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WiFind: Driver Fatigue Detection with Fine-Grained Wi-Fi Signal Features

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ABSTRACT: Driver fatigue is a leading factor in road accidents that can cause severe accidents. Existing fatigue detection works focus on vision and electroencephalography(EEG) based means of detection. However, vision-based approaches suffer from view-blocking or vision distortion problems and EEG-based systems are intrusive, and the drivers have to use/wear the devices with inconvenience or additional costs. In our work, we propose a novel Wi-Fi signals based fatigue detection approach, called WiFind to overcome the drawbacks as associated with the current works. WiFind is simple and (wearable) device-free. It can detect the fatigue symptoms in the vehicle without relying on any visual image or video. By applying self-adaptive method, it can recognize the body features of drivers in multiple modes. It applies Hilbert-Huang transform(HHT) based pattern extract method results in accuracy increase in motion detection mode. WiFind can be easily deployed in a commodity Wi-Fi infrastructure, and we have evaluated its performance in real driving environments. The experimental results have shown that WiFind can achieve the recognition accuracy of 89.6% in a single driver scenario.

KEYWORDS: Driver fatigue detection; Channel State Information; Wireless signal processing.

I. INTRODUCTION

ACCORDING to World Health Organization, over 3400 people die every day, and tens of millions of people are injured or disabled in road traffic crashes every year[1].Among the crashes, driver fatigue had been the first-class killer reason,especially for many truck drivers, who used to drive day and night to transform goods on time.According to the report of the Insurance Institute for Highway Safety, truckers who drive more than twelve hours were 86% more likely to be involved in a crash than those who drive less than eight hours. Even worse, truckers continuously driving more than five hours face twice risk than peers who drive one to five hours [2]. Traffic safety is the primary goal for both the drivers, pedestrians as well as the goods owners. To protect the safety of all the parties, an accurate monitor system, which can adaptively detect the driver fatigue in a device-free way, is in a pressing need.

Driver fatigue detection approaches have been studied for many years.There are two primary kind methods:driver-performance based method and driving behavior based method. Driver-performance based methods are the primary orientation of studies, and it can be divided into two main categories: vision-based detection and EEG-based detection. Vision-based detection is sensitive to drivers surface features, relating to the eye and eyelid movements[3].When the drivers wear a pair of sunglasses or drivers’ driving postures are variable, the system cannot detect the eyes. For drivers, it is costly to install these systems with corresponding equipment, such as camera monitoring system. In EEG-based detection, users are required to wear specialized equipment, such as a hat [4], to monitor EEG during the whole period of driving. Nevertheless, the invasive device inherently brings the uncomfortable driving feeling, which may further deteriorate driver fatigue. Besides, install the systems are also costly.

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In the foreseeable future, we consider Wi-Fi is the standard configuration for a vehicle. Leveraging the Wi-Fi signals without any specialized equipment has the advantage than those who work with various sensors in driver fatigue detection. In fact, Radio Frequency(RF)-based sensor research is hot for a long time. From visible light to RF signal, the researchers put a lot of efforts both in location and motion sensing. Especially, with the advantages of non-intrusion and device-free, Wi-Fi signals contribute to human activities recognition by the received signal strength(RSS)- based method [5] and the Channel State Information(CSI)- based method [6]. It had been proved that the RSS-based method is less sensitive than the CSI-based method which is fine-grained with plenty of sub-carriers [7]. Although a series of CSI based sense systems have been proposed, we cannot directly apply the previous work to driver fatigue detection due to lacking of easy and direct detecting methods to this prominent problem.

In our work, we study the driver fatigue features and the impact of driver fatigue body features on Wi-Fi signal, and verify the feasibility of detecting the fatigue by its effects on Wi-Fi signals. We leverage the commercial off-the-shelf(COTS) Wi-Fi infrastructures to detect driver fatigue with WiFind. The design of WiFind is realized through detecting the features of driver fatigue, including that of facial features and body movement features. We will identify thetypical/unique features via the CSI-based method.

There are two main challenges in driver fatigue detection using Wi-Fi signals. The first challenge is that how to detect driver fatigue wirelessly while fatigue is a subjective psychological feeling. We carefully select the corresponding features in driver fatigue scene. Based on the preliminary finding, We design and implement a self-adaptive method to turn WiFind into the corresponding mode to detect the fatigue features with targeted processing.
Another challenge is how to extract information in an efficient and targeted way. Raw CSI information includes lots of environment noisy, especially in the in-vehicle environment which is much narrower than an indoor environment.In the motion detection mode, based on our experiments in the real driving scenario, we found that the pre-processing phase has more impact on the final fatigue recognition than the indoor environment. We have com- pared the behave of the pre-processing methods, and decide to apply the Hilbert-Huang transform(HHT) [8] to increase the accuracy of WiFind. When there are no motions can be detected, we use breath detection mode to keep track driver performance. In the breath mode, we use Hampel-filter and smooth method on the top five sensitive sub-carriers to filter environment noise.

In this work, our contributions are:
We analyze the features of driver fatigue and its impact on wireless signals. We examine the chal- lenges of driver fatigue detection in the real driving environment, and carefully design the recognition features based on the preliminary findings.

- We take the first attempt to present a device-free fatigue detection system, WiFind. We design WiFind to prejudge the state of drivers by the Coefficient of Variation(CV) of Wi-Fi signals to detect the corre- sponding features depending on different strategy. We divide the fatigue detection process into two modes, breath mode and motion mode. Especially, in motion mode, we design the HHT-based pattern extract method to minimize the influence of environment.

- We implement WiFindwith commercial hardware in real driving environments. The results show that WiFind can detect the driver fatigue with the total accuracy of 89.6%, along with an false positive rate(FPR) less than 10% in a single driver scenario. In the mutil-passenger scenario, WiFind can detect the driver fatigue with the total accuracy of 73.9%. We also evaluate WiFind in different scenarios, the results show the WiFind is robust.

The remainder of this paper is organized as follows. In Section 2, we introduce the background of this work. In Section 3, we introduce the research motivation by exploring the correlation between driver fatigue and CSI. We present the detailed design in Section 4, which is followed by Evaluation, Discussion and Related work in Section 5,6 and 7, respectively. Finally, we give the conclusion and future work in Section 8.

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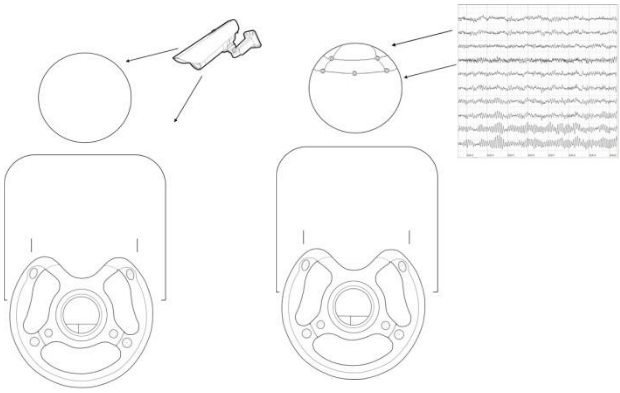

(a) Vision-based methods (b) EEG-based methods

Fig. 1: Existing methods

II. RELATED WORK

In this section, we review three domains of prior works that are tightly related to WiFind.

Vision-based methods. The vision-based fatigue detection methods have a long history. On the one hand, with the surveillance camera , researchers locate the face by using the features of skin colors [9], then detect the symptoms related to fatigue, such as the percentage of eye closure, eyelid distance changes with respect to the normal eyelid distance and eye closure rate in the method based on driver's state [10]. On the other hand, based on the driver's performance, researchers detect the head statement by the vision-based method in which recognize the hair and head relation position to detect the nod or yawn phenomenon [19]. With the development of portable devices, smart glasses [21] and smartphones [22] also are used to do the fatigue monitoring.

EEG-based methods. Researchers are devoted to finding an effective indicator or developing accurate algorithms for EEG-based methods. From the statistical methods on all EEG bands [23], the mathematics combination of different bands [4], to focus on the index of one band, such as the alpha spindle [24]or Frobenius distance between 6 brain region of alpha band [25], most of the effect is put on the indicator selection of the EEG signals in recent years. Other researchers focus on the classification algorithm of EEG, such as the improved Support VectorMachine(SVM) [26] and independent component classification [27].

Wireless signals. Researchers establish a series of motion [28] and gestures detection systems [29] [7] results in quite accurate detection. Pioneers release the modified wireless driver firmware to measure CSI based on the IEEE 802.11 standard in [6]. With the help of USRP software radios, WiSee was proposed for indoor gesture recognition [29]. WiHear is designed to focus the lip motion to identify the words they say [30]. To further explore human activity recognition, researchers in [31] recognizes human activity in the modeling and matching ways. Wifall uses the commercial Wi-Fi to detect the human fall [28]. WiKey gets the keystroke recognition by identifying the CSI pattern [32]. Smokey leverage rhythmical patterns of smoking impact the Wi-Fi signals to detect smoking [33]. In human respiration detection field, some researchers explore the Radio frequency method to recognize user breath rate [34] [35] [36]. The other researchers explore the propagation rule of Wi-Fi to understand and evaluate the human respiration detection in [15] [17].

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III. BACKGROUND

In this section, we introduce the scenario, the overview of the driver fatigue researches and the foundation of channel state information.

2.1 Scenario

During the corresponding transport high period, it is a typical situation that driver have to continuous working. We consider a scenario where a truck driver who is lack of sleep due to insomnia or carrying on night-shifting duty frequently. The driver driving along the highway for many hours, and feel drowsy with boring driving. Then the driver begins to feel heavy in the head, and get tired over the whole body. He or she give some yawns, then feels strained in the eyes. After several minutes, with the breath rate down he enters light sleep and intermittently nods. Finally, he or she unconsciously falls asleep on the steering wheel. Without alert in time, the truck is just like a monster running on the road ready creates dangerous for other cars and itself. We consider the Internet of Vehicles(IOV) case in which a Wi-Fi hotspot can be set up in the car for communication and collaborative driving. Once the driver enters the cab, his mobile phone can connect to the in-vehicle Wi-Fi. With the help of our wireless sensing method, the driver's performance will be monitored during driving while the router continuous sends and receive the CSI and analyze them. Warning message will be sent to the driver's phone when the driver is detected with fatigue phenomena. In our work, we will show our approach will efficiently alert the driver fatigue.

2.2 Existing Methods

As shown in Fig.1, existing work in driver fatigue detection with driver performance can be divided into vision-based methods and EEG-based methods based on the signal they use.
Vision-based methods deploy one video capture device close to the driver, which could be a camera. The camera will focus on the drivers' status and performance. When the driver begins to drive the car, the camera can monitor the driver' s special features by checking the image of every frame and obtain suspected driver fatigue raw data.

Another form of useful awareness to routing in networking is the historical awareness. If the encountered node A had met many nodes in the previous t time, whereas node B only encountered few nodes in the past t time, this suggests that the node carrier of undelivered messages is supposed to pass its copies to node A. This is justified based on A is most likely to meet the destination node once A continue its behavior of meeting and traveling between nodes. Figure 2 present the historical awareness concept in ICN routing. It indicates that messages are forwarded to nodes that encountered a high number of nodes in the past.

Fig. 2: Driver fatigue detection with CSI of Wi-Fi

With the help of image algorithm, the vision-based system recognizes the real driver fatigue fragments. In the most of case, the vision-based methods focus on only one kind of fatigue features. So they may fail in a specific case.

EEG-based methods monitor the electrical activity of the brain and focus on the 1 20 Hz band which corresponding to human's activities. This method deploys an EEG acquisition instrument on the driver' s head. The acquisition instrument was continuously collecting EEG signals for driver fatigue recognition. Compared with the vision-based methods, EEG-based methods directly try to explore the relationship between the human mind and EEG signals. But they are coarse-grained somehow because the signal they collect come from multi-zone of the brain. Signal analysis methods are widely used in EEG-based detection. In our opinion, the data collection process for EEG-based methods could be not comfortable for practical use. Besides EEG- based methods and vision-based methods are costly due to requirement of special equipments or devices.

Our work only uses simple Wi-Fi access points to collect the CSI signals when monitoring driver performance and detecting driver phenomena. As shown in Fig.2, this method collects continuous CSI data in a non-invasive way and provide effective and cheap way to detect driver fatigue.

2.1WirelessCommunication

Wireless technology now is developing rapidly. Currently the modern commonly used high rate wireless communication technologies are the Multiple Input Multiple Out- put(MIMO) technology and the Orthogonal Frequency Di- vision Multiplexing(OFDM) technology, and we briefly introduce thembelow.

MIMO is an emerging technology that is attracting wide attentions. It use multiple antennas and some coding technologies at the transmitter and the receiver. There are three main categories of coding technologies: precoding, spatial multiplexing and diversity coding. In a MIMO system, the transmitter and the receiver sends and receives multiple streams by multiple antennas. For each party, the signal Y received can be described as:

$$Y = HX + n$$

where H is the channel matrix, and X and n are the original signal and noise, respectively. In the most of case,H is equivalent to CSI. Every element hij In H include an group of OFDM channel information.

The main idea behind the OFDM is to split the data stream to be transmitted into N streams of reduced data rate and to transmit each of them on a separate sub-carrier. OFDM is similar to FDMA in that the multiple user access is achieved by subdividing the available bandwidth into multiple channels, which are then allocated to users. However, OFDM uses the spectrum much more efficiently by spacing the channels much closer together. This is achieved by making all the carriers orthogonal to one another, preventing interference between the closely spaced carriers. Therefore, spectral overlapping among sub-carriers is allowed, since the orthogonality will ensure that the receiver can separate the OFDM sub-carriers, and better spectral efficiency can be achieved than by using simple frequency division multiplex. In OFDM, each channel has a large number of orthogonal sub-carrier signals which maintain data rate equal to a single-carrier modulation scheme bandwidth. Compared to the single-carrier modulation scheme, OFDM has the advantage of robust when facing severe environmental condition. The communication link properties, such as scattering, fad- ing, and power decay with distance will affect PHY layer information CSI.

2.4 CSI

In wireless communications, channel state information (CSI) refers to known channel properties of a communication link. This information describes how a signal propagates from the transmitter to the receiver and represents the combined effect of, for example, scattering, fading, and power decay with distance. The CSI makes it possible to adapt trans- missions to current channel conditions, which is crucial for achieving reliable communication with high data rates in multi-antenna systems.

CSI needs to be estimated at the receiver and usually quantized and fed back to the transmitter (although reverse-link estimation is possible in TDD systems). Therefore, the transmitter and receiver can have different CSI. The CSI at the transmitter and the CSI at the receiver are sometimes referred to as CSIT and CSIR, respectively.

The CSI report field is used by the CSI frame to carry explicit channel state information to a transmit beamformer. The report field for 20MHz has 56 CSI matrices for cor- responding sub-carriers. Each matrix includes N r * N t CSI streams, where N r and N t are the number of receive antenna and the number of transmit antenna. Each stream from a pair of receive antenna and transmit antenna include a group of OFDM channel state information elements.And each element in one stream includes the real part and the imaginary part. The time array of these elements are called sub-carriers which correspond to channels.

Since the received signal reflects the constructive and destructive interference of several multi-path signals scattered from the wall and surrounding objects, the movements of the driver while driving can generate a unique pattern in the time-series of CSI values, which can be used for driver fatigue recognition.

Researchers release the CSI tool for IEEE 802.11n measurement and experimentation platform. The CSI Tool is

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built on the Intel Wi-Fi Wireless Link 5300 802.11n MIMO radios, using a custom modified firmware and open source Linux wireless drivers. The IWL5300 provides 802.11n channel state information in a format that reports the channel matrices for 30 sub-carrier groups, which is about one group for every 2 sub-carriers at 20 MHz or one in 4 at 40 MHz. Each channel matrix entry is a complex number, with signed 8-bit resolution each for the real and imaginary parts. It specifies the gain and phase of the signal path between a single transmit-receive antennapair.

III.MOTIVATION

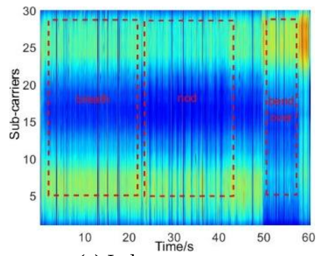
In this section, we illustrate the rationale behind CSI based driver fatigue signals using real-world experiment.

Before we experiment in driving scene, the first challenge is how to define driver fatigue exactly in a detectable way and how to measure it. Despite the huge progress of science in physiology and psychology, there is still no precise defini- tion of fatigue. According to the medical observation, there is a relationship between fatigue and symptoms including body motions, temperature, skin electrical resistance, eye movement, breathing rate, heart rate, and brain activity. In some previous work [9] [10], researchers choose one or two symptoms to express fatigue activity because of the limitation of methods. In the same way, instead of defining fatigue, we choose some fatigue features to represent fatigue itself.

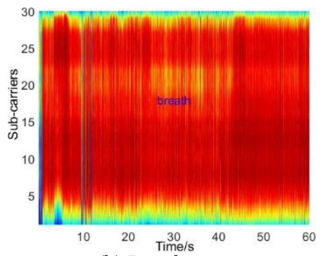
In the earlier fatigue studies, researchers try to find the relation between the fatigue and subjective symptoms by questionnaire survey [11]. They listed three groups symp- toms which represent three fatigue factors: drowsiness and dullness, the difficulty of concentration and projection of physical impairment. The results show that the drowsiness and dullness factors have the highest frequencies than the other two factors. For both physical workers and mental workers, the drowsiness and dullness factors are the obvi- ous symptoms during all day. The drowsiness and dullness factors include feel heavy in the head, get tired over the whole body, give a yawn, feel the brain hot or muddled, become drowsy, feel strained in the eyes, become rigid or clumsy in motion, feel unsteady in standing and want to lie down.

We reference the drowsiness and dullness factors and the typical driving scene which a truck driver drives alone along the highway in a night. In this scene, due to the lack of sleep and the boring driving, he feels sleepy and begins yawn. After several minutes, with the breath rate down he enters into light sleep and nod. Then he even asleep on the wheel. Therefore, how to effectively monitor and prevent driver fatigue has the extremely vital significance to reduce traffic accidents. Besides, with the help of vehicular communications [12] and fog computing to support mobility [13], it is possible to conduct such driver fatigue detection system inside the car. We try to use above typical features to represent driver fatigue and choose the following human body features:

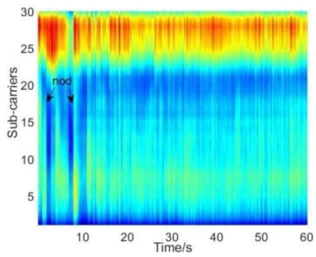
Yawn. The meaning of yawn is not clear yet since lots of physiologists try to give different paraphrase vision. Yawning associated with a series of emotion state, and most often occurs during a fatiguing time. It consists of deep



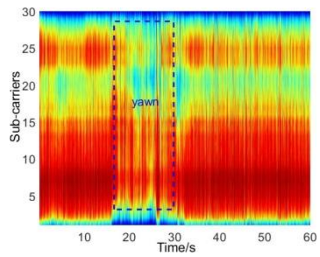
(a) Indoor test



(b) Breath



(c)Nod



(d)Yawn

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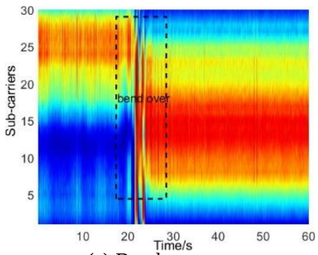
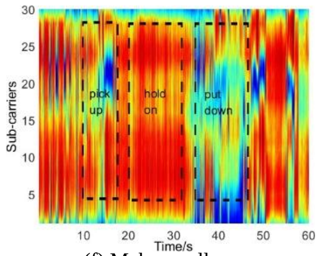


(e) Bend over



(f) Make a call

Fig. 3: The way driver fatigue affects CSI

breathing, stretching of the upper body, opening mouth and covering mouth with hands.Decrease of breath rate. Driver spirit state change to fa- tigue from awake couples with the decrease of breath rate at the start phase. Adults respiration usually has the frequency of 12-18 breath per minute [14]. When we breathe, our chest will have a expand and shrink because of inhalation and exhalation.

Nod. Unconsciousness nod which is one of the most dangerous motion for drivers often occurs light sleep phase. During nod, our head slowly down and sharp rise.
Sleep on the steering wheel. In some more worse cases, even the drivers bend over on the steering wheel. Note this is not the usual case in fatigue detection.

These features which represent driver fatigue all are time-phase activities, and the typical case has the common features and the possibility to be detected. Meanwhile, there are many confused drivers' motions which will also affect the CSI in the vehicle. We choose some of them: make a call, turn head, turn the steering wheel, start the car, and stop the car. We do not take these confused motions as fatigue motions. Because when the driver can make a call or turn the steering wheel, he is not fatigued.

We explore the driver fatigue impact on CSI in two cases. In the first case, the laptop is 5 meters from the router, and it sends ICMP packet every 300 milliseconds to router indoor. Then a person does above driver fatigue features on a chair and confused motions such as turn head, turnthe wheel and make a phone call between the transmitter and receiver, about 2 meters away from the receiver. In the second case, we deploy devices on the front of a car. Then the driver behaves the same motions about 0.5 meters from the receiver while driving. From the laptop, we obtain the raw CSI data based on Orthogonal Frequency Division Multiplexing(OFDM) system in each process windows. Re- garding communication theory, the capacity of a Multiple Input Multiple Output(MIMO) channels is min(m,n) times of a corresponding channel with a single antenna, where m and n are the numbers of antennas of receiver and transmitter. To get more information about CSI, we use MIMO technology for multiplying the capacity of a radio link using two antennas for transmitting and two antennas for receiving to form a 2 2 MIMO system to detect driving fatigue. As a result, the raw CSI data can be divided into 4 streams and has 30 sub-carriers in each stream. Then there are 120 groups of CSI data from each packet.

In Fig. 3, we plot the CSI sequences of one stream obtained during the two cases. The results present CSI varies over the time. The results show that the driver motions dur- ing driving are the major factors that cause the fluctuation of CSI waveform and shed light on detecting fatigue activities. Fig. 3(f) presents how one of the confused activities affect CSI. We can find that the CSI sequences show different cycle when performing confusing activities. The change of CSI already can be recognized while the noisy signals are also strong. Besides in the data streams from a different group of transmit antenna and receive antenna, the CSI sequences presented the similar characteristic.

Above figure shows that the features we choose indeed can be recognized with CSI. Besides, the variation of CSI have some characteristics which need to be extracted with new method.

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IV.SYSTEM DESIGN

Fig. 4 presents the architecture of WiFind. First of all, the CSI is sampled in the same interval. In each interval, the self-adaptive mode will select the process mode, the motion detection mode or the breath detection mode. In the motion detection mode, we carefully extract the signal patterns with Hilbert-Huang transform and recognize driver fatigue with SVM method. When there are no driver's motions, we turn to breath detection mode. In the breath detection mode, we firstly filter and smooth the signals, then use the peak recognition method to get the drivers' breath rate for fatigue recognition.

Next, we elaborate the designs of WiFind relied on key function, such as data collection, self-adaptive mode, data pre-processing, pattern extraction, features extraction and recognition.

4.1 Data Collection and Self-adaptive Mode

We collect CSI data during the driver driving on the real road by the receiver use the Internet Control Message Protocol(ICMP) get the transmitter's responses. And we find that different features impact CSI in different ways, but presented correlation with others. We find the characteristic of CSI as follow:

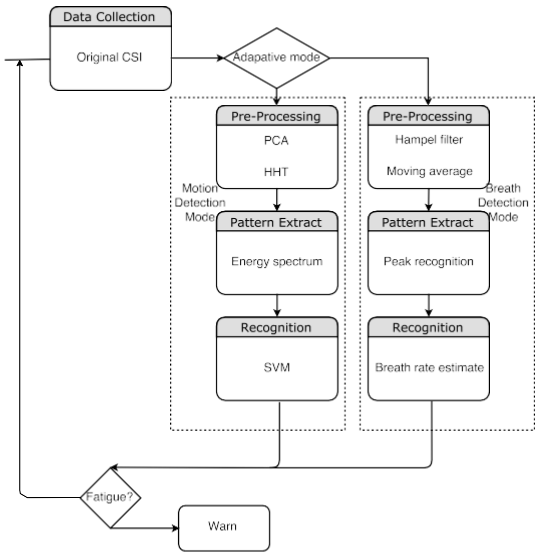

Fig. 4: Architecture of WiFind

Sub-carrier sensitivity. In Fig. 3(a)-3(e) we plot the typical process of a human breath, nod, yawn and bend over indoor and in a vehicle, respectively. We can find the CSI sequences of a person on a chair or in a car presents strong correlation with human body features. These sub-carriers have different sensitivity. On one hand, 15-20 sub-carriers have less SNR in most of the case. On the another hand, for breath, nod, yawn all sub-carriers vary in a similar way which turns down while the motions happen. But bend over motion impact sub-carriers in another way that 5-20 sub-carriers SNR rise whereas others turns down. Besides, the impact of yawn and nod on CSI cause more fluctuations. The reason behind these is that different frequency motions have the main impact channel region. The sub-carriers which mean the different channel state inherently have a unique law.

Sub-carrier correlation. The movements of head and hands result in correlated changes in the CSI sequences, and the sub-carriers that are closely spaced in frequency show similar variations whereas some sub-carriers that farther away in frequency show opposite changes. Despite the diversity of change, a strong correlation still exists, such as the 5-15 sub-carriers and the sub-carriers around 25 in Fig. 3(d).

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The characters of noise. From the raw CSI sequences, we can find the high-frequency noise full of the data stream, especially in the car scenario in Fig. 3(b)-3(f). For different features, the impact of noise has an evident difference. The impact on the sequence of breath is larger than other motions because the displacement of the chest is not of the same magnitude with others.

Uncertainty. Actually, from Fig. 3(a)-3(f) we can notice the total CSI is entirely different with these signal come from different experiment and separate stream. We find even in the same car same driver behave same motion may result in a different variation of CSI. This characteristic keeps us from signal match methods, such as dynamic timewrapping(DWT), and turn us to the training methods.

According to the above findings, we find sub-carriers have different features in each case. Hence, how to de- noise, extract and leverage rich information for fatigue detection, from time-varying and regular CSI, needs detailed designs. We divide the system into two modes: motion detection mode and breath detection mode and use the basic and key function of WiFind, self-adaptive mode, to choose the corresponding mode. We will first judge whether the environment is relative 'stationary' which means there are no distinct human activities. This section relies on the observation of the top five sensitive subcarriers judgment. Here sensitive are defined by the coefficient of variation(CV) which can balance the difference caused by the environment. If CV value is less than the threshold value,WiFind will go to breath detection mode. Oppositely, it will go to the motion detection mode to detect corresponding motions. We set the process windows length to 20 seconds which longer than general human activities.
(a)Motion mode date pre-processing

$$\sigma cv = S/M \qquad (1)$$

S means standard deviation(STD), and M means the mean value(MEAN).
M = Mm σcv> σ
Mb σcv< σ
Where Mm and Mb are the motion detection mode and breath detection mode, respectively.

4.2Data Pre-Processing

For the motion detection mode, WiFind leverages sub- carriers correlation and calculates the principal components from all CSI time series by Principal Component Analysis(PCA). It then chooses the first principal components that represent the most common variations among all CSI time series. Notice sub-carriers in each TX-RX stream carry part of the information from motions impact, we will not devise a newsubcarriers select method. But the computational complexity of the method using all sub-carrier directly is unfriendly for further processing. PCA here reduces the dimensionality of the CSI information and removes noise by taking advantage of correlated variations of different sub-carriers.

Unlike in the indoor scene in the series of previous works, the motion detection environment is a narrow and noisy set. The methods based on the signal wave are invalid. We turn to the inherent characteristic and find that the key characteristic of the signal affected by the driver is the variation of the instantaneous frequency. There are two problems when we extract instantaneous frequency. Firstly, in the traditional Fourier's analysis method, the frequency is defined in idealized infinite time sequence with constant sine or cosine waves. For the non-stationary time series, researchers developed the analysis methods with window-based methods, for instance, the Short-Time Fourier Transform(STFT) and Wavelet transform(WT). STFT method assumptions the signals are segment-wise stationary and neglects the instantaneous frequency of signals beyond or less than the window scale. WT methods have multi-resolution choose

(a) Motion mode datepre-processing
(b) Motion mode datepre-processing

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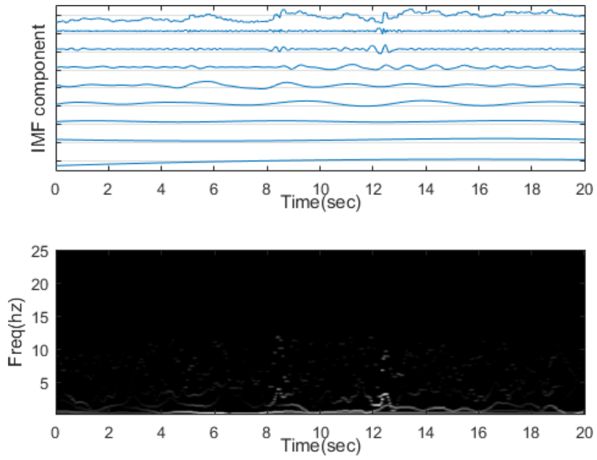
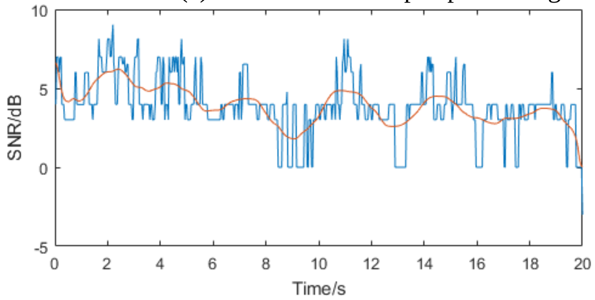


(a)Motion mode datepre-processing



(b) Breath mode date pre-processing

Fig. 5: Date pre-processing

wavelet basis. But how to choose the wavelet basis relies on the researcher's experiences. The wavelet function has to be given before the analysis. These methods are all affected by uncertainty principle between time and frequency. Secondly, how to extract the instantaneous frequency uniquely needs detailed discussions.

In our work, we choose Empirical Mode Decomposition(EMD) and the Hilbert spectrum, which has been called HHT [8] together, to solve above problems.It had been applied in a series of signal process area, such as the earthquake detection, sound analysis. EMD method decom- poses the non-stationary time series into several component functions, which are symmetric concerning the local zero mean, and have the same numbers of zero crossings and extremum. Researchers named the oscillation mode imbedded in the data as Intrinsic Mode Function(IMF). We use the Algorithm 1 to self-adaptively decomposes signals into IMFs based on the signal inherent character rather than a predefined primary function like other previous methods did.

The IMFs have the certain physical meaning of the high- low frequency. The outliers of these components include the part that affected by the drivers' motions. The reason that we don't directly use the outliers of IMFs is that we find the data still have high-frequency noise which affects all the sub-carriers come from the change after we get the principal components of CSI. Besides, the most of the outliers are

Algorithm 1 Calculate the IMF of signals

Input: CSI time series after PCA: s(t) = s(1), . . . , s(K)
Output: IMF series: IMF= imf (1), . . . ,imf (N)
1: while s(t) is nonmonotonic function do
2:   x(t) = s(t)

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3: loop
4: Find the local maximum values series of s: smax = smax(1), . . . , smax(M)
5: Find the local minimum values series of s: smin = smin(1), . . . , smin(N)
6: Find the zero crossing point series of s: s0 = s0(1), . . . , s0(O)
7: Use cubic spline function f (t) to fit smax 8: Use cubic spline function g(t) to fit smin 9: d(t) = [f (t) + g(t)] /2
10: if M + N O 1 and d(t) == 0 then
11: Break
12: end if
13: s(t) = s(t) d(t)
14: end loop
15: imf (i) = s(t)
16: s(t) = x(t) s(t)
17: end while

the environment noise. If we set the threshold higher, we will neglect some motions such as the nod. Otherwise, we will confuse these motions with noise.

V. CONCLUSION

We present WiFind, a device-free passive fatigue detection system that leverages the CSI variation information of Wi- Fi signals to detect the fatigue activity. We design a self- adaptive method to detect the breath and motions driver fatigue. We also elaborately leverage the common featuresto recognize the series of motions during fatigue. We prototype WiFind on commodity Wi-Fi devices and evaluate it in real driving environments. Experimental results showWiFind can achieve a recognition accuracy of 89.6% in a single driverscenario.

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