WIFIND:DRIVER FATIGUE DETECTION WITH FINE-GRAINED WI-FI SIGNAL FEATURES

Seminar Report

Submitted in partial fulfillment of the requirements for the award of degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

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Submitted By

MEGHA SONY

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CERTIFICATE

This is to certify that the report entitled **WiFind: Driver Fatigue Detection with Fine-Grained Wi-Fi Signal Features** *submitted by* **Ms. MEGHA SONY**, *Reg.No.***MAC15CS037** *towards partial fulfillment of the requirement for the award of Degree of Bachelor of Technology in Computer science and Engineering from APJ Abdul Kalam Technological University for December 2018 is a bonafide record of the seminar carried out by him under our supervision and guidance.*

....	....	....
Prof. Joby George	**Prof. Neethu Subash**	**Dr. Surekha Mariam Varghese**
Faculty Guide	***Faculty Guide***	***Head Of Department***

Date: Dept. Seal

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ABSTRACT

Driver fatigue is a leading factor in road accidents that can cause severe fatalities. Existing fatigue detection works focus on vision and electroencephalography (EEG) based means of detection. However, vision-based approaches suffer from view-blocking and in EEG-based systems the drivers have to use or wear the devices with inconvenience or additional costs. The proposed method is Wi-Fi signals based fatigue detection approach, called WiFind to overcome the drawbacks as associated with the current works. WiFind is simple and device-free. By applying self-adaptive method, it can recognize the body features of drivers in multiple modes. It applies Hilbert-Huang Transform (HHT) based pattern extraction method which results in accuracy increase in motion detection mode. WiFind can be easily deployed in a commodity Wi-Fi infrastructure, and its performance in real driving environments has been evaluated. The experimental results have shown that WiFind can achieve the recognition accuracy of 89.6% in a single driver scenario.

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LIST OF ABBREVIATION

CSI	Channel State Information
HHT	Hilbert Huang Transform
SVM	Support Vector Machine
PCA	Principal Component Analysis
EMD	Empirical Mode Decomposition

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.

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[3]. In fact, Radio Frequency(RF)-based sensor research is hot for a long time[4]. 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.

The proposed system identifies 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.It 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. The system identify the typical/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 compared 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.

Related Works

2.1 Vision-based Methods

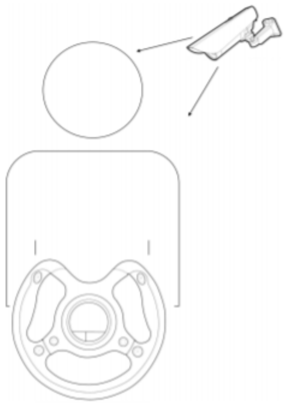

Figure 2.1: Vision-based Methods

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 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.Vision-based detection is sensitive to drivers surface features, relating to the eye and eyelid movements 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.

2.2 Electroencephalogram based Methods

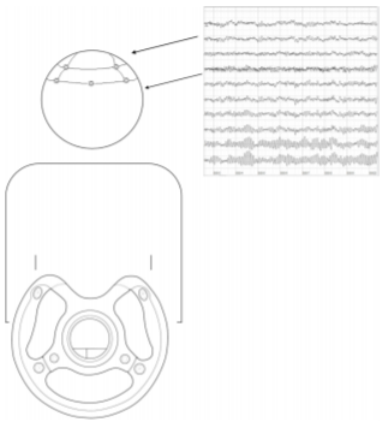

Figure 2.2: EEG-based Methods

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.[9] But they are coarse-grained somehow because the signal they collect come from multi-zone of the brain. 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.EEG-based detection, users are required to wear specialized equipment, such as a hat to monitor EEG during the whole period of driving.[10] Nevertheless, the invasive device inherently brings the uncomfortable driving feeling, which may further deteriorate driver fatigue. Installation of the systems are also costly.

Proposed System

3.1 Scenario

Figure 3.1: Driver fatigue detection with CSI of Wi-Fi

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

3.1.1 Wireless Communication

Wireless technology now is developing rapidly. Currently the modern commonly used high rate wireless communication technologies are the Multiple Input Multiple Output(MIMO) technology and the Orthogonal Frequency Division Multiplexing(OFDM) technology, and we briefly introduce them below.

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:

$$Y = HX + n \tag{Eq:3.1}$$

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. 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, fading, and power decay with distance will affect PHY layer information CSI.

3.1.2 Channel State Information

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 transmissions 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 reverselink 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 corresponding sub-carriers. Each matrix includes Nr * N t CSI streams, where Nr 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 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 antenna pair.

3.2 Fatigue 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 breathing, stretching of the upper body, opening mouth and covering mouth with hands. [2].

Decrease of breath rate- Driver spirit state change to fatigue 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. [3].

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. [3].

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. [3].

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.

From the laptop, we obtain the raw CSI data based on Orthogonal Frequency Division Multiplexing(OFDM) system in each process windows. Regarding 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.

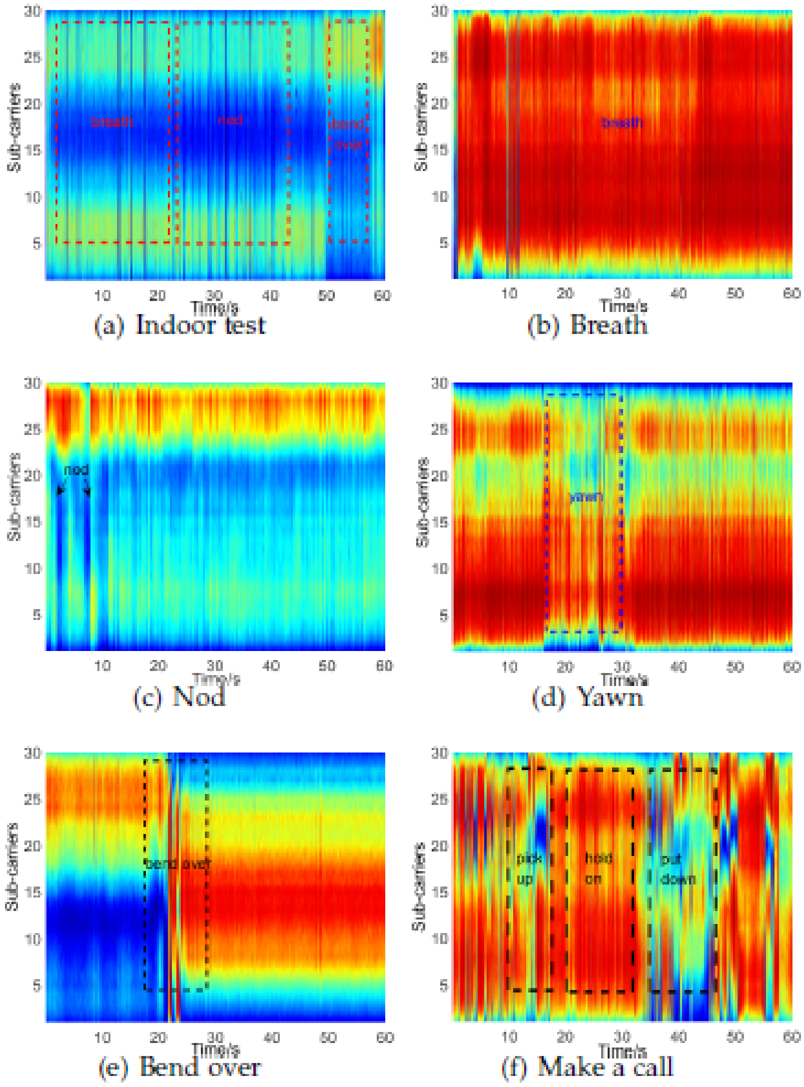

Figure 3.2: The way driver fatigue affects CSI

In Fig. 3.2, 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 during driving are the major factors that cause the fluctuation of CSI waveform and shed light on detecting fatigue activities. Fig. 3.2(f) presents how one of the confused activities affect CSI.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 that are choosen indeed can be recognized with CSI. Besides, the variation of CSI have some characteristics which need to be extracted with new method.

3.3 System Design

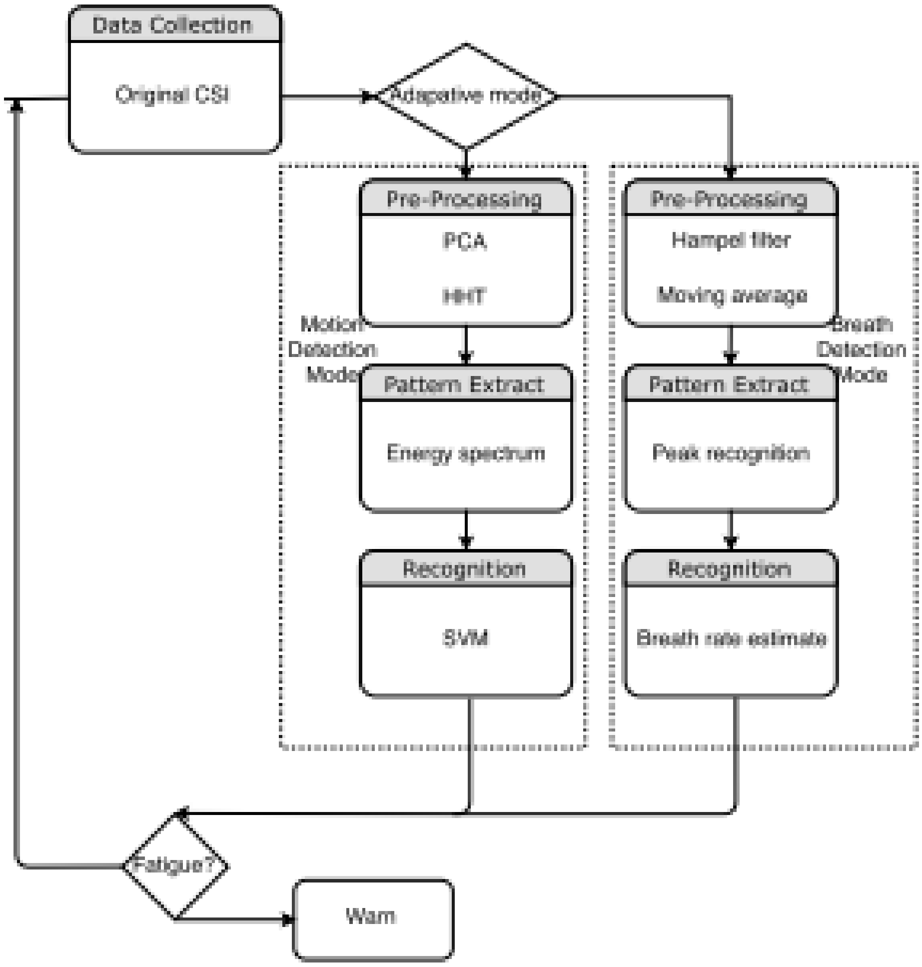

Figure 3.3: Architecture of WiFind

Figure 3.3 depicts the system design.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.

3.3.1 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:

Sub-carrier sensitivity -In Fig. 3.2(a)-3.2(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 subcarriers 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. 3.2(d)

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. 3.2(b)-3.2(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 -From Fig. 3.2(a)-3.2(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 time wrapping(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 denoise, 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 sub-carriers 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.

$$\sigma cv = \frac{S}{M} \tag{Eq:3.2}$$

S means standard deviation(STD), and M means the mean value(MEAN).

$$M = \begin{cases} M_m, & \sigma_{cv} > \sigma \\ M_b, & \sigma_{cv} < \sigma \end{cases} \tag{Eq:3.3}$$

Where Mm and Mb are the motion detection mode and breath detection mode, respectively

3.3.2 Data Pre-Processing

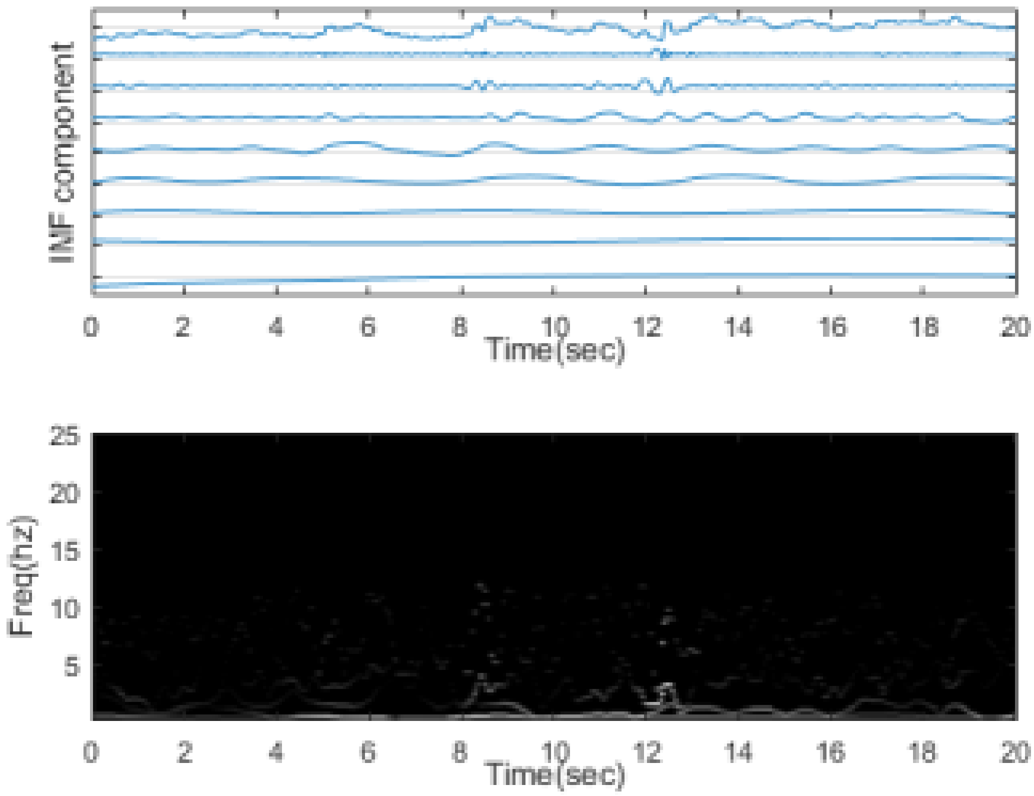

Figure 3.4: Motion mode date pre-processing

For the motion detection mode, WiFind leverages subcarriers 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 new sub-carriers 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 subcarriers.

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 wavelet basis

In this system,Empirical Mode Decomposition(EMD) and the Hilbert spectrum, which has been called HHT [8] together,is used to solve above problems.It had been applied in a series of signal process area, such as the earthquake detection, sound analysis. EMD method decomposes 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 highlow 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 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. Here we change to the total instantaneous frequency because the influence motions cause signals include noise and itself.

We apply the Hilbert transform to each IMF component and computing the instantaneous frequency. For a non-stationary time series, X(t), we can always have its Hilbert Transform,

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)

while *s(t) is non monotonic function* **do-**
    $x(t)$ =s(t)
loop
Find the local maximum values series of s:smax = smax(1), . . . , smax(M)
Find the local minimum values series of s:smin = smin(1), . . . , smin(N)
Find the zero crossing point series of s:s0 = s0(1), . . . , s0(O)
Use cubic spline function f(t) to fit smax
Use cubic spline function g(t) to fit smin
d(t) = [f(t) + g(t)] /2
Iff($M + NO$) $<$ 1 and d(t) == 0
Break
end if
s(t) = s(t) d(t)
imf(i) = s(t)
s(t) = x(t) s(t) =0
end While

X'(t) as the convolution of X(t) with frequency 1/t

$$X'(t) = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{X(T)}{t-T} dT \quad \text{(Eq:3.4)}$$

where P indicates the Cauchy principal value. With this definition, X(t) and Xˆ(t) form the complex conjugate pair, so we can have an analytic signal, Z(t), as

$$Z(t) = X(t) + iX'(t) = a(t)e^{i\Theta(t)} \quad \text{(Eq:3.5)}$$

in which

$$a(t) = [X^2(t) + (X'(t))^2]^{\frac{1}{2}}, \Theta(t) = arctan(\frac{X'(t)}{X(t)}) \quad \text{(Eq:3.6)}$$

the instantaneous frequency is defined as

$$w = \frac{d\Theta(t)}{dt} \tag{Eq:3.7}$$

express the signals processed with performing the HHT on each IMF component as

$$X'(t) = \sum_{j=1}^{n} a_j(t) e^{i \int w_j(t) dt} \tag{Eq:3.8}$$

This equation enables us to use a three-dimensional plot to represent the functions of amplitude and frequency and time. This plot is the Hilbert spectrum.Then we use the squared values of amplitude to produce Hilbert energy spectrum In the real driving scene, the breath detection is established with the assumption that the car is running on an ideal road which is long and smooth enough. The driver has no other motions during the detection intervals.This assumption corresponds to a 667m distance when the car run in 120km/h in a process windows. This is common speed for a highway transportation. We continue to use the top five variance sub-carriers because they are sensitive to the breathing activity. To detect the breath rate in breath detection mode based on the above findings, the data stream of top five sensitive sub-carriers will firstly be applied with Hampel filter to remove significant outliers compared with neighbor measurements. Notice that these outliers will not confuse the motion detection because here we defined the significant outliers as the CSI sequences whose frequency is less than 1Hz

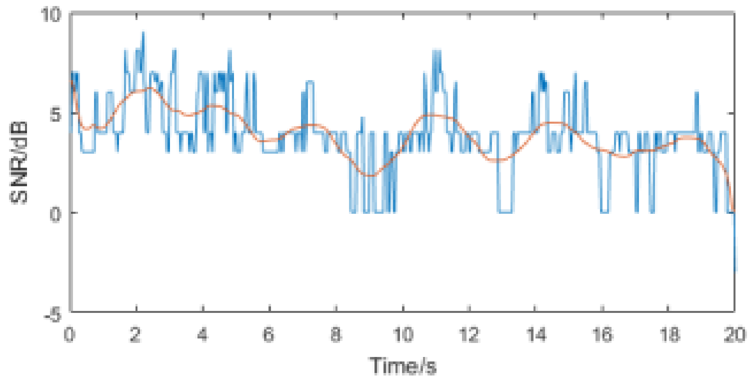

Figure 3.5: Breath mode date pre-processing

3.3.3 Pattern Extraction

After we extract the HHT-based energy spectrum. We use the threshold value based method to extract the patterns that occur in driver motions. We sum the energy in time and compare it with the threshold. If the energy is greater than the threshold, it will be regarded as the start point of the driver motion. Next point whose energy less than the threshold will be regarded as the end point. Since the threshold is related to the environment, we set it with the average energy value of static environment as usual.

For the breath mode, we calculate the peak number to identify the frequency and use the Fake Peak Removal algorithm [7] to remove the peaks which are too close to others in the breath detection mode. Here we define the peak as the data sample that is larger than its two neighboring samples as usual. Then we filter the fake peak which is larger than two neighboring samples but smaller than most other samples or is very close to neighboring peaks.

3.3.4 Features Extraction and Fatigue Recognition

For the motion detection mode, from above steps, we obtain the data series, which is caused by different motions. Now it is important for us to extract the features that can stand for different motions from the data series. Based on the characters of the driver fatigue and the car scene, we choose the following features: (1) max total frequency energy, (2) mean of total frequency energy, (3) standard deviation(STD) of total frequency energy, (4) median absolute deviation(MAD) of total frequency energy, (5) length of the patterns extract from principal component, (6) mean of the pattern, (7) STD of the pattern, (8) MAD of the pattern

In most of the cases, the data sets are not linearly separable in original space. Therefore, SVM method transforms the original space into a higher dimensional space to find a hyperplane which can discriminate the data sets by a good separation that has the largest distance to the nearest data point of any class. The SVM model can be formally described as:

$$min_{w,b}\frac{||w||^2}{2} \quad \text{(Eq:3.9)}$$

Subject to yi

$$w^T\varphi(xi) + b \geq 1, i = 1, 2, n \quad \text{(Eq:3.10)}$$

where xi is the the character of ith sample in higher dimensional space, yi is the the value of ith sample in higher dimensional space, (x) is the kernel function and (w, b) is the hyperplane with weight vector w and bias b . For linearly separable data, using Lagrange multipliers, we can attain the Lagrangian function as:

$$L(w, b, \alpha) = \frac{1}{2}||w||^2 - \sum_{i=1}^{n} \alpha_i(y_i(w^T\varphi(x_i) + b) - 1) \quad \text{(Eq:3.11)}$$

Then, we put partial derivatives nd get the Lagrangian conjugate function

$$L(w, b, \alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i\alpha_j y_i y_j \varphi(x_i)\varphi(x_j) \quad \text{(Eq:3.12)}$$

It turns to optimization problem about . Then we can obtain w,b

$$w = \sum_{i=1}^{n} \alpha_i y_i \varphi(x_i) \quad \text{(Eq:3.13)}$$

$$b = y_i - \sum_{j=1}^{n} \alpha_i y_i \varphi(x_i)\varphi(x_j) \quad \text{(Eq:3.14)}$$

We use the w, b to construct the hyperplane to separate data

$$f(x) = sign(w^T \varphi(x) + b) \qquad \text{(Eq:3.15)}$$

For performance and availability, we choose LIBSVM [16], an open source machine learning libraries to construct the classifier to recognize the motion is fatigued driving or not. This tool train a classifier for every pair of labels to extend the one class classification to multi-class classification

For the breath detection mode, we notice the breathing activity is not a stable activity which has a fixed interval during driving. During each recognition windows, instead of estimating the fixed breathing circle, we directly sum the peak number up in each sub-carriers and achieve the breathing rate by using the following equation:

$$R = \frac{kT}{\sum_{i=1}^{k} N_j} \qquad \text{(Eq:3.16)}$$

Here T is the length of recognition windows, Nj is the peak number of the jth sub-carrier, and k is the number of the sub-carriers we select. Compared with the previous result, the decrease of breath rate which exceeds threshold will be judged into fatigue

3.4 System Setup

WiFind is built with the off-the-shelf hardware, which is a ThinkPad X200s laptop computer equipped with Intel Wi-Fi Link 5300 NIC, as shown in Fig.6. The laptop runs Ubuntu 14.04 LTS with a modified Intel driver [6] to collect CSI data and is connected to a TP-LINK TL-WR842N wireless router which is used as a transmitter. WiFind serves as the receiver to request and receive the packets from the transmitter. Both devices operate in IEEE 802.11n mode at 2.4GHz. To obtain the CSI data related to the driver's motions, WiFind sends ICMP packets with the sampling rate of 10 packets/s. In single driver scenario of this evaluation, the transmitter and receiver are placed in the front of driver's and co-pilot's seats, respectively. In multi-passenger and more complex path scenario, the transmitter and receiver are placed in the front of driver's seat and in the armrest box, respective

(a) Equipment (b) Car

Figure 3.6: Minimal WiFind setting

Currently, WiFind can only work for the situation that the drivers have fix driving habit such as the using hands when they yawn, and the AP and receiver need to be placed in a stable environment(This setting can be imagined as the central console with some advanced carsettings). But in reality, the driver may do the motions in a more free way(e.g., he may only open mouth when yawn orturn the wheel or other actions when yawn). Unfortunately, these are common problems in driving fatigue detection [19] [20]. This limitation can be overcome with continuous training similar to face recognition technology.

Conclusion

WiFind is a device-free passive fatigue detection system that leverages the CSI variation information of WiFi 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 features to recognize the series of motions during fatigue. We prototype WiFind on commodity Wi-Fi devices and evaluate it in real driving environments. Experimental results show WiFind can achieve a recognition accuracy of 89.6% in a single driver scenario and 73.9% in Multi-passenger case.

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