifically choose ten dominant time domain and four frequency domain features from the all extracted features, as shown in Table 3.

We constitute a feature vector Ƒ as:

$$Ƒ = \{T_m, T_{sd}, T_{max}, T_{min}, T_v, T_r, T_c, T_k, T_{cr}, T_{sk}, F_e, F_{ent}, F_{frq}, F_{fft}\} \quad (9)$$

Table 2. Preliminary investigations for selection of discriminative features

Feature name	Average accuracy (a)%
Mean	≥ 90
Standard deviation	≥ 90
Maximum value	≥ 90
Minimum value	≥ 90
Variance	≥ 90
Range	≥ 90
Auto-correlation	≥ 90
Kurtosis	≥ 90
Mean crossing rate	≥ 90
Skewness	≥ 90
Normalized energy	≥ 90
Normalized entropy	≥ 90
Dominant frequency ratio	≥ 90
FFT peaks	≥ 90
Median	80 ≤ a ≤ 90
Median absolute deviation	80 ≤ a ≤ 90
25th Percentile	80 ≤ a ≤ 90
75th Percentile	80 ≤ a ≤ 90
2nd central moment	80 ≤ a ≤ 90
3rd central moment	80 ≤ a ≤ 90
Interquartile range	80 ≤ a ≤ 90
Root mean square	80 ≤ a ≤ 90

Table 3. Features selected

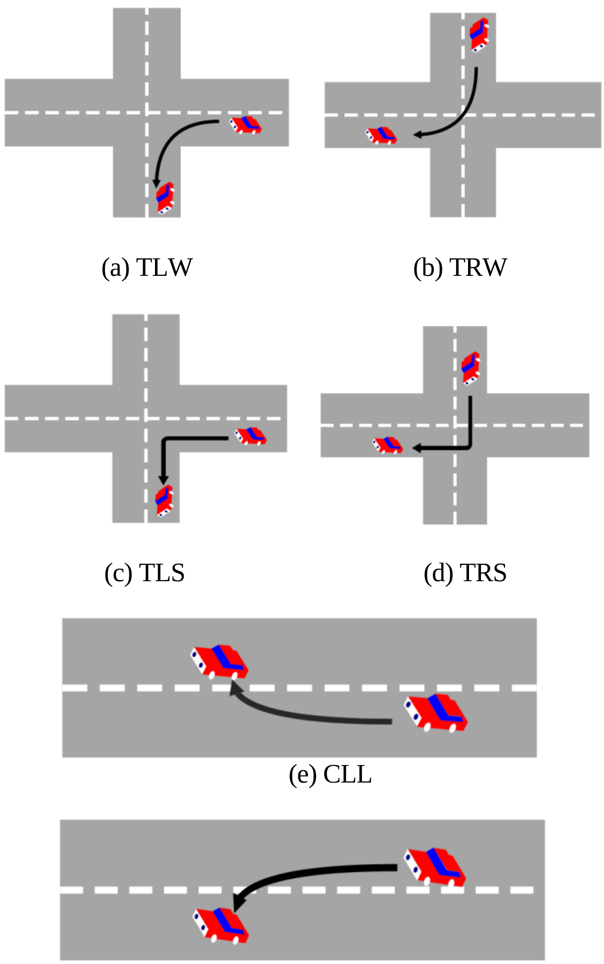
Activity Performed	Activity Label
Time domain feature	Mean T_m , Standard deviation T_{sd} , Maximum value T_{max} , Minimum value T_{min} , Variance T_v , Range T_r , Autocorrelation T_c , Kurtosis T_k , Mean crossing rate T_{cr} , Skewness T_{sk}
Frequency domain feature	Normalized energy F_e , Normalized entropy F_{ent} , Dominant frequency ratio F_{frq} , FFT peaks F_{fft} (5 largest frequencies and magnitudes)

Authentication

The above mentioned method is used to decide the activity type (i.e. turning left or right without stop event, turning left or right with stop event, change of left or right lane) and build user profile. To train the input samples and build user profile, we follow the procedure as described in [50]. We suggest using conventional SVM classifier with the Gaussian kernel function. Using feature vector Ƒ, we construct the one-class model for each authenticated driver in the users profiles. Finally, we calculate a score (S) to compares the similarity between the features extracted from testing samples and user's profile support vectors, represented as $Ƒ_{test}$ and $Ƒ_{user}$ respectively. Mathematically, we can show

$$S = \operatorname{sign}\left(\sum_{n=1}^{N} k(F_{\text{test}}, F_{\text{user}})\right) \quad (10)$$

where N denotes the number of authenticated drivers, k represents the Guassian kernel function. If value of S is greater than threshold, it means testing sample has comparatively less distance to the user in profile. Similarly, if value of S is less than it means an un-authorized driver.



(a) TLW (b) TRW

(c) TLS (d) TRS

(e) CLL

(f) CRL

Fig. 2. Performance of different turns.

6. Experimentation and Evaluation

In this section, we will demonstrate the experimentation settings and performance evaluation of presented framework.

Experimentation Settings

In this research work, all proposed experiments are per- formed with off-the-shelf WiFi devices. We used a laptop equipped with Intel 5300 NIC as a receiver that has three receiving antennas i.e. $N_{Rx} = 3$, to record the CSI data. On the receiver, we specifically run 802.11n CSI Tool as discussed in [49] with Ubuntu 11.04 LTS operating system. A simple WiFi router (TP-Link) operating at frequency of 2.4GHz with single antenna is used as a transmitter i.e. $N_{Tx} = 1$. The receiver pings the router at a rate of 80 packets/s. The setup forms a 1 × 3 MIMO system with three CSI streams of thirty subcarriers each and channel bandwidth of 20MHz, MATLAB R2016a is used to perform all signal processing. All the proposed experiments are performed in a locally manufactured vehicle that does not have pre-installed WiFi devices. Therefore, we placed a commercially available WiFi router (TP-Link) in front of driver on vehicle's dashboard. To record CSI data, the receiver i.e. a laptop is installed at co-pilot's seat. The vehicle is derived with an average speed of 25km/hr on a road which is not thoroughfare for 25km long.

In each experiment, 6 turning actions, as shown in Fig. 2 are performed by 5 volunteers (2 university students of age less than 24 years, two males of age less than 40 years, and one female of age less than 50 years). Each volunteer repeated each of the proposed turning action 20 times. The overall data set comprises of total 600 samples (5-volunteers×6-actions×20-times repeated) for each experiment. For training purpose, the 50% of the total samples are used while remaining 50% are used for the testing of proposed algorithm. The cross validation is performed by keeping the training data separate from the testing data.

Performance Evaluation

Performance evaluation is performed by specifically choosing the activity recognition and identification accuracy utilizing confusion matrix. For activity recognition, the actual activity performed by driver is presented on the columns of confusion matrix and the activity classified is represented on the rows of confusion matrix. Similarly, the actual driver is placed at the columns of confusion matrix and the identified driver is placed on the rows of confusion matrix. The confusion matrix in Fig. 3 shows that the proposed framework can recognize 6 turning actions with an average accuracy of 92.5% and driver identification with an average accuracy of 91.8%.

To evaluate the reliability of proposed framework, the recognition detection is evaluated by different performance metrics including precision, recall, specificity, F1-score, accuracy, and Mathew Correlation-coefficient (MCC) defined as [51]:

1. Precision is defined as the positive predictive measurement, mathematically shown as:

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

where TP is true positive rate and defined as the probability that any model can correctly predict the positive class. FP is false positive rate and defined as the probability that any model can incorrectly predicts the positive class.

Actual Activity	TLW	TRW	TLS	TRS	CLL	CRL
TLW	0.92	0.01	0.03	0.00	0.04	0.00
TRW	0.02	0.92	0.00	0.02	0.00	0.04
TLS	0.02	0.02	0.93	0.00	0.03	0.00
TRS	0.00	0.02	0.03	0.91	0.01	0.03
CLL	0.01	0.00	0.02	0.01	0.94	0.02
CRL	0.00	0.02	0.00	0.02	0.03	0.93

Activity Classified

(a) Activities

Actual Driver	D-1	D-2	D-3	D-4	D-5	D-6	D-7	D-8	D-9	D-10
D-1	0.92	0.00	0.01	0.02	0.01	0.00	0.01	0.01	0.01	0.01
D-2	0.01	0.93	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.02
D-3	0.00	0.01	0.91	0.01	0.02	0.01	0.00	0.02	0.01	0.01
D-4	0.02	0.01	0.00	0.93	0.00	0.00	0.02	0.02	0.00	0.00
D-5	0.01	0.00	0.01	0.02	0.91	0.00	0.00	0.01	0.02	0.02
D-6	0.01	0.02	0.00	0.00	0.00	0.94	0.01	0.00	0.01	0.01
D-7	0.02	0.00	0.00	0.01	0.00	0.03	0.92	0.01	0.00	0.01
D-8	0.00	0.00	0.02	0.02	0.00	0.01	0.02	0.90	0.01	0.02
D-9	0.00	0.02	0.00	0.01	0.02	0.00	0.01	0.02	0.91	0.01
D-10	0.02	0.01	0.00	0.01	0.01	0.02	0.00	0.00	0.02	0.91

Identified Driver

(b) Drive identified

Fig. 3. Confusion matrix for recognition accuracy

2. Recall is the sensitivity and it measures the true positive rate (TPR), formulated as:

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

where FN is the false negative and determines the probability that any model can incorrectly predict the negative class.

3. Specificity quantifies the ratio of accurately identified negative cases among all true negative instances. It is calculated as:

$$Specificity = \frac{TN}{TN + FP} \tag{13}$$

where TN is the true negative and FP is false positive.

4. F-measure or F_1-score is calculates the weighted average of recall and precision, shown as:

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{14}$$

5. Accuracy is the overall performance of the model. It is formulated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

6. Mathew Correlation-coefficient (MCC) is a correlation coefficient between predicted results and actual outcomes. Below is the formula used to compute MCC values:

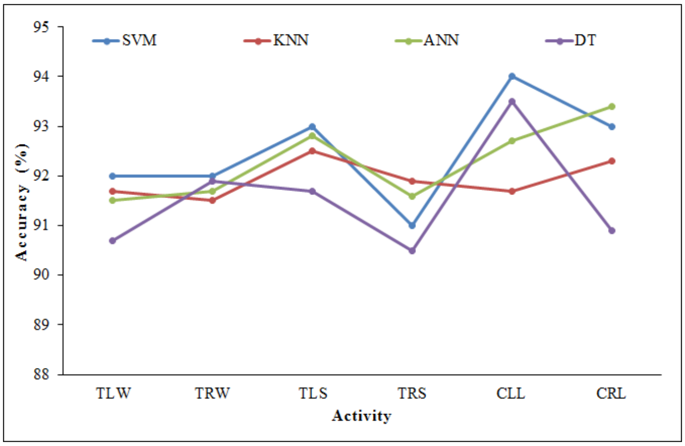
$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{16}$$

The summarized result for average minimum and maximum values of precision, recall, specificity, F_1-score, accuracy, and MCC are shown in Table 4. From the obtained outcomes, one can conclude that all the activities are determined with acceptable values of precision, recall, specificity, F_1-score, accuracy, and MCC. Similarly, the drivers are identified with very good average values of precision, recall, specificity, F_1-score, accuracy, and MCC.

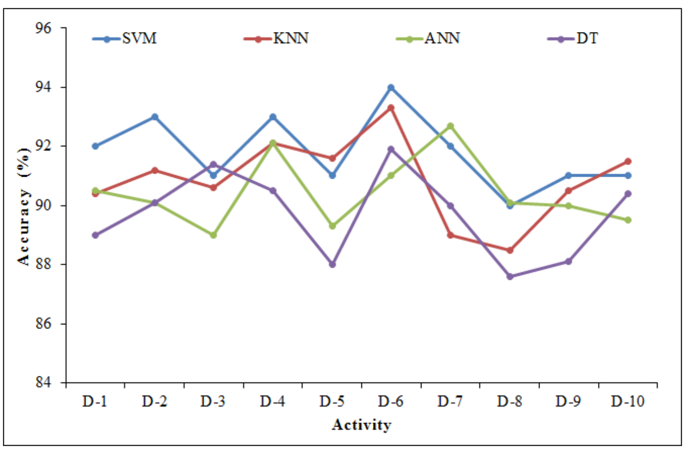
Table 4. Overall detection rate with precision, recall, specificity, F1 -score, accuracy, and MCC

Experiment	Average rate (%)											
	Precision		Recall		Specificity		F1 -score		Accuracy		MCC	
	min.	max	min.	max.	min.	max.	min.	max	min.	max.	min.	max.
Activity	89	94	88	97	89	95	89	94	88	97	85	90
Identification	90	94	88	95	89	94	90	93	88	95	85	91

The performance accuracy of SVM classifier is compared with state-of-the-art conventional classification algorithms i.e. K-nearest neighbor (KNN), artificial neural networks (ANN) [52, 53], and decision tree (DT) [54], as shown in Fig. 4. For KNN implementation, we used K=7 nearest neighbors where the system achieves the acceptable recognition performance. For ANN implementation, three layers model i.e. the input layer, hidden layer, and output layer is used [55]. Each layer consists of one or multiple nodes depending on the features. The input layer nodes receive a single value without data modification. The nodes in the hidden and output layers have the capability to alter the data, whereas the nodes in the input layer simply receive a single input value and replicate it across multiple outputs without altering the data. In the meantime, the nodes within the hidden and output layers are engaged in altering the data. For DT implantation, we choose C.45 algorithm.



(a) Activities



(b) Identification

Fig. 4. Performance evaluation of SVM with state-of- the-art classifiers.

The Fig. 4 depicts that the SVM classifier has comparatively better accuracy in terms of both cases i.e. activity recognition and driver identification as compared to the other state-of-the-art classifiers. The summarized results for state-of-the-art algorithms (KNN, ANN, DT) are discussed in Table 5. From the obtained results, it is clear that the DT algorithm has the lowest accuracy for both activity recognition and driver identification. The SVM classifier outperforms as compared to KNN, ANN, and DT in terms of both activity recognition and driver identification.

Table 5. Performance evaluation of SVM with state-of- the-art classifiers.

Experiment	Average recognition accuracy (%)			
	SVM	KNN	ANN	DT
Activity	92.5	91.9	92.3	91.5
Identification	91.8	90.9	90.4	89.7

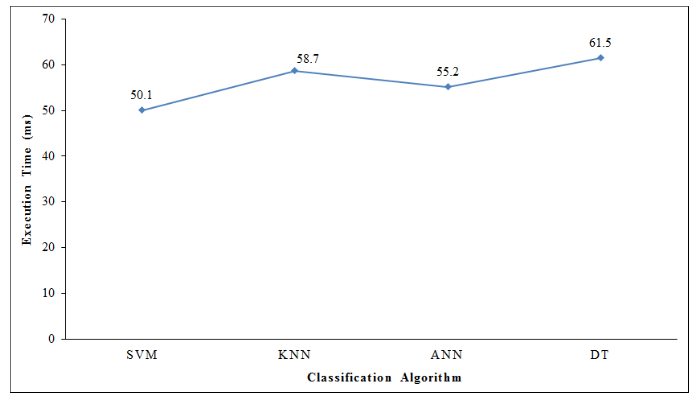


Fig. 5. Comparison of execution time

Table 6. Execution time of processing modules

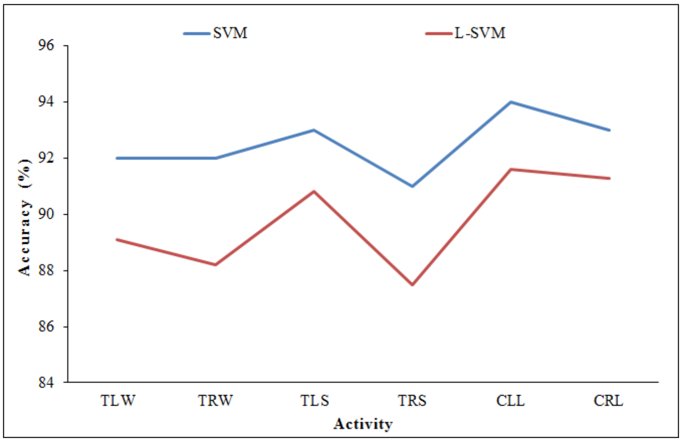
Parts	CSI Pre-processing	Feature extraction	Authentication	Total
Time (ms)	11.3	20.5	18.3	50.1

To observe the computational efficiency of our presented scheme, we compared the execution time using SVM, KNN, ANN, and DT as shown in Fig. 5. The results show that the SVM classifier has less execution time i.e. 50.1ms, as compared to other classification methods. This is the main reason of using SVM algorithm in our proposed work. The DT algorithm has highest execution time i.e. 61.5ms. The detailed processing time of each of the execution block is calculated and illustrated in Table 6.

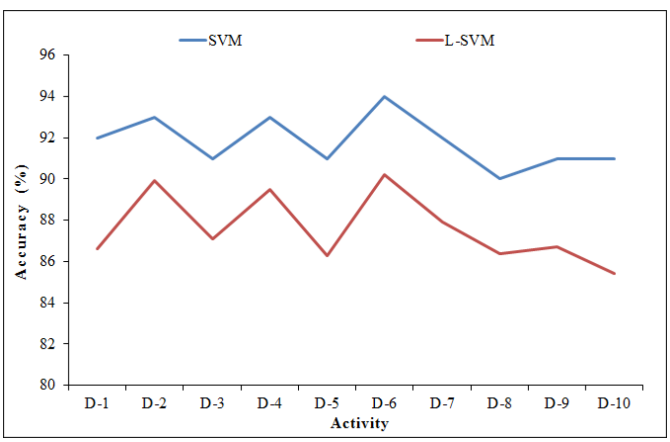
Table 7. Overall generalization performance

Experiment	Average accuracy (%)							
	SVM		KNN		ANN		DT	
	Original	LOPO-CV	Original	LOPO-CV	Original	LOPO-CV	Original	LOPO-CV
Activity	92.5	89.7	91.9	86.8	92.3	87.8	91.5	87.4
Identification	91.8	87.6	90.8	83.9	90.4	84.3	89.7	82.7

The proposed framework has generalization capability i.e. it is independent of user. To test the generalization capability, we particularly choose leave-one-participant-out cross-validation (LOPO-CV) scheme [56]. In this scheme, the training data and testing data are separated from each other. To compare the results of each algorithm, we have tested the proposed algorithm by applying LOPO-CV on SVM, KNN, ANN, and DT, represented as L-SVM, L-KNN, L-ANN, and L-DT respectively. The summarized results are shown in Fig. 6, Fig. 7, Fig. 8, and Fig. 9 respectively for SVM, ANN, KNN, and DT algorithms. From the obtained results, it is clear that the SVM algorithm has better generalization efficiency as compared to KNN, ANN, or DT algorithm. The summarized results are illustrated in Table 7.



(a) Activity



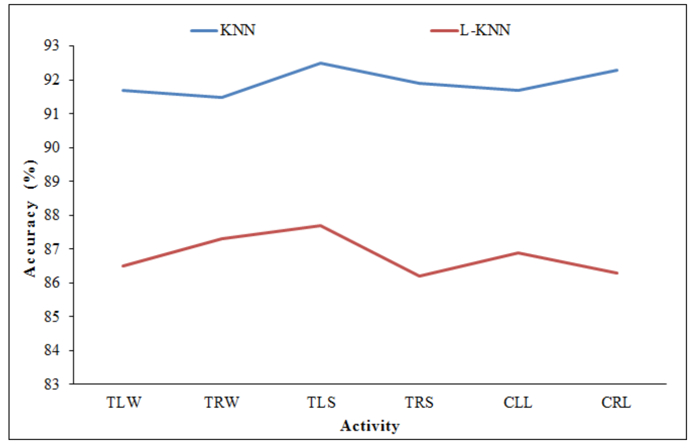
(b) Identification

Fig. 6. Accuracy test of SVM with LOPO-CV scheme

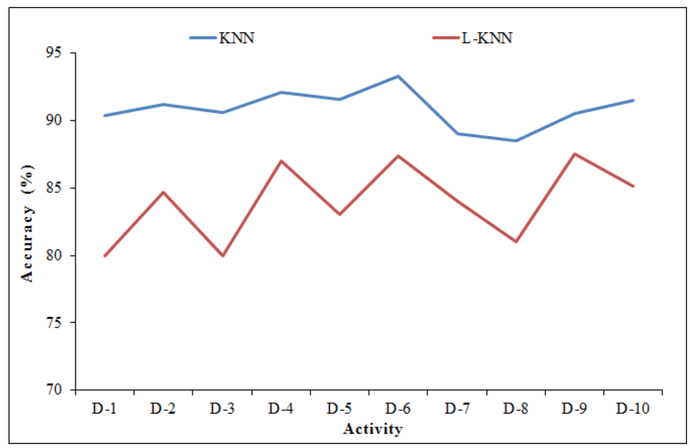
The generalization accuracy of SVM is 89.7% and 87.6% for activity recognition and driver identification respectively. Other conventional algorithms i.e. KNN, ANN, and DT have very less generalization accuracy.

Table 8. Varying layouts for robustness evaluation

Experiment	Average recognition accuracy (%)		
	L-1	L-2	L
Activity	89.8	91.1	92.5
Identification	90.5	90.3	91.8



(a) Activity



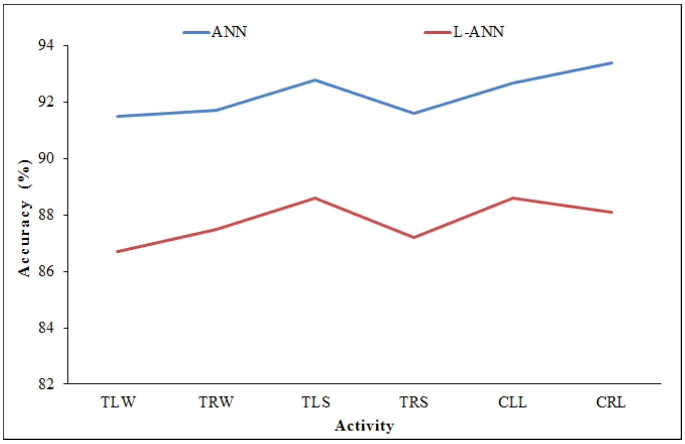
(b) Identification

Fig. 7. Accuracy test of KNN with LOPO-CV scheme

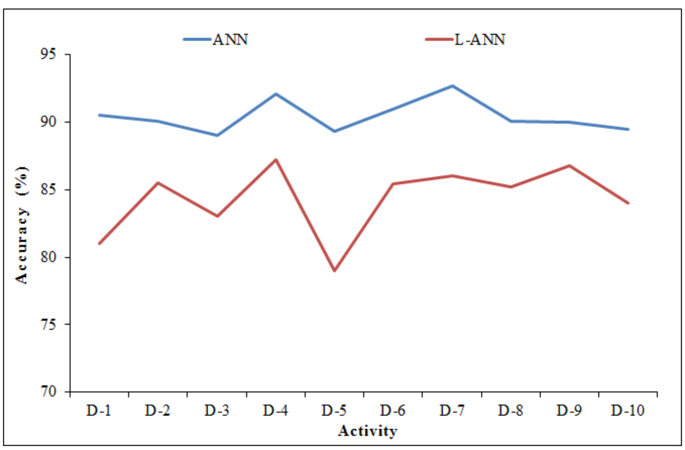
We have also evaluated the robustness of presented framework using variant layouts of transmitter i.e. the router and receiver i.e. the laptop. The layout 'L' as described in Fig. 10a is our actual layout. Two other layouts are 'L-1' and 'L-2' which are described in Fig. 10b and Fig. 10c respectively. From the results shown in Table 8, we can observe that our propose scheme is independent of in-vehicle layouts.

7. Results Analysis and Discussion

From the obtained results, it is clear that all activities and identifications are performed with very good recognition accuracy; however, there are some limiting factors which may degrade the system efficiency. In this context, the obtained CSI data may be influenced by other people and vehicles on the road [48], which is not considered in this study. Moreover, the proposed framework is based on considering a single person inside the vehicle, however, in practical life scenario; there may be more than one person present inside the vehicle. Furthermore, the personalized driving habits may influence the system performance and are needed to be focused in future study. In this presented framework work, we have not considered the congestion at access point [57, 58], which may affect the execution time.



(a) Activity

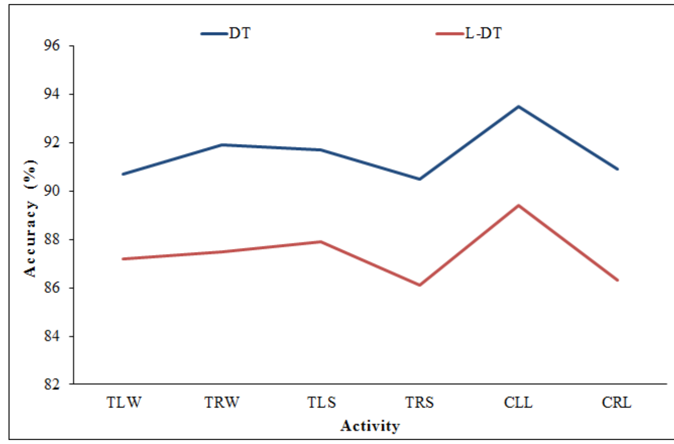


(b) Identification

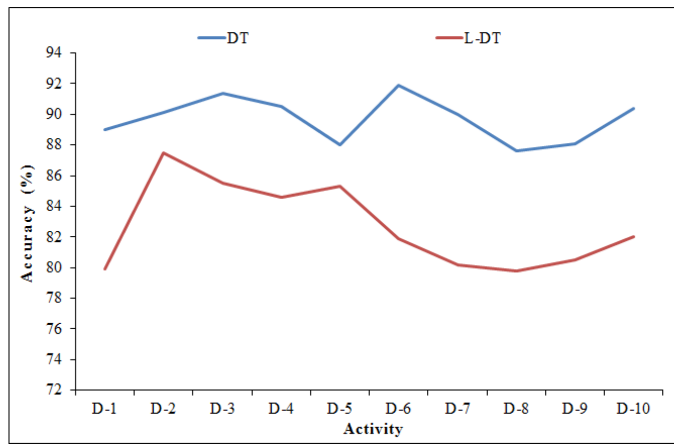
Fig. 8. Accuracy test of ANN with LOPO-CV scheme

In this research, we have considered regular stop conditions only including stop signs, pedestrians, and red traffic lights. We have not focused on the random stop conditions caused by road accidents or traffic situation, which actually have small probability to occur in practical driving scenarios. In future, we are going to explore this model with more complex road scenarios and driving conditions.

Although, the presented WiFi-based device-free system has some limitations but this framework is more scalable and easy to deploy. It is a generalized solution and can be utilized to solve any WiFi-based device- free activity recognition problem. We have tested this system with state-of-the-art classification methods e.g. SVM, KNN, ANN, and DT. It is clear that all the presented classification algorithms have very good results for both activity recognition and driver identification. In future, the proposed framework may be tested with more sophisticated deep learning techniques to improve the recognition performance.

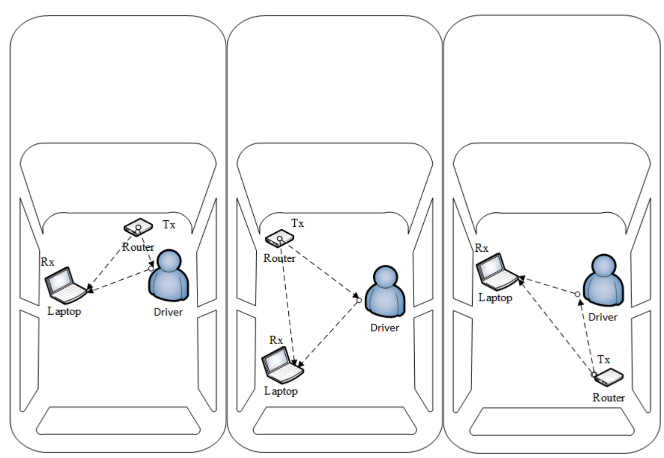


(a) Activity



(b) Identification

Fig. 9. Accuracy test of DT with LOPO-CV scheme



(a) In-vehicle layout L (b) In-vehicle layout L-1 (c) In-vehicle layout L-2

Fig. 10. Varying layouts

8. Conclusion

In this novel study, we have presented a device-free in- vehicle driver identification system exploiting CSI of WiFi signal. The proposed scheme utilizes peak/valley detection algorithm to segment steering wheel turning data and one-class SVM algorithm is used for identification. From the obtained results, we can conclude that the proposed system has enough accuracy for in-vehicle driver identification. This device-free WiFi based recognition system opens a new window for researchers and scientists to utilize in diverse scale of applications. Based on the experimental results, we aim to implement this device-free system in future for more complex scenarios with advanced deep learning techniques. As the future step, we intend to analyze the passengers' behavior on received signals to get more precise identification.

Conflict of Interest Statement

The authors declare that there is no conflict of interest in the study.

CRediT Author Statement

Zain Ul Abiden Akhtar: Conceptualization, Methodology, Supervision, Writing-original draft, Formal analysis.
Hafiz Faiz Rasool: Data curation, Conceptualization, Validation, Writing - review & editing.

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