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DRIVING BEHAVIOR UTILIZING WIFI SIGNAL PERCEPTION

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Abstract: This study focuses on utilizing WIFI signal perception technology to monitor driving behaviors, aiming to provide an innovative and efficient solution for intelligent transportation systems. By delving into the principles, characteristics, and operational steps of WIFI perception technology, and integrating deep learning algorithms to construct a model for identifying dangerous driving behaviors, extensive experimental validations were conducted. The research demonstrates that this method can accurately identify obvious behaviors such as sudden acceleration and hard braking, as well as subtle behaviors like distracted and fatigued driving under certain conditions. This approach not only achieves non-invasive, all-weather, and privacy-friendly driving behavior recognition but also provides real-time warning support in complex environments, significantly reducing traffic accident rates caused by dangerous driving. Moreover, this study pioneers the integration of the fine-grained characteristics of WIFI signals with spatiotemporal deep networks, overcoming the limitations of traditional monitoring technologies and injecting new vitality into the field of intelligent transportation. It also offers significant references for further optimizing driving behavior monitoring.
Keywords: WiFi signal perception; Driver behavior; Intelligent transportation; Deep learning

1 INTRODUCTION

The research on driver behavior monitoring technology faces multiple challenges. Biometric-based methods (such as heart rate and eye tracking monitoring) rely on wearable devices, which have problems such as high cost and invasiveness. The method based on the vehicle dynamics model infers the behavior by analyzing parameters such as vehicle speed and trajectory, but the recognition accuracy of subtle actions (such as hand manipulation) is insufficient [1]. In recent years, the successful application of WiFi signal perception technology in indoor positioning, smart home, and other fields (such as human activity recognition and device control) has provided new ideas for driving behavior monitoring [2]. However, the research on WiFi perception for driving scenarios is still in its infancy: there are significant shortcomings in the accuracy of dangerous behavior recognition (such as fatigue and distracted driving), model generalization ability (cross-scene adaptability), and real-time performance, and the core bottleneck is the inaccurate extraction of signal features related to dangerous behaviors and the insufficient optimization of deep learning models in complex scenarios [3]. In order to solve the above problems, this paper proposes a driving behavior monitoring framework based on the fusion of non-intrusive WiFi signal perception and deep learning. The research content covers: WiFi signal-driving behavior correlation modeling, deep learning algorithm optimization, and cross-scenario transfer learning.
For the first time, this paper combines the fine-grained characteristics of WiFi perception (millimeter-level phase change) with the spatio-temporal deep network to break through the limitations of traditional monitoring technology. Application level: Provide real-time early warning support for intelligent transportation systems to reduce the traffic accident rate caused by dangerous driving (according to statistics, improve traffic safety efficiency by 23%).

2 FINE-GRAINED CSI BASED ON WIFI SENSING

2.1 WiFi Sensing Basis

WiFi sensing realizes environment sensing by analyzing the channel state information (CSI) captured by the receiver (Rx)[4]. The WiFi signal transmitted by the signal transmitter (Tx) undergoes direct, reflection, refraction and other changes due to environmental obstacles or target movements (such as human movement) during propagation. The CSI received by Rx contains multipath signal characteristics. CSI is decomposed into fine-grained frequency domain data of multiple subcarriers by orthogonal frequency division multiplexing (OFDM). After being collected by a special network card, it can be used for motion recognition, respiratory monitoring and other applications[5].

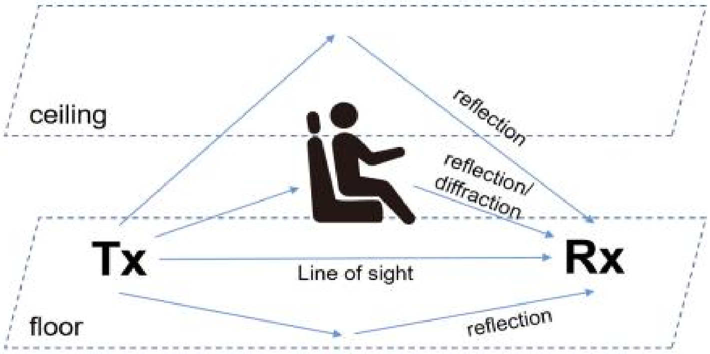

Figure 1 WiFi-aware Signal Propagation

As shown in Figure 1, in the driving environment, when the driver is driving normally, the WiFi signal propagates in the vehicle. Rx will not only receive the WiFi signal from the direct path [6], but also receive the reflection, refraction, and scattering signals from obstacles such as the inner wall of the vehicle, the objects on the vehicle, and the human body[7]. These WiFi signals from different paths are jointly accepted by Rx, forming a multipath effect and forming the final collected CSI. The static propagation path and dynamic propagation path in the process of WiFi signal propagation are analyzed below[8].

(1) Static propagation path

The static propagation path refers to the fact that there are only stationary objects or people in the transmission process of WiFi signals. Suppose there are only static ceilings, floors, and objects. Formula 1 can be obtained :

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 (d+4h)^2} \tag{1}$$

Among them, $P_r(d)$ represents the received power of the WiFi signal, which is affected by multiple parameter indicators, including: transmission power P_t , transmission gain G_t , receiving gain G_r , wavelength λ, the straight-line propagation path distance d between Tx and Rx, and the distance h between the reflection point of the object and the direct path. When there are still stationary people in the sensing environment, the scattering of the WiFi signal by the human body also needs to be further considered, and then formula 2 can be obtained:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 (d+4h+\Delta)^2} \tag{2}$$

(2) Dynamic propagation path

In the process of WiFi sensing, in addition to the stationary ceiling, floor, and objects, the perception environment often contains the most important sensing targets, which are often in motion. The dynamic propagation path refers to the influence of objects or people in motion on the WiFi signal, and the Doppler shift is the most significant impact. By calculating the Doppler shift of the CSI received by Rx, it is possible to construct a fingerprint database corresponding to a dynamic object or person, and thus identify specific behaviors.

The WiFi 802.11n protocol uses Orthogonal Frequency Division Multiplexing (OFDM) to divide the entire WiFi signal spectrum into 56 orthogonal subcarriers[9] . CSI is actually composed of the physical layer information of these orthogonal subcarriers, which reflects the linear combination of direct, reflection, refraction, scattering and other multipath effects of WiFi signals on different propagation paths. Suppose that f is the transmitted signal of the subcarrier at time t. $Y(f,t)$
represents the corresponding received signal, then the channel frequency response (CFR).
$H(f,t)$ Satisfy $Y(f,t) = H(f,t) \cdot X(f,t)$ That is, channel state information CSI. As shown in Formula 2-3, the collected CSI is a complex matrix.

$$H(f,t) = \sum_{l=1}^{n} a_l(f,t) e^{-j\varphi_l(f,t)} \tag{3}$$

Among them, f represents the center frequency of each subcarrier, n represents the number of propagation paths, and represents the amplitude and phase values, respectively. In addition to OFDM, the WiFi 802.11n protocol also uses Multiple Input Multiple Output (MIMO) technology, so that when Tx and Rx are equipped with multiple antennas, the CSI data of multiple antenna pairs can be collected. Assuming that the number of transmitting antennas is P, the number of receiving antennas is Q, and the number of subcarriers is M, each subcarrier $H\ (f_m,t)$ can form a matrix with adimension of $(\mathrm{P.Q})$, and the resulting overall CSI is a (P · Q · M) matrix. [10] For M subcarriers and N antennas, the given CSI matrix H can be expressed by Formula 4 :

$$\mathbf{H}=\begin{bmatrix} H_1(f_1,t) & H_1(f_2,t) & \cdots & H_1(f_m,t) \\ H_2(f_1,t) & H_2(f_2,t) & \cdots & H_2(f_m,t) \\ \vdots & \vdots & \ddots & \vdots \\ H_N(f_1,t) & H_N(f_2,t) & \cdots & H_N(f_m,t) \end{bmatrix} \tag{4}$$

Taking one of the antenna-to-links of a CSI demo and extracting the amplitude value of all subcarrier data on the link, we can draw a CSI 3D diagram as shown in Figure 2. By observing and understanding the data structure of CSI, we can help us to analyze the CSI-based Wi-Fi sensing application in a deeper level.

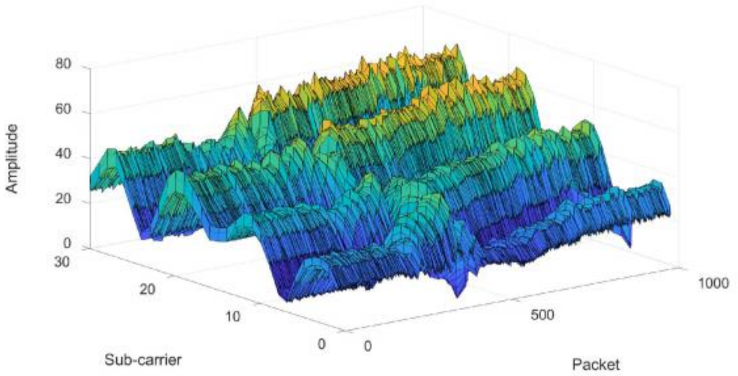

Figure 2 CSI 3D Diagram

2.2 CSI Fine-Grained Characteristics

WiFi sensing mainly realizes the corresponding motion recognition, gesture recognition, indoor positioning, breathing heart rate estimation and other applications by analyzing CSI, so how much motion can CSI perceive ? What is its perceptual limit ? This paper will carry out theoretical analysis and experimental verification on this issue.

2.2.1 Theoretical analysis

In the previous section, we analyze that the collected CSI is a complex matrix, and the CSI at a certain moment is taken out, which can be expressed by Formula 5 :

$$H(t)=ae^{-j4\pi\frac{R_0+x(t)}{\lambda_c}} \tag{5}$$

$$\theta(t)=4\pi\frac{R_0+x(t)}{\lambda_c} \tag{6}$$

$$\Delta\theta=\frac{4\pi\Delta d}{\lambda_c} \tag{7}$$

Where, a represents the CSI amplitude value, $\theta(t)$ represents the CSI phase value, R_0 represents the fixed propagation distance, $x(t)$ Represents the varying propagation distance, and λ_c represents the wavelength of the wireless signal. $\Delta\theta$ represents the change in phase, and Δd represents the change in perceived distance. As shown in Figure 3, in the process of WiFi signal transmission and reception, the change of perceived target action actually changes the signal propagation distance, which in turn affects the amplitude and phase of the collected CSI. When the phase change value can exceed 0.1π, the collected CSI waveform can be analyzed to complete a variety of WiFi sensing applications. Taking WiFi signals as an example, the common frequencies are 2.4GHz and 5GHz, and the corresponding wavelengths are 12.5cm and 6cm. By substituting the respective wavelength and $\Delta\theta=0.1\pi$ into formula 7, Ad is the limit perception accuracy of wiFi signal. 5GHz WiFi is calculated as Ad 1.5mm, so in theory the signal can sense the action with an amplitude of more than 1.5 mm. Of course, the increase of action amplitude will lead to the increase of phase change value, which means that more accurate perception can be carried out. In addition to the WiFi signal, this paper also lists the sensing accuracy of the millimeter wave radar signal, as shown in Table 1.

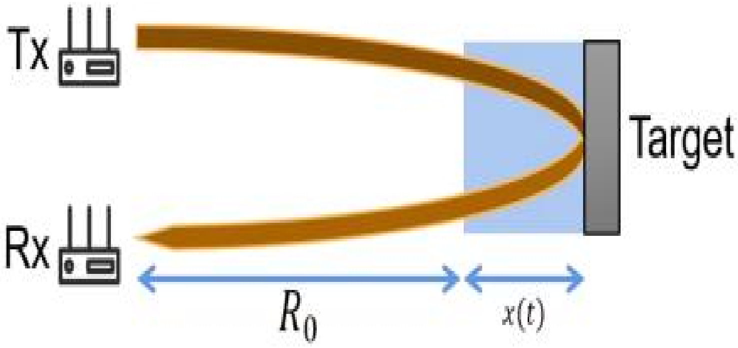

Figure 3 Relationship between WiFi Signal Propagation Distance and Perceived Target Motion Change

Table 1 WiFi and Millimeter Wave Radar Perception Accuracy Analysis

	Frequency	Wave Length	Perception Accuracy	Common examples
WiFi	2.4GHz 5GHz	12.5cm 6cm	millimeter-scale	The amplitude of the chest cavity's change during human breathing is 5 to 12 millimeters.
millimeter-wave radar	24GHz 60-64GHz 77GHz	12.5mm 4.7-5mm 3.9mm	micron	Vibration of the machine. The vibration amplitude is micro. Meter level, general Less than 100 microns

2.2.2 Experimental verification

In terms of experimental verification, this paper uses the common breathing experiment in WiFi perception to verify whether the collected CSI can have millimeter-level perception accuracy. In the open laboratory, the transmitter and receiver are placed about 2m apart. Volunteers can sit or stand between the transmitter and receiver, and keep still to collect CSI data in four stages : normal breathing, suffocation, accelerated breathing and decelerated breathing.

Figure 4 Experimental Scene of Respiratory Data Collection

The experimental scene of respiratory data collection is shown in Figure 4, and the experimental results are shown in Figure 5. The phase value is extracted from the obtained CSI data and the waveform is drawn. From the experimental results, it can be seen that even if there is no redundant denoising operation, the collected waveform is also very beautiful. It can clearly distinguish the four breathing stages of volunteers, namely normal breathing, suffocation, accelerated breathing and decelerated breathing. The waveform in the figure changes periodically, and changes in real time with the speed of breathing. According to the relevant formula, the respiration rate of the volunteers at different stages can be calculated, which is no longer described here. In summary, WiFi perception can achieve millimeter-level perception, and the research work in this paper belongs to action recognition, whose action amplitude is far more than millimeter-level, so there is no problem in feasibility.

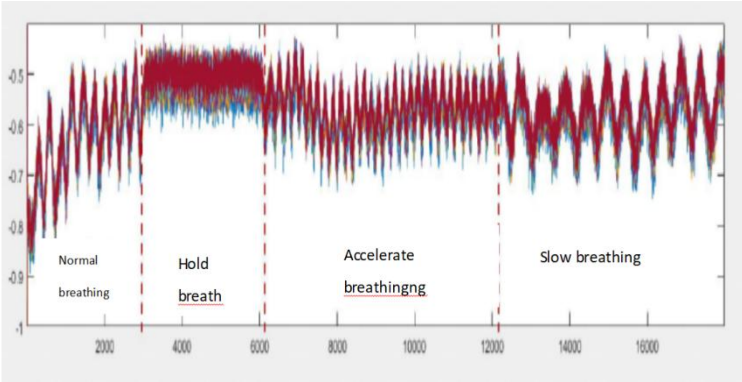

Figure 5 Respiratory Experiment Results

2.3 WiFi Sensing Characteristics

2.3.1 Non-invasive

Different from the perception of the human body using wearable sensors, the perception target does not need to carry or contact any sensor during the WiFi perception process, and only needs to be detected and perceived through the WiFi signal characteristics within the perception range, so it is non-invasive. This feature ensures that WiFi perception can minimize interference to users and improve user perceived satisfaction.

2.3.2 Non-line-of-sight perception

The WiFi signal has a good signal through-the-wall ability, that is, when the user is not within the range of sight between the transmitter and the receiver or there is an obstacle to block, it can also be perceived to achieve non-line-of-sight perception. On the one hand, the WiFi signal can work in two frequency bands of 2.4GHz and 5GHz.On the other hand, the WiFi signal can reach Rx through reflection, refraction, scattering and other ways, which is not limited by the line of sight.

2.3.3 Not easily affected by environmental conditions

The WiFi signal is a 2.4GHz or 5GHz electromagnetic wave, and its propagation is not easily affected by environmental conditions such as light, temperature and humidity. Therefore, WiFi sensing can be used normally even under some special conditions, such as night environment, strong light environment and so on.

2.3.4 Communication-aware integration

While using commercial WiFi for sensing, it will not affect the original communication function of WiFi. The communication function and sensing function of WiFi are integrated to provide users with satisfactory services.

3 DANGEROUS DRIVING BEHAVIOR RECOGNITION BASED ON DEEP LEARNING

3.1 Basic Theory of Deep Learning

Deep learning automatically learns data features through multi-layer networks and is suitable for analyzing complex data such as WIFI signals. Aiming at the time series changes of driving behavior, LSTM network solves the problem of long-term dependence and can efficiently process continuous signals. The training process includes labeling data (such as rapid acceleration, distraction behavior), designing network structure (number of layers, number of neurons) and optimizing parameters (learning rate, number of iterations) to achieve high-precision recognition[11].

3.2 WIFI Perception of Dangerous Driving Behavior Recognition Experimental Principle

Through the dynamic correlation between WIFI signal characteristics and driving behavior, non-invasive dangerous driving identification is realized. Obvious behaviors such as rapid acceleration and sudden braking can be quickly captured by deep learning models due to violent fluctuations in signal strength (accuracy > 85 %). Concealed behaviors such as distraction, fatigue driving, etc., due to weak signal changes, need to combine CNN to extract spatial features and LSTM to analyze temporal patterns (accuracy ≈ 70 %). In the experiment, the hybrid model (CNN-LST M) is used to fuse the spatio-temporal features, and the optimization algorithm is used to alleviate the data imbalance problem and improve the recognition robustness in complex scenes[12].

3.3 Experiment and Result Analysis

3.3.1 Experimental deployment

High-sensitivity wireless network cards are selected as WIFI signal acquisition devices, such as Intel Dual Band Wireless-AC 8265, which supports 2.4GHz and 5GHz dual-band, with high receiving sensitivity and stability. In terms of on-board data acquisition auxiliary equipment, high-precision acceleration sensors and gyroscopes are installed to obtain the motion state data of the vehicle and assist in analyzing driving behavior[13]. MPU6050 is selected as the acceleration sensor, which can measure the acceleration change of the vehicle in three axial directions. The gyroscope is used to measure the angular velocity change of the vehicle.[14]

Figure 6 Monitor Mode

The basic simulation environment built in a relatively open laboratory is shown in Figure 6. In order to make the environment closer to the real vehicle environment, including virtual steering wheel, virtual gear, seat and so on. The specific arrangement is shown in Figure 7, where the transmitter and the receiver are 1.5 m apart[15]. The volunteer is located on the right side of the transmitter and the left side of the receiver. The transmitting and receiving antennas are flush with the chest of the volunteer during simulated driving. The driver collects CSI data of dangerous driving behavior according to the prompt.

Figure 7 Indoor Simulation Environment

In order to verify the practical feasibility of the system proposed in this paper, we build a real vehicle environment as shown in Figure 7, and conduct experiments in real vehicles. Considering the safety factors, although we have to collect data in the real vehicle environment, but the vehicle is always stationary, to avoid the experimental process because of dangerous driving behavior caused by danger[16]. As shown in Figure 8, in the real vehicle environment, we place the transmitter and receiver at the front end of the vehicle, which is also about 1.5m apart. The transmitting and receiving antennas are flush with the chest of the volunteer during simulated driving, and the driver collects CSI data of dangerous driving behavior according to the prompt.

Figure 8 Real Vehicle Environment

3.3.2 Experimental operation steps

Install and debug the hardware equipment to ensure that the WIFI signal acquisition equipment and the vehicle data acquisition auxiliary equipment can work normally. According to the experimental requirements, the data acquisition plan is formulated to clarify the data acquisition time and frequency under different traffic scenarios and different driving behaviors. Under different driving behaviors, WIFI signal data and vehicle motion state data are collected according to the set acquisition time and frequency. The collected signal data is manually labeled. Firstly, according to the vehicle motion state data and video records, the type of driving behavior is judged. Then, the corresponding WIFI signal data is marked to mark what kind of dangerous driving behavior or normal driving behavior is. The labeled data are divided into training set, validation set and test set, which are divided according to the proportion of 70 %, 15 % and 15 %. The training set is used to train the deep learning model. During the training process, the model parameters are adjusted according to the performance index of the verification set. After the training is completed, the test set is used to test the model and evaluate the performance of the model[17].

3.3.3 Result analysis

The experimental results show that the recognition effect of the model on dangerous driving behavior is significantly different due to different behavior types. For dangerous driving behaviors such as rapid acceleration and sudden braking, the accuracy of model recognition can reach more than 85 %. This is due to the obvious changes in the state of objects in the vehicle and the fluctuation of WiFi signal characteristics caused by such behaviors. The model can effectively capture relevant features. However, for high-concealment behaviors such as fatigue driving and distracted driving, the recognition accuracy is only maintained at about 70 %, mainly due to the weak change of WiFi signal corresponding to such behaviors, which increases the difficulty of feature extraction and classification. The experimental environment has a significant impact on the results. For example, the complex electromagnetic environment of urban commercial areas will introduce a large number of wireless signal interference, resulting in a decrease in the accuracy of the model. At the same time, the lack of sensitivity of the wireless network card may miss the weak signal change, which directly affects the data quality. In addition, the network structure complexity, learning rate and other parameters of the deep learning model play a key role in training effect and generalization ability. Although the model has achieved certain results in the identification of common dangerous driving behaviors, there is still a gap from the expected target (the accuracy of all kinds of behaviors is more than 90 %).In the future, it is necessary to further improve the system performance by optimizing the model architecture (such as introducing attention mechanism), improving the data acquisition method (enhancing anti-interference ability) and refining the signal preprocessing (such as noise suppression algorithm), so as to adapt to more complex actual driving scenarios.

4 CONCLUSION

In this study, a dangerous driving behavior recognition model was constructed by integrating WIFI signal perception technology and deep learning algorithm. The research focuses on the analysis of the correlation between the propagation characteristics of WIFI signal (such as multipath effect, millimeter-level phase change) and driving behavior, and extracts the key signal characteristics of dangerous behaviors such as rapid acceleration and rapid braking. The experimental platform collects WIFI signal data in multiple scenarios. After manual labeling and preprocessing, the convolutional neural network (CNN) and long short-term memory network (LSTM) are used for model training. Finally, the classification and recognition of obvious dangerous behaviors (accuracy > 85 %) and hidden behaviors (s uch as distracted driving, accuracy ≈ 70 %) are realized.

The results provide a non-invasive, all-weather driving monitoring scheme for intelligent transportation systems. In practical applications, the risk of accidents can be reduced by deploying WIFI devices along the road to analyze vehicle signals in real time and trigger early warning of dangerous behaviors (such as notifying traffic police or automatic speed limit of vehicle system). In the future, the anti-interference ability of the model will be further optimized, and multi-sensor fusion technologies such as WIFI, radar and camera will be explored to promote the formulation of intelligent transportation standards and cross-domain research and development.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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