RESEARCH ON MOTION RECOGNITION BASED ON CHANNEL STATE INFORMATION

Xu GUAN[1], Hailong YAN1, Zirui WANG[2], Peng GAO[1]

Aiming at the problems that Fourier transform cannot process non-stationary signals and wavelet transform cannot identify the frequency changes in windows, a data processing method based on adaptive variational modal decomposition is proposed. The adaptiveness of the empirical modal decomposition method is used to determine the signal decomposition layers of the variational mode, and the channel state information (CSI) energy signal is decomposed. Based on the more fine-grained CSI signal, according to the characteristics of CSI when no human performs the actions indoors, the direction of arrival on the receiving antenna is monitored, and the indoor human action detection is realized. The effectiveness of the method in the laboratory environment is verified, and the influence of different parameters on action recognition is discussed. The experimental results show that the accuracy of the proposed method is about 93.3%.

Keywords: WiFi, Motion recognition, Subcarrier, CSI

1. Introduction

With the rapid development of wireless intelligence and Internet of Things (IOT), a large number of intelligent terminals based on behavior detection and location-based services (LBS) are applied in smart home and city. When realizing the interaction between information sensing device and human, it is necessary to analyze and monitor human motion in the environment to realize the perception and recognition of human actions. WiFi-based device-free motion recognition technology is widely used due to its advantages of no sensor, ubiquitous signal, low-cost and no contact.

In 2011, a new CSI extraction tool was published to obtain more fine-grained CSI from commercial network cards [1]. Since then, there have been many studies on using CSI information for perception, and it has gradually replaced RSS-based methods as a new research trend. Wang et al. proposed a system E-eyes for human activity recognition through CSI. The CSI data was segmented by the dynamic movement variance, and the similarity between each CSI and the preset action template was calculated to realize the classification and

[1] School of Information Engineering, Liaoning Institute of Science and Engineering, Jinzhou, 121010, China, E-mail: 1261416621@qq.com

[2] School of Electronic and Information Engineering, Liaoning Technical University, Huludao, 125105, China

recognition of activities [2]. However, if the experimental environment changes, the template needs to be redefined. Wang et al. proposed a WiFall system with prompt function, which can detect the sudden fall of a target in an indoor environment, but the system only considers the amplitude of CSI and does not make full use of it [3]. Zeng Zheng used a singular value decomposition method to obtain its singular value features from CSI. The support vector machine was used to identify and classify the extracted CSI features, but some effective information during the processing of CSI was lost [4].

In this paper, a more fine-grained CSI is used as the base signal. Through analyzing the characteristics of CSI when there are no human or human actions indoors, the Direction of Arrival (DOA) on the receiving antenna is monitored to realize indoor human action detection, and the influence of different parameters on action recognition is studied in the experimental environment.

The following content of the paper is organized as: In Section II, we mainly introduce the indoor propagation characteristics of wireless signals. In Section III, we mainly introduce the theoretical analysis and method simulation of CSI positioning. In Section IV, we mainly propose the experimental verification method and the acquisition of CSI positioning data in the actual environment. Finally, we conclude this work with discussion on future work in Section V.

2. Indoor propagation characteristics of wireless signals

2.1. Static propagation model

WiFi-based wireless sensing technology essentially exploits the influence of objects on the propagation path of wireless signals [5]. In free space, i.e. in the ideal state of wireless signal propagation, although the propagation of wireless signal is not blocked and other propagation paths are not generated, such as refraction or absorption, the signal energy of a single path will still decay after the signal propagates through a section of a path. The attenuation degree is related to the wavelength and propagation distance of the signal. According to Friis free space propagation equation [6], when the transmission power is fixed, the received power decays exponentially with the distance. The received power $P_r(d)$ of the wireless signal is:

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

where P_r and P_t are the power of the receiving end and the transmitting end respectively; G_r and G_t are the gain of the receiving antenna and the transmitting antenna respectively; λ is the wavelength of the transmission signal carrier, and d is the distance from the transmitting antenna to the receiving antenna.

It can be seen from Eq. (1) that when the transmission power P_t is constant, the power P_r at the receiving end decreases exponentially with the distance d. The farther the distance, the smaller the received power. If the receiving power and transmitting power of WiFi signal in free space can be obtained, the environment around the transceiver can be perceived and analyzed according to the relationship between the signal attenuation degree and λ and d.

However, in the actual indoor environment, the wireless signal not only propagates along the line of the sight (LOS), but also is affected by various factors. This makes it transmit and refract during the transmission process and reach the receiving antenna. Wireless signals on different propagation paths will decay to varying degrees. The attenuation signals on these different transmission paths will be superimposed on the receiver side to simultaneously interpret the overall effect and the so-called multi-path effect [7]. Therefore, in the indoor environment, the transmission path of a transceiver with fixed WiFi signals is not only the LOS path between the transceiver antennas, but also a plurality of non-line-of-sight (NLOS) paths refracted, scattered and reflected by obstacles in the transmission environment. When the indoor environment is unmanned, there are multiple paths between the sending and receiving ends of WiFi signals, mainly LOS paths and NLOS paths. LOS path is the main direct path, while NLOS path is the path reflected by obstacles such as ceilings, walls, floors, tables and chairs in the indoor environment. As shown in Fig. 1, when there are humans in the indoor environment, the propagation path of the wireless signal will change, and some parameters of the wireless signal received on the receiving antenna will also change, such as RSSI, CSI, and DOA.

Considering the reflection of ceiling and floor, and the energy of other paths, Eq. (1) is written as:

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

where h represents the vertical distance from the ceiling or floor to the LOS path. When someone enters, considering the scattering of the signal by the human body, the received power of the signal is written as:

$$P_r\left(d\right)=\frac{P_t G_t G_r \lambda^2}{\left(4\pi\right)^2\left(d+4h+\Delta\right)^2} \tag{3}$$

wherein, Δ is the approximate path length changed by the human body.

According to Eq. (2) and Eq. (3), $P_r(d)$ remains stable when there is no one in the room.

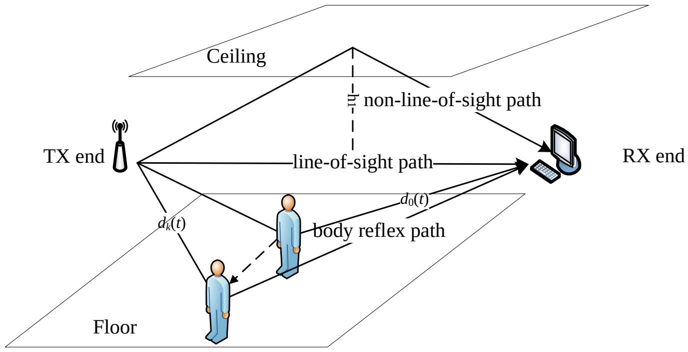


Fig. 1: Wireless signal propagation when there are humans indoors

When human moves indoors, they will disturb the wireless signal to change its propagation path, so as to change the power of the receiving end and the incident angle of the signal.

2.2. Dynamic propagation model

During the transmission process of wireless signals, the wireless channel will change variedly according to the environment, and the movement of the human body will constantly change the wireless transmission path [8]. In order to describe the multi-path characteristics, the multi-path effect of the channel is generally described by channel impulse response (CIR), which is the delay spread in time domain. Thereby CIR can be expressed as:

$$h(f,t) = \sum_{i=1}^{N_l} \alpha_i(f,t) \mathrm{e}^{-\mathrm{j}\varphi_i(f,t)} \delta(\tau - \tau_i(f,t)) \tag{4}$$

where N_l represents the number of paths in the wireless channel; j represents the complex unit, and $a_i(f,t)$, $\varphi_i(f,t)$ and $\tau_i(f,t)$ represent the amplitude, phase and delay of the i^{th} path of the WiFi signal with carrier frequency f respectively. Then the channel frequency response (CFR) obtained by CIR Fourier transform at the receiving end can be expressed as:

$$H(f,t) = \mathrm{e}^{-\mathrm{j}2\pi\Delta f} \sum_{i=1}^{N_l} \alpha_i(f,t) \mathrm{e}^{-\mathrm{j}\varphi_i(f,t)} \mathrm{e}^{-\mathrm{j}2\pi f \tau_i(f,t)} \tag{5}$$

where $a_i(f,t)e^{-j\varphi_i(f,t)}$ represents the amplitude and initial phase of the i^{th} path of WiFi signal with carrier frequency f; $e^{-j2\pi f\tau_i(f,t)}$ represents the phase offset generated by the transmission delay $\tau_i(f,t)$ of the i^{th} path of WiFi signal with carrier frequency f, and $e^{-j2\pi\Delta f}$ is the phase difference caused by the non-synchronization of carrier frequencies at both ends of the transceiver.

In order to realize the accurate recognition of human motion, the influence of human motion on wireless signal is modeled [9]. When the human body moves, the propagation path of wireless signal can be divided into two categories: static propagation path and dynamic propagation path, that is, the part not affected by human motion and the part affected by human motion. $H_s(f,t)$ and $H_d(f,t)$ are used to represent the CFR of static path and dynamic path respectively, where:

$$H_d\left(f,t\right)=\sum_{i\in P_d}\alpha_i(f,t)\mathrm{e}^{-\mathrm{j}\varphi_i(f,t)}\mathrm{e}^{\frac{-\mathrm{j}2\pi d_i(t)}{\lambda}} \tag{6}$$

where P_d is all dynamic paths, and $d_i(t)$ represents the length of the i^{th} propagation path at time t.

Therefore, the total CFR of the receiving end can be expressed as:

$$H\left(f,t\right)=\mathrm{e}^{-\mathrm{j}2\pi\Delta f}\left(H_s\left(f,t\right)+\sum_{i\in P_d}\alpha_i(f,t)\mathrm{e}^{-\mathrm{j}\varphi_i(f,t)}\mathrm{e}^{\frac{-\mathrm{j}2\pi d_i(t)}{\lambda}}\right) \tag{7}$$

Eq. (7) is time-varying. The dynamic path part is composed of a series of paths whose phase and amplitude change with time. In the whole process of a specific action of human, assuming that the speed of the action segment is constant in a short time, for a certain path i in this period, it can be considered that the path length changes uniformly with time, and the speed is v_i. Then $d_i(t)$ in Eq. (6) can be expressed as:

$$d_i\left(t\right)=d_i\left(t-1\right)+v_i t \tag{8}$$

where $d_i(t\text{ -}1)$ is the path length of the time immediately before time t.

The total CFR energy at the receiving end can be expressed as the sum of a group of sine waves and constants. The frequency of sine wave is a function of the path change velocity v_i. Through multiplying the frequency of the estimated sinusoidal function of its carrier wavelength, the change speed of the path can be obtained to correlate the human motion speed with the CFR energy of the wireless signal. Then the instantaneous energy of CFR at time t is:

$$\begin{aligned}\left|H\left(f,t\right)\right|^2&=\left|\mathrm{e}^{-\mathrm{j}2\pi\Delta f}\left(H_s\left(f,t\right)+\sum_{i\in P_d}\alpha_i(f,t)\mathrm{e}^{-\mathrm{j}\varphi_i(f,t)}\mathrm{e}^{\frac{-\mathrm{j}2\pi d_i(t)}{\lambda}}\right)\right|^2\\&=\sum_{i\in P_d}2H_s\left(f,t\right)\alpha_i(f,t)\cos\left(\tfrac{2\pi v_i t}{\lambda}+\tfrac{2\pi d(t-1)}{\lambda}+\varphi_i(f,t)\right)\\&+\sum_{i\in P_d}|\alpha_i(f,t)\mathrm{e}^{-\mathrm{j}\varphi_i(f,t)}|^2+|H_s\left(f,t\right)|^2\end{aligned} \tag{9}$$

2.3. Experimental design

Due to the technical limitation in the initial stage, CSI can only be measured by specific equipment such as software definition radio (SDR). In 2010, Halperin et al. Disclosed the open-source tool of 802.11n CSI tool based on Linux, which uses Intel 5300 network card and wireless router supporting 802.11n protocol to collect CSI data. This method modifies the underlying driver and can collect CSI on ordinary commercial wireless WiFi devices.

The acquisition of CSI data is carried out in the WiFi environment [10]. TP-LINK with three transmitting antennas is used as the wireless signal transmitter, and the desktop computer equipped with Intel 5300 network card and CSI tool provided by Halperin is used as the wireless signal receiver. The operating system is Ubuntu 16.04, and equipped with three peripheral antennas, the two ends formed the 3×3 MIMO system [11].

Intel 5300 wireless network card is shown in Fig. 2. The network card is a wireless network adapter based on IEEE 802.11a/b/g/n standard. It has three antennas and can send and receive data.

Fig. 2: Intel 5300 wireless network card

CSI tool was used to obtain CSI information on Intel 5300 [12]. CSI tool supports 2.4GHz and 5GHz. Since this research focuses on the indoor environment, the wireless signal with 5GHz will lead to the loss of CSI energy, sand 2.4GHz is selected.

3. Experiment

Wireless transceiver equipment shall be arranged indoors. The experimental environment is a 120m^2 laboratory with tables, chairs and other experimental equipment. First, keep no one indoors at the initial stage, and then the experimenters enter the room to walk freely for a period of time with basic actions such as walking, sitting and squatting at intervals on the LOS path of the transceiver, and repeat the above behaviors. Fig. 3 is the CSI amplitude comparison diagram of the same sub-carrier in the same antenna pair in indoor unmanned and manned environments. Observing the CSI amplitude curve under indoor invasion, it is found that after the experimenter enters the room, that is, after the 40th data packet, the sub-carrier fluctuates obviously, and the CSI amplitude changes from the original fluctuation between [3, 5] to the fluctuation between [1, 10]. Therefore, the CSI amplitude meets the stability of static environment and the sensitivity of dynamic environment. It can be used to judge the changes of indoor environment.

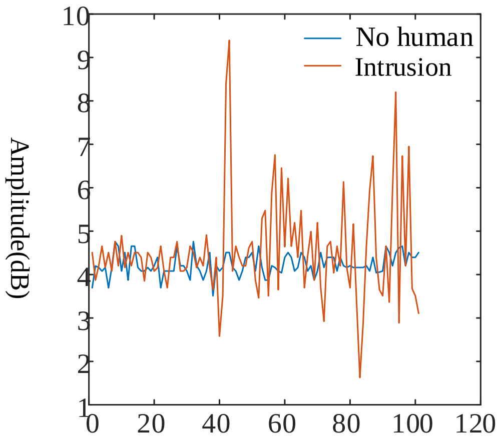
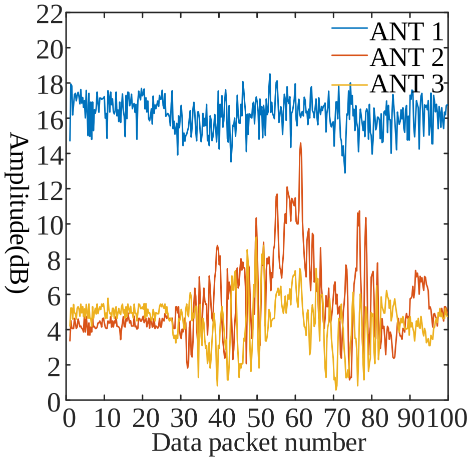


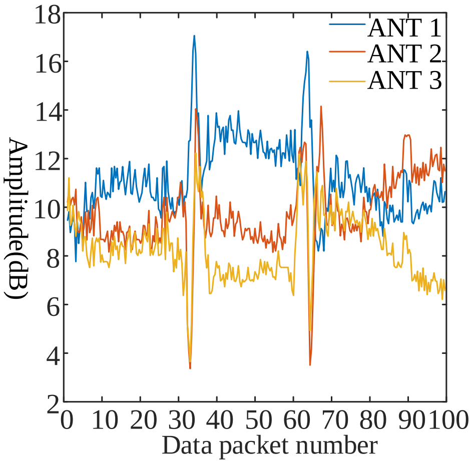
Fig. 3: Comparison of CSI amplitude in unmanned and human environments

In the aspect of action recognition, when testers make different basic actions, the propagation path of wireless signal will change variedly to affect the CSI amplitude. Figs. 4 and 5 compare the CSI amplitudes of different actions and the CSI amplitudes of the same action and the same sample. It is found that the CSI fluctuations of (1), (2) and (3) actions are different under the same data flow, but the CSI amplitudes of the same action have similar fluctuations. Therefore, the CSI amplitude of WiFi signal can be used to realize action recognition.

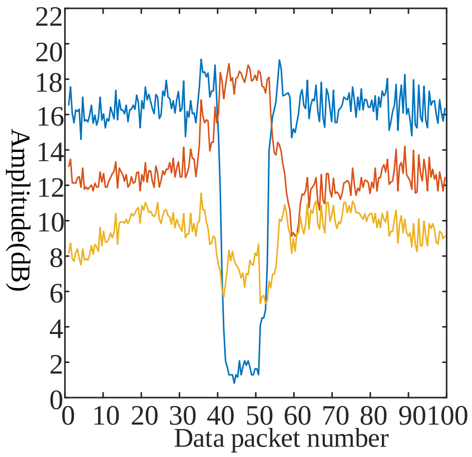
Generally, the original CSI phase has random phase transition, which cannot directly reflect the channel state and needs further processing. Although the CSI amplitude is also doped with high-frequency noise, it still meets the stability of static environment and the sensitivity of dynamic environment and can be used to judge the changes of indoor environment. In addition, it is verified through experiment that the change trend of CSI amplitude in different sub-carriers of the same data stream is consistent, the change trend in different data streams in the same sub-carrier is different, and the overall trend of different samples in the same action is similar. Therefore, CSI signal can be used as the characteristic signal of indoor intrusion detection and action recognition.



(1) Walking

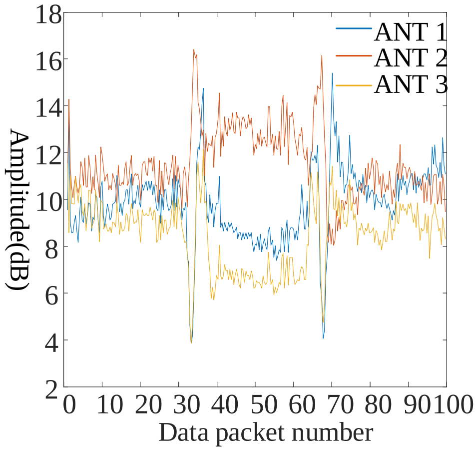


(2) Sitting

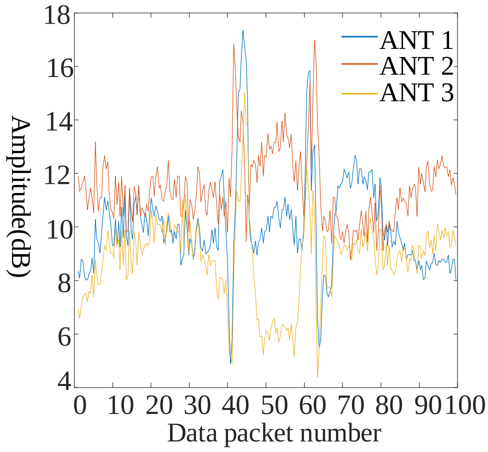


(3) Squatting

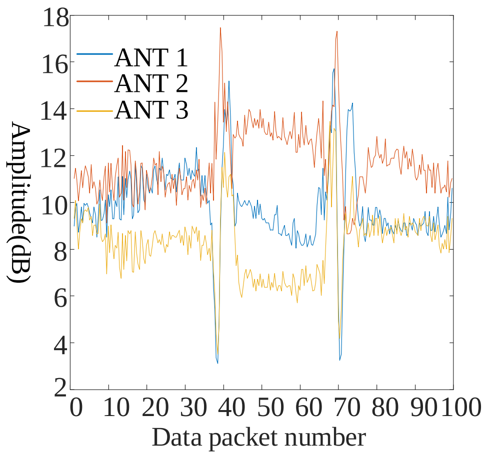
Fig. 4: CSI amplitude of different motions



(1) Sample one



(2) Sample two



(3) Sample three

Fig. 5: Comparison of CSI amplitudes of different samples in the same motion

4 Discussion

In order to verify the feasibility of the proposed method, this experiment collected the data with rich multi-path effect in the laboratory. The experimental layout is shown in Fig. 6, where the experimenter stands in the center of the LOS path and the distance between the transmitting and receiving antenna is 2m.

The collected data comes from the laboratory tests, including three basic movements: walking, sitting and squatting. In different time periods in the laboratory, the number of samples for each movement was 200 times and the sampling frequency was 30Hz. There were 10 experimenters of different genders in each movement. The height of the experimenter ranged from 140cm to 184cm and the weight ranged from 42kg to 71kg. Therefore, this experiment has certain universality.

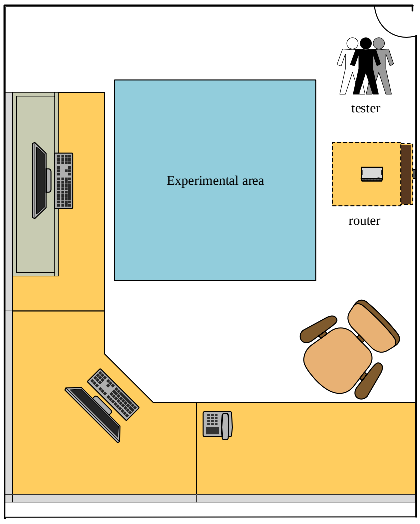


Fig. 6: Experimental environment

In order to further verify the performance of the action recognition method used in this paper, different classification algorithms are compared. The method in this paper is compared with SVM-PCA on the public open-source data sets, Wiar and UJIIndoorLoc [13-14]. The data sets contain 16 action categories, including 10 upper limb movements, 2 lower limb movements and 4 full-body movements. Table 1 describes the accuracy and accuracy comparison of the two methods.

Based on the experimental results in Table 1, the motion recognition accuracy of this method is higher than that of the comparison method. Methods SVM-PCA was effective in identifying the full-body movements such as bending, walking and sitting, but it was poor in identifying the movements with similar movement such as making phone calls and drinking water. This is because in the process of data processing, PCA tends to lose some useful motion information, which is more conducive to separating the reflection signals with large surface areas such as human trunk, doors and windows. Therefore, the action recognition effect with small motion amplitudes and similar logic is poor.

Table 1

Comparison of motion recognition results by different methods

Action	SVM-PCA	this paper
Horizontal wave	0.88	0.93
One hand swing	0.89	0.92
Waving with both hands	0.92	0.94
High throw	0.91	0.94
Arm drawing fork	0.94	0.96
Arm tick	0.91	0.93
Throw paper	0.86	0.89
Forward kick	0.88	0.93
Lateral kick	0.90	0.94
Bending	0.96	0.96
Clap your hands	0.91	0.92
Walking	0.96	0.99
Call phone	0.90	0.96
Drink water	0.89	0.91
Sitting	0.95	0.97
Squatting	0.96	0.96

5. Conclusion

With the wide application of intelligent wireless terminal equipment in daily life, human motion recognition had far-reaching research significance and value. This paper mainly studies the action recognition based on CSI. The experimental results showed that the comprehensive recognition accuracy rate on Wiar and UJIIndoorLoc data sets is 93.3%, and the accuracy and precision of action recognition were higher than those of the comparison methods. In the further research the influence of human motion on the frequency of CSI data could be analyzed, that is, the human activity could be judged by analyzing the change of the frequency of CSI data. In practical applications, there might be multiple APs in the surrounding environment, so how to choose a suitable AP to improve the recognition accuracy could be studied.

Acknowledgement

Thanks for the support of the project of the Educational Department of Liaoning Province - Research on resource allocation of multi-user and multi-channel cognitive radio network (2019-BS-114).

REFERENCES

[1] *Halperin D., Hu W., Sheth A., Wetherall D.,* Tool release: Gathering 802.11 n traces with channel state information. ACM SIGCOMM Computer Communication Review, vol. 41, no. 1, pp. 53, 2011. Doi: 10.1145/1925861.1925870.

[2] *Wang Y., Liu J., Chen Y., Gruteser M., Yang J., Liu H.,* E-eyes: device-free location-oriented activity identification using fine-grained WiFi signatures. Proceedings of the 20th annual international conference on Mobile computing and networking, pp. 617-628, 2014. Doi: 10.1145/2639108.2639143.

[3] *Wang Y., Wu K., Ni L.M.,* WiFall: Device-free fall detection by wireless networks. IEEE Transactions on Mobile Computing, vol. 16, no. 2, pp. 581-594, 2016. Doi: 10.1109/TMC.2016.2557792.

[4] *Chowdhury T.Z., Leung C., Miao C.Y.,* WiHACS: Leveraging WiFi for human activity classification using OFDM subcarriers' correlation. 2017 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Montreal, QC, Canada, pp. 338-342, 2017. Doi: 10.1109/GlobalSIP.2017.8308660.

[5] *Yang D., Wang T., Sun Y., Wu Y.,* Doppler shift measurement using complex-valued CSI of WiFi in corridors. 2018 3rd International Conference on Computer and Communication Systems (ICCCS), Nagoya, Japan, pp. 367-371, 2018. Doi: 10.1109/CCOMS.2018.8463285.

[6] *Wu X., Chu Z., Yang P., Xiang C., Zheng X., Huang W.,* TW-See: Human activity recognition through the wall with commodity WiFi devices. IEEE Transactions on Vehicular Technology, vol. 68, no. 1, pp. 306-319, 2018. Doi: 10.1109/TVT.2018.2878754.

[7] *Zeng Z., Zhang L., Chen J.C., Huang M., Yang J.J.,* Intrusion detection mechanism and experimental study based on WiFi signal. Application of Electronic Technique, vol. 45, no. 3, pp. 92-95+99, 2019. Doi: 10.16157/j.issn.0258-7998.183031.

[8] *Foliadis A., Garcia M.H.C., Stirling-Gallacher R.A., Thoma R.S.,* CSI-based localization with CNNs exploiting phase information. 2021 IEEE Wireless Communications and Networking Conference (WCNC), Nanjing, China, pp. 1-6, 2021. Doi: 10.1109/WCNC49053.2021.9417561.

[9] *Song Q., Guo S., Liu X., Yang Y.,* CSI amplitude fingerprinting-based NB-IoT indoor localization. IEEE Internet of Things Journal, vol. 5, no. 3, pp. 1494-1504, 2017. Doi: 10.1109/JIOT.2017.2782479.

[10] *Murakami T., Otsuki S., Ogawa T., Takatori Y.,* A Study of an Environment Recognition Scheme Using WLAN CSI for Dynamic Spectrum Sharing. 2020 14th European Conference on Antennas and Propagation (EuCAP), Copenhagen, Denmark, pp. 1-4, 2020. Doi: 10.23919/EuCAP48036.2020.9136090.

[11] *Chen S., Gao Q., Chen R., Li H., Sun S., Liu Z.,* A CSI acquisition approach for mmWave massive MIMO. China communications, vol. 16, no. 9, pp. 1-14, 2019. Doi: 10.23919/JCC.2019.09.001.

[12] *Liu W., Cheng Q., Deng Z., Chen H., Fu X., Zheng X., Zheng S., Chen C., Wang S.,* Survey on CSI-based indoor positioning systems and recent advances. 2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Pisa, Italy, pp. 1-8, 2019. Doi: 10.1109/IPIN.2019.8911774.

[13] *Yue G.Y.,* Indoor body motion detection based on WiFi signal research and application. Henan: Zhengzhou University, 2018.

[14] *Guo L., Wang L., Lin C., Liu J., Lu B., Fang J., Liu Z., Shan Z., Yang J., Guo S.,* Wiar: A Public Dataset for WiFi-Based Activity Recognition. IEEE Access, vol. 7, pp. 154935-154945, 2019. Doi: 10.1109/ACCESS.2019.2947024.