International Journal of Smart Home
Vol. 10, No. 9 (2016), pp. 103-112
http://dx.doi.org/10.14257/ijsh.2016.10.9.10

Device-Free Multiple People Daily Activity Recognition Using The Channel State Information Of Wi-Fi Signals

Mohammed Abdulaziz Aide Al-qaness, Fangmin Li

Key Laboratory of Fiber Optical Sensing Technology and Information Processing, Ministry of Education, Hubei Key Laboratory of Broadband Wireless Communication and Sensor Network, Wuhan University of Technology, Wuhan, 430070, China
alqaness@whut.edu.cn

Abstract

This paper demonstrates on the problem of device-free multiple people daily activity recognition, which is very crucial for human computer interaction. The main idea of this paper lies in that we introduce channel state information of Wi-Fi signals to recognize multiple people daily activity. Channel state information is used in the receiver end to analyze features of a communication channel to detect tampering through the transmitter. In order to alleviate the negative influence of radio frequency interference, we define window size to build up vectors of Channel state information. Afterwards, the proposed device-free multiple people daily activity recognition method is implemented by solving the sparse representation classification problem using minimization. To testify the effectiveness of the proposed method, we set the experiment setting with a bedroom and a living room; moreover, two persons and a cat are set in this experiment. Experiments results show that proposed device-free multiple people daily activity recognition method is able to promote activity recognition accuracy under different experiment settings.

***Keywords**: People daily activity recognition, Channel state information, Wi-Fi signal, Device-free, Radio frequency interference*

1. Introduction

People daily activity recognition is a hot research area in human computer interaction, which aims to recognize human action by analyzing human motion and posture, and it has been widely utilized in video surveillance, human computer interaction, and so on [1-3]. However, traditional image recognition approach is not able to interference complex background, because there are lighting changes, shadows and objects and other factors, in the problem of people daily activity recognition[4,5]. Considering structure of human body is very complex, there are many difficulties which human action recognition research should face. Hence, several studies have been proposed for human action recognition, and recognition algorithms with image visual features and regions have been studied and developed carefully [6,7].

Exiting people daily activity recognition research focus on augmented reality and multimedia processing, and conventional researches mainly concentrate on extracting features from RGB camera, which is difficult for human detection and tracking[8]. As a hot research topic in visual information process, people daily activity recognition is belonged to a new multi-interdisciplinary research subject which is intersected by image and video processing, computer vision, pattern recognition, statistic learning, artificial intelligence, and so on[9][10]. The main task of people daily activity recognition is to analyze the content of videos and images, extract features of human actions, and then mine correlations between visual contents and high level semantics[11,12].

ISSN: 1975-4094 IJSH

For the existing studies, people daily activity recognition can be divided into three classes, that is, 1) Device-Bound (DB) systems, which depend on wearable sensors (such as GPS, accelerometer, and so on), 2) Device-Free Active (DFA) systems, which do not need user's cooperation, and used a particular transmitter for recognition and 3) Device-Free Passive(DFP) systems [13], that need RF signals, such as Wi-Fi[14], cellular2G/3G/4G, DVB-T, and FM analog radio.

In this paper, we concentrate on the third kind of people daily activity recognition, which exploits the Device-Free model. Several Device-free based activity recognition has been proposed, such as E-eyes system[15], FIMD system[16], and WiFall system[17]. The main idea of this paper lie in that Channel State Information (CSI) [18,19] of Wi-Fi signals are used in activity recognition.

In recent years, there are many studies on people activity recognition. Saisakul et al. investigated the utilization and contribution of wrist-worn multi-sensors for elderly people activity recognition [20]. Marcos et al. presented a general framework for tracking simultaneously the body postures of multiple people from non-intrusive visual sensors [21]. Chu et al. proposed a model of interactive activity recognition and prompting for use in an assistive system for persons with cognitive disabilities [22]. Roy et al. studied on designing a formal model of activity recognition in smart homes based on possibility theory and environmental contexts [23].

Different from the above works, in this paper, we aim to solve the device-free daily activity recognition for multiple persons, which have not successfully tackled in existing research. On the other hand, in this work, we utilize the sparse representation classification algorithm and define window size to build up vectors of channel state information. The rest of the paper is organized as follows. Section 2 introduces channel state information. In section 3, device-free multiple people daily activity recognition method is proposed. Section 4 proposes experimental results and provides related analysis. Finally, the conclusions are drawn in section 5.

2. Overview of Channel State Information

Channel state information refers to a fine-grained information from physical layer has been utilized for the Wi-Fi fingerprinting to tackle the problems in the localization systems, which adopt Channel Impulse Response based signatures[24,25]. Particularly, channel state information is utilized in the receiver end to analyze features of a communication channel to detect tampering via the transmitter. Channel state information relies on the number of spatial data streams utilized for each data transmission [26]. Because each transmission is able to use a various number of spatial streams, this aspect has to be accounted for in the design of a tamper detection mechanism [27].

In the theory of wireless network, channel state information is defined as the channel quality of the communication channel. Channel state information depends on the number of spatial data streams exploited for each data transmission. A Multiple-Input Multiple-Output system in a narrow band flat fading channel is represented as follows.

$$y_i = Hx_i + N_i \tag{1}$$

where symbol y_i and x_i denote the signal vectors received and sent, M refers to channel matrix and N_i means the vector with noisy data.

Assume that a training sequence is represented as $x_1, x_2, \cdots x_n$, and channel matrix M is computed as the receiving end. Afterwards, signal y_i is calculated as follows.

$$Y = \left(y_1, y_2, \cdots, y_n \right) = MX + N$$
(2)

Therefore, the channel matrix M is gained by the following equation.

$$M = \frac{Y}{X}$$
(3)

Where M refers to the physical layer complex information for N channels. For a specific Multiple-Input Multiple-Output system with multiple transmit and antennas, M_i refers to a matrix with $s \times t$ dimensions.

$$M_i = \begin{bmatrix} m_{11} & m_{12} & m_{13} & \cdots & m_{1t} \\ m_{21} & m_{22} & m_{23} & \cdots & m_{2t} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ m_{s1} & m_{s2} & m_{s3} & \cdots & m_{st} \end{bmatrix}$$

(4)

Based on the above analysis, it can be see that dimensions of channel matrix M is equal to $s \times t \times N$, and h_{st} denotes the complex value to describe the amplitude and phase for each carrier.

Suppose that $X\left(f,t \right)$ and $Y\left(f,t \right)$ denote frequency of sent and received signals with the carrier frequency f. Then, two signals are represented as follows.

$$Y\left(f,t \right) = H\left(f,t \right) \times X\left(f,t \right)$$
(5)

Where the function $H\left(f,t \right)$ represents the complex channel frequency response for frequency f at the time point t.

3. Device-free Multiple People Daily Activity Recognition Method

Assume that L antennas are utilized to receive Wi-Fi signals, and a person may locate at each possible location $i(i \in \{1, 2, \cdots, I\})$ and perform the $j^{th}(j \in \{1, 2, \cdots, J\})$ activity. Furthermore, received signal strength gained from Wi-Fi signal receiver when a target person appears at position i and performs the j^{th} activity is defined as follows.

$$R_{ij} = \left\{ R_{i,j}^{l}\left(k \right) \middle| k \in \left\{ 1, 2, \cdots, K \right\}, l \in \left\{ 1, 2, \cdots, L \right\} \right\}$$
(6)

where the symbol $R_{i,j}^{l}\left(k \right)$ refers to the received signal strength collected by the l^{th} Wi-Fi antenna at the k^{th} time point. Thus, the device-free multiple people daily activity recognition problem can be obtained by solving the following equation.

$$\left(\tilde{i}, j\right) = \arg\min_{i,j} \left\| R - R_{ij} \right\|, i \in \{1, 2, \cdots, I\}, j \in \{1, 2, \cdots, J\}$$
(7)

The main idea of the proposed algorithm is to perform the device-free multiple people daily activity recognition task by utilizing L_1 minimization, and then activity recognition is implemented by sparse representation classification.

As radio frequency interference may significantly let the CSI vector with noisy data. To alleviate the negative influence of radio frequency interference, the concept of window size is proposed to construct CSI vectors. Assume that $y_1, y_2, \cdots, y_{ws}$ represents the vectors of channel state information, then the following optimal problem should be solved.

$$x_i = \arg\min_{x} \left\| x \right\|_1$$
(8)

s. t. $\left\| y_i - Dx \right\|_2 < \delta$

where symbol D refers to a dictionary. Suppose that the i^{th} class is represented as a sub-dictionary $D_i = \left(d_{i1}, d_{i2}, \cdots, d_{in_i}\right)$, where d_{ij} refers to feature vectors. Afterwards, data dictionary is represented as $D = \left(D_1, D_2, \cdots, D_s\right)$.

Algorithm 1: Device-free multiple people daily activity recognition based on sparse representation classification

Input: Matrix of training samples $X = \left(X_1, X_2, \cdots, X_l\right) \in R^{m \times n}$ for l classes, testing sample $t \in R^m$, error tolerance value $\delta > 0$

Output: Device-free multiple people daily activity recognition results y.

Step 1: Normalize columns of X to satisfy unit L_2 norm.

Step 2: Tackle the L_1 minimization problem as follows

$$x_1 = \arg\min_x \left\| x \right\|_1$$

s.t. $\left\| Ax - y \right\|_2 \le \delta$

Step 3: Calculate residuals $r_i\left(y\right) = \left\| y - A\gamma_i\left(x_1\right) \right\|_2, i \in \{1, 2, \cdots, l\}$

Step 4: $y = \arg\min_{i} r_i\left(y\right)$

4. Experiment

To demonstrate the effectiveness of our proposed method, a series of experiments are designed and implemented. Floor design scheme of the experiment environment is shown in Fig. X., and two persons and a cat are set in this experiment. As we aim to implement the device-free multiple people daily activity recognition, we set three daily activities (such as Lying, Walking and Sitting) in the living room and bedroom. Moreover, seven types of people daily activities ($A_1 - A_7$) are considered in this experiment.

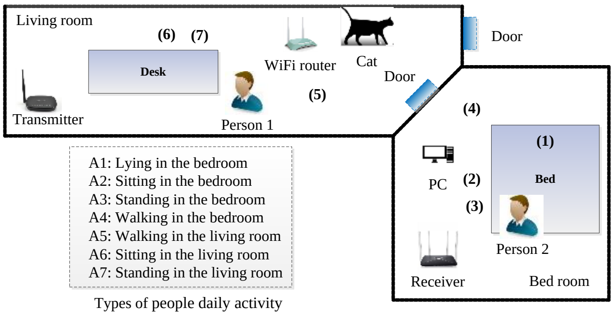

Figure 1. Floor Design Scheme of the Experiment Environment

Particularly, we make a distinction between sitting and standing in various locations to test the location-oriented people daily activity recognition, and we test the most common activities in the human's daily life. For each kind of people daily activity, channel state information is collected in one minute. To construct the dataset, we have collect Channel state information samples for each location-oriented activity. Furthermore, we set a computer and a Wi-Fi router to generate Channel state information in the testing environment.

Particularly, we choose the 802.11a protocol running at 5.8 GHz to communicate in 20 MHz channel. To make the experiment environment be close to the real environments, we set a Wi-Fi router in the room, and the distance between two Wi-Fi routers are set to five meters. Moreover, distance between the computer and the receive end is set to two meters. Performance evaluation criteria used this experiment is listed as follows.

1) True positive rate: $TPR = \frac{TP}{TP + FN}$

(9)

2) False positive rate: $FPR = \frac{FP}{FP + TN}$

(10)

3) F1: $F1 = \frac{2TP}{2TP + FP + FN}$

(11)

Where symbols TP , TN , FP , FN denote the number of true positive samples, true negative samples, false positive samples, and false negative samples respectively. Performance evaluation of various window size settings with and without Radio frequency interference is proposed in Fig. 2 and Fig. 3.

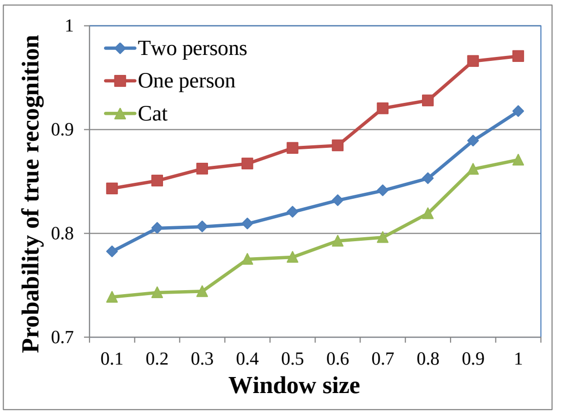

Figure 2. Performance Evaluation of Various Window Sizes without Radio Frequency Interference

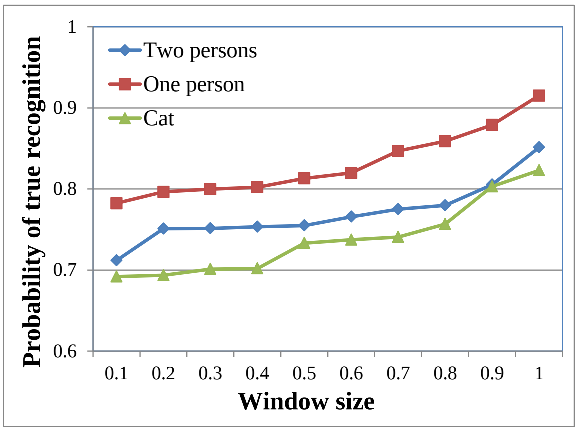

Figure 3. Performance Evaluation of Various Window Size with Radio Frequency Interference

Furthermore, performance evaluation of various bandwidth settings with and without Radio frequency interference is proposed in Fig. 4 and Fig. 5.

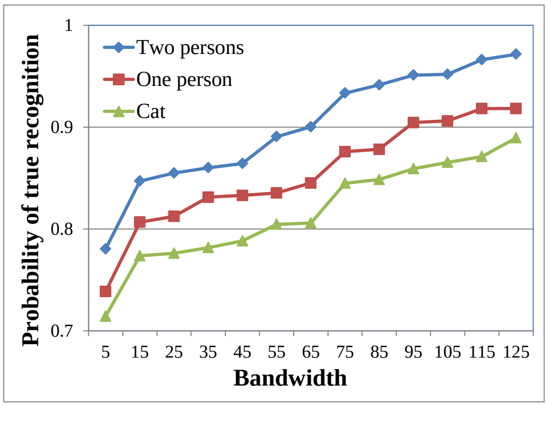

Figure 4. Performance Evaluations of Various bandwidths without Radio Frequency Interference

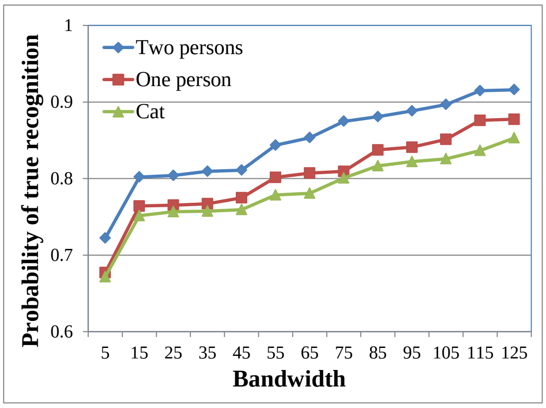

Figure 5. Performance Evaluations of Various bandwidths with Radio Frequency Interference

From the experimental results in Fig. 2 to Fig. 5, we find that radio frequency interference significantly affect the accuracy of activity recognition, and our proposed can effectively alleviate negative influence of radio frequency interference.

Next, we provide confusion matrix of different experiment setting ((1) one person, (2) two persons, and (3) a cat) to demonstrate the effectiveness of our method (shown in Fig. 6 to Fig. 8).

	A1	A2	A3	A4	A5	A6	A7	Other
A1	0.93	0	0.02	0	0	0.05	0	0
A2	0	1	0	0	0	0	0	0
A3	0.05	0	0.91	0	0	0	0.04	0
A4	0	0	0	0.87	0.02	0	0.11	0
A5	0	0	0	0	1	0	0	0
A6	0.01	0.06	0	0.04	0	0.84	0	0.05
A7	0.02	0	0.02	0	0	0	0.96	0
Other	0	0	0	0	0	0	0	1

Figure 6. Confusion Matrixes for the Experiment Environment of One Person

	A1	A2	A3	A4	A5	A6	A7	Other
A1	0.89	0	0.01	0	0.02	0.04	0	0
A2	0	0.94	0	0.03	0	0	0.03	0
A3	0.04	0.01	0.85	0	0.02	0	0.04	0.02
A4	0	0.08	0.01	0.81	0.02	0	0.06	0.02
A5	0	0	0.01	0	0.96	0.03	0	0
A6	0.01	0.03	0.05	0.04	0.03	0.77	0.02	0.05
A7	0.02	0	0.02	0	0.05	0	0.91	0
Other	0.03	0	0	0.04	0	0	0	0.93

Figure 7. Confusion Matrixes for the Experiment Environment of Two Persons

Particularly, for the cat, $A4, A5$ are replaced by $A4^*$ (Crawling in the bedroom) and $A5^*$ (Crawling in the living room) respectively.

	A1	A2	A3	$A4^*$	$A5^*$	A6	A7	Other
A1	0.84	0.03	0.01	0	0.02	0.04	0	0.02
A2	0	0.91	0.03	0.03	0	0.02	0	0.01
A3	0.02	0.01	0.82	0.03	0.02	0.02	0.04	0.02
$A4^*$	0.04	0.04	0.01	0.78	0.02	0.03	0.06	0.02
$A5^*$	0	0	0.01	0.02	0.94	0.01	0.02	0
A6	0.03	0.05	0.03	0.04	0.03	0.75	0.03	0.04
A7	0.02	0.01	0.02	0.01	0.03	0.01	0.89	0.01
Other	0.03	0	0.02	0.04	0	0.02	0	0.89

Figure 8. Confusion Matrixes for the Experiment Environment of the Cat

Afterwards, as is shown in Table. 1, we take the activity of walking in the bedroom for one person as an example to test performance of the proposed algorithm.

Table 1. Performance Evaluation for One Person Walking in the Bedroom

Policy	**Without radio frequency interference**			**With radio frequency interference**		
Bandwidth	5MHz	10MHz	20MHz	5MHz	10MHz	20MHz
TPR	0.734	0.975	0.982	0.456	0.681	0.939
FPR	0.0135	0.0168	0.0025	0.1152	0.0853	0.0439
F1	0.857	0.9702	0.9645	0.4967	0.8361	0.9256

From all the above experimental results, conclusions can be drawn that the proposed device-free multiple people daily activity recognition method can effectively enhance recognition accuracy under different experiment settings.

5. Conclusion

In this paper, we aim to solve the problem of device-free multiple people daily activity recognition, which is a key problem in human computer interaction. We utilize channel state information of Wi-Fi signals to recognize multiple people daily activity, and channel state information is exploited in the receiver end to analyze features of a communication channel. Particularly, to lower the negative affect of radio frequency interference, window size is defined to build up vectors of Channel state information. Furthermore, the proposed device-free multiple people daily activity recognition method is developed through sparse representation classification.

References

[1] Vishwakarma D K, Kapoor Rajiv, Hybrid Classifier Based Human Activity Recognition Using the Silhouette and Cells, Expert Systems with Applications, 2015, 42(20): 6957-6965.

[2] Gonzalez Silvia, Sedano Javier, Villar Jose R, Corchado Emilio, Herrero Alvaro, Baruque Bruno, Features and Models for Human Activity Recognition, Neurocomputing, 2015, 167: 52-60.

[3] Gaglio Salvatore, Lo Re Giuseppe, Morana Marco, Human Activity Recognition Process Using 3-D Posture Data, IEEE Transactions on Human-Machine Systems, 2015, 45(5): 586-597.

[4] Kushwaha Alok Kumar Singh, Srivastava Rajeev, Multiview Human Activity Recognition System Based on Spatiotemporal Template for Video Surveillance System, Journal of Electronic Imaging, 2015, 24(5), Aritle No 051004.
[5] Ziaeefard Maryarn, Bergevin Robert, Semantic Human Activity Recognition: A Literature Review, Pattern Recognition, 2015, 48(8): 2329-2345.
[6] Wang, Y.; Jiang, X.L.; Cao, R.Y.; Wang, X.Y. Robust Indoor Human Activity Recognition Using Wireless Signals, Sensors, 2015, 15(7): 17195-17208.
[7] Su, J.Y.; Cheng, S.C.; Huang, D.K. Unsupervised Object Modeling and Segmentation with Symmetry Detection for Human Activity Recognition, Symmetry-Basel, 2015, 7(2): 427-449.
[8] Sheng, W.H.; Du, J.H.; Cheng, Q.; Li, G.; Zhu, C.; Liu, M.Q.; Xu, G.Q..Robot Semantic Mapping through Human Activity Recognition: A Wearable Sensing and Computing Approach, Robotics and Autonomous Systems, 2015, 68: 47-58.
[9] Uddin Md Zia, Kim Deok-Hwan, Kim Tae-Seong, A Human Activity Recognition System using HMMs with GDA on Enhanced Independent Component Features, International Arab Journal of Information Technology, 2015, 12(3): 304-310.
[10] Capela Nicole A, Lemaire Edward D, Baddour Natalie, Feature Selection for Wearable Smartphone-Based Human Activity Recognition with Able bodied, Elderly, and Stroke Patients, Plos One, 2015, 10(4): Article No e0124414.
[11] Azkune Gorka, Almeida Aitor, Lopez-de-Ipina Diego, Chen Liming, Combining Users' Activity Survey and Simulators to Evaluate Human Activity Recognition Systems, Sensors, 2015, 15(4): 8192-8213.
[12] Sim Jae Mun, Lee Yonnim, Kwon Ohbyung, Acoustic Sensor Based Recognition of Human Activity in Everyday Life for Smart Home Services, International Journal of Distributed Sensor Networks, 2015: Artile No 679123.
[13] Moustafa Youssef, Matthew Mah, Ashok Agrawala, Challenges: Device-Free Passive Localization for Wireless Environments, 13th Int. conf. on Mobile computing and networking (Mobicom '07), 2007, pp. 222-229.
[14] F. Colone, P. Falcone, C. Bongioanni, P. Lombardo, WiFi-Based Passive Bistatic Radar: Data Processing Schemes and Experimental Results, IEEE Trans. on Aerospace and Electronic Sys., 2012, 48(2): 1061-1079
[15] Y. Wang.; J. Liu.; Y. Chen.; M. Gruteser, J. Yang.; H. Liu.. E-eyes: Device-free Location-oriented Activity Identification Using Fine-grained WiFi Signatures, 20th Int. Conf. on Mobile computing and networking (Mobicom '14), Sept. 7-11, 2014, pp. 617-628.
[16] J. Xiao.; K. Wu.;Y. Yi.;L. Wang.; L. M. Ni.. FIMD: Fine-grained Device-free Motion Detection, 18th IEEE Int. Conf. on Parallel and Distributed Systems (ICPADS 2012), 2012, pp. 229-235.
[17] Chun,M.H.; Kai,S.W.;Yu,X.W.; Lionel M. Ni.. WiFall: Device-Free Fall Detection by Wireless Networks, IEEE Conf. on Computer Communications (IEEE INFOCOM 2014), April 27 2014-May 2 2014, pp. 271-279.
[18] Taki Mehrdad, Delay Constrained throughput Optimised Joint Scheduling and Link Adaptation Scheme Based on Imperfect Channel State Information, Iet Communications, 2015, 9(15): 1812-1820.
[19] Mo Jianhua, Heath Robert W Jr, Capacity Analysis of One-Bit Quantized MIMO Systems With Transmitter Channel State Information, IEEE Transactions on Signal Processing, 2015, 63(20): 5498-5512.
[20] Chernbumroong Saisakul, Cang Shuang, Yu Hongnian, Genetic Algorithm-Based Classifiers Fusion for Multisensor Activity Recognition of Elderly People, IEEE Journal of Biomedical and Health Informatics, 2015, 19(1): 282-289.
[21] Marcos A, Pizarro D, Marron M, Mazo M, A Bayesian Approach to Markerless Motion Capture and Activity Recognition of Multiple People, Revista Iberoamericana De Automatica E Informatica Industrial, 2013, 10(2): 170-177.
[22] Chu, Y.; Song, Young Chol, Levinson Richard, Kautz Henry, Interactive activity recognition and prompting to assist people with cognitive disabilities, Journal of Ambient Intelligence and Smart Environments, 2012, 4(5): 443-459.
[23] Roy Patrice C, Bouzouane Abdenour, Giroux Sylvain, Bouchard Bruno, Possibilistic Activity Recognition in Smart Homes for Cognitively Impaired People, Applied Artificial Intelligence, 2011, 25(10): 883-926.
[24] Chapre Yogita, Ignjatovic Aleksandar, Seneviratne Aruna, Jha Sanjay, CSI-MIMO: An Efficient Wi-Fi Fingerprinting Using Channel State Information with MIMO, Pervasive and Mobile Computing, 2015, 23: 89-103.
[25] Lin,M.; Wei, H.;An, K.; Ou,Y.J.; Huang, Y.M.. Effect of Imperfect Channel State Information and Co-Channel Interferences on Two-Hop Fixed Gain Amplify-And-Forward Relay Networks with Beamforming, International Journal of Communication Systems, 2015, 28(13): 1921-1930.
[26] Molu Mehdi M, Burr Alister, Goertz Norbert, Statistical Analysis of Multiantenna Relay Systems and Power Allocation Algorithms in a Relay With Partial Channel State Information, IEEE Transactions on Wireless Communications, 2015, 14(9): 5123-5134.
[27] Fodor Gabor, Di Marco Piergiuseppe, Telek Miklos, On Minimizing the MSE in the Presence of Channel State Information Errors, IEEE Communications Letters, 2015, 19(9): 1604-1607.

