Weight updating technique in spectrum sensing based on CAF shared diversity combining

Shusuke Narieda\textsuperscript{1a)}, Daiki Cho\textsuperscript{2+}, Kenta Umebayashi\textsuperscript{2}, and Hiroshi Naruse\textsuperscript{1}

\textsuperscript{1} Dept. Inform. Eng., Graduate School of Eng., Mie Univ.,
1577 Kurimamachiyacho, Tsu, Mie 514–8507, Japan
\textsuperscript{2} Dept. Elect. and Electron. Eng., Tokyo Univ. of Agric. and Technol.,
2–24–16 Nakacho, Koganei, Tokyo 184–8588, Japan
\textsuperscript{a)} narieda@pa.info.mie-u.ac.jp

Abstract: This paper proposes weight updating techniques for spectrum sensing based on a cyclic autocorrelation function (CAF) shared diversity combining. We had reported that CAF shared diversity combining can improve the performance by the weight calculated from the time-averaged CAF value. However, the performance is degraded when the weight includes CAFs calculated from purely additive white Gaussian noise. To avoid this, this paper proposes the weight updating technique in which only the CAFs are employed to obtain the time-averaged CAF when it is judged that a primary user is present. This paper provides theoretical analysis results of the proposed technique. The proposed results show that the performance of signal detection can be improved as compared to the conventional technique.

Keywords: cognitive radio network, spectrum sensing, sequential detection, multiple antennas

Classification: Terrestrial Wireless Communication/Broadcasting Technologies

References

[1] S. Haykin, D. J. Thomson, and J. H. Reed, “Spectrum sensing for cognitive radio,” Proc. IEEE, vol. 97, no. 5, pp. 849–877, May 2009. DOI:10.1109/JPROC.2009.2015711
[2] M. Öner and F. Jondral, “Air interface recognition for a software radio system exploiting cyclostationarity,” Proc. IEEE Int’l. Symp. Personal, Indoor, Mobile and Radio Communications (IEEE PIMRC 2004), vol. 3, pp. 1947–1951, Sept. 2004. DOI:10.1109/PIMRC.2004.1368338
[3] K. Muraoka, M. Ariyoshi, and T. Fujii, “A robust spectrum sensing method based on maximum cyclic autocorrelation selection for dynamic spectrum access,” IEICE Trans. Commun., vol. E92-B, no. 12, pp. 3635–3643, Dec. 2009. DOI:10.1587/transcom.E92.B.3635

\textsuperscript{+}Presently, the author is with Panasonic Corporation, 1006 Oaza Kadoma, Kadoma-shi, Osaka 571-8501, Japan
\textsuperscript{†}The earlier version of this paper has been proposed at IEEE ICAIIC 2019.
1 Introduction

Frequency bands are public resources, and they must be utilized effectively in wireless communications. Cognitive radio is technology that can realize the effective utilization of frequency bands. Spectrum sensing techniques are employed to seek a spatial and temporal vacancy frequency bands, and it is important for the cognitive radio networks [1]. Various feature detection, which is referred to as cyclostationary detection, can execute signal detection without the measurement noise floor have been reported [2, 3, 4, 5]. Among these techniques, the technique [5] can obtain a good sensing performance with a low computational complexity. To improve the performance, this technique employs a weight factor that is obtained by a time-averaged cyclic autocorrelation function (CAF). The technique extracts the information of channel gain by time-averaged CAFs, and it needs to gather the CAF having the information of channel gain. However, the conventional technique uses the weight factor obtained from both the CAF of received signals and purely AWGN. To solve the problem, this paper proposes a weight updating technique for statistics shared CAF diversity combining based spectrum sensing.

2 Preliminary notion

2.1 Spectrum sensing

We consider the spectrum sensing of primary user’s (PU’s) orthogonal frequency division multiplexing (OFDM) signals that are composed of samples for a useful symbol duration (a fast Fourier transform (FFT)) $N_{\text{FFT}}$ and cyclic prefix (CP) duration $N_{\text{CP}}$, and the OFDM symbol duration $N_{\text{OFDM}} (N_{\text{OFDM}} = N_{\text{FFT}} + N_{\text{CP}})$ at secondary users (SUs) with $N_R$ received antennas and RF chains. We let $H_1$ and $H_0$ denote the hypotheses in which the PU is active and inactive, respectively. Further, the received signal at $i$th receive antenna $r_i(n)$ is determined by using a binary hypothesis testing problem [6] as

$$H_1 : r_i(n) = h_i s(n) + v_i(n), \quad i = 1, \ldots, N_R,$$

$$H_0 : r_i(n) = v_i(n),$$

where $h_i$, $s(n)$ and $v_i(n)$ are a channel coefficient, a PU’s OFDM signal and AWGN respectively, and the subscript (-) $i$ represents the receive antenna index. Moreover, $v_i(n)$ follows a circularly symmetric complex Gaussian, and $v_i(n) \sim \mathcal{CN}(0, \sigma_v^2/2)$. $h_i$, $s(n)$ and $v_i(n)$ are identically, independent distributions to each other.
2.2 Weighted CAF shared diversity combining

In the spectrum sensing technique based on multiple receive antennas, the computational complexity for signal detection increases as the number of receive antenna increases. This is because the statistics are computed from received signals obtained from each receive antenna. To reduce the complexity so as not to degrade the performance of signal detection, we proposed weighted CAF shared diversity combining techniques [5]. In this technique, two statistics $T_{a_i}(mN)$ and $T_{b_k}(mN)$, which are based on the CAFs at cyclic frequencies $\alpha$ ($\alpha = 1/NO_{OFDM}$) and $\beta_k$ ($\beta_k = (k + 0.5)/NO_{OFDM}$) respectively, are computed. These can be written as

$$T_{a_i}(mN) = \left| \sum_{n=1}^{N_k} w_{1}^{(\alpha)}(mN) R_{r,\alpha}^{\alpha}(mN) \right|$$  \hspace{1cm} (2)

$$T_{b_k}(mN) = \left| R_{r,\beta_k}^{\beta_k}(mN) \right|, \quad k = 0, \ldots, N_D - 1,$$  \hspace{1cm} (3)

where $N$, $N'$, $N_D$, $w_{1}^{(\alpha)}(mN)$, $R_{r,\alpha}^{\alpha}(mN)$, $I$ and $R_{r,\beta_k}^{\beta_k}(mN)$ are the number of samples to compute the CAF at $\alpha_1$, the number of samples to compute the CAF at $\beta_k$ ($k = 0, \ldots, N_D - 1$), the number of CAFs at $\beta_k$, a weight factor that can be obtained using a time-averaged CAF $R_{N_N}(tN)$, the approximated CAF at $\alpha_1$ computed by $r_1(n)$ for $N$ samples, an arbitrary integer and $1 \leq I \leq N_R$ and the approximated CAF at $\beta_k$ computed by $r_2(n)$ for $N'$ samples, respectively.

$R_{r,\alpha}^{\alpha}(mN)$ and $R_{r,\beta_k}^{\beta_k}(mN)$ are given by

$$R_{r,\alpha}^{\alpha}(mN) = \frac{1}{N} \sum_{n=mN-N_\alpha+1}^{mN} r_1(n)r_1(n + N_{FFT})e^{-j2\pi\alpha_i n\Delta t}, \quad i = 1, \ldots, N_R$$  \hspace{1cm} (4)

$$R_{r,\beta_k}^{\beta_k}(mN) = \frac{1}{N'} \sum_{n=mN-(k+1)N'+1}^{mN-kN'} r_2(n)r_2(n + N_{FFT})e^{-j2\pi\beta_k n\Delta t}, \quad k = 0, \ldots, N_D - 1,$$  \hspace{1cm} (5)

where $\Delta t$ is a sampling interval. Further, $P_{FA} = 1/(N_D + 1)$ where $P_{FA}$ is a target false alarm probability. $w_{1}^{(\alpha)}(mN)$ and $R_{N_N}(tN)$ are given by respectively as

$$w_{1}^{(\alpha)}(mN) = \frac{|R_{N_N}^{(\alpha)}(m - 1)N|}{\sqrt{\sum_{q=1}^{N_k} |R_{N_N}^{(\alpha)}(m - 1)N|^2}}, \quad i = 1, \ldots, N_R$$  \hspace{1cm} (6)

$$R_{N_N}(tN) = \frac{1}{N_T} \sum_{i=m-N_T+1}^{m} R_{r,\alpha}(tN), \quad i = 1, \ldots, N_R,$$  \hspace{1cm} (7)

where $N_T$ is the number of $R_{r,\alpha}(mN)$ used for the time-averaged computation. From these, a final judgment can be obtained as

$$T_{\alpha_1}(mN) \geq \max_{k \in K} \frac{T_{b_k}(mN)}{N}$$  \hspace{1cm} (8)

where $\max_k \{\lambda_k\}$ is a maximum value of $\lambda_k$ for $k$.

3 Weight updating techniques and its analyses

The CAF shared diversity combining extracts the information of channel gain by averaging computed CAFs, and it requires gathering the CAFs that hold such information. Therefore, this paper proposes the weight updating technique for the CAF shared diversity combining. The proposed technique employs the CAF having
information regarding channel gain for the computation of the time-averaged weight factor. Concretely, when the final judgment of signal detection is true ($H_t$), the weight factor is computed. From these, we let $w_{t_{(i)}}^{(i)}(q_r)$ and $R_{N_t}^{(i)}(q_r)$ be newly defined as a weight factor and time-averaged CAF at $q_r (q_r > q_{r-1})$ respectively, as

$$w_{t_{(i)}}^{(i)}(q_r) = \frac{R_{N_t}^{(i)}(q_r)}{\sqrt{\sum_{i=1}^{N_t} R_{N_t}^{(i)}(q_{r-1})^2}}, \quad i = 1, \cdots, N_R \tag{9}$$

$$R_{N_t}^{(i)}(q_r) = \frac{1}{N_t} \sum_{p=1}^{N_t} \hat{R}_{r,N}(u_{p,q};|H_t|), \quad i = 1, \cdots, N_R, \tag{10}$$

where $\hat{R}_{r,N}(u_{p,q};|H_t|)$ is a newly defined $\hat{R}_{r,N}(tN)$ when the final judgment is true ($H_t$). $u_{p,q}$ is the time in which the $p$th CAF for $R_{N_t}^{(i)}(q_r)$ is obtained, and it is given by

$$u_{p,q} = \{n|\text{final judgment is true } (H_t)\}, \quad p = 1, \cdots, N_t, \quad q_r > u_{N_t, u_{p,q}} > u_{N_t-1, u_{p,q}} > \cdots > u_{1, u_{p,q}} \geq q_{r-1}. \tag{11}$$

Next, the effect of the technique is theoretically proved. We let $\Psi$ denote a channel occupancy ratio which is the probability of the target signal occupancies in the channel to be monitored by SUs, and $0 \leq \Psi \leq 1$. Further, we let $\zeta$ denote the probability that the final judgment is true ($H_t$) whether or not the target signal is included in the CAF. Note that $\zeta$ also represents the probability the weight factor is updated in the proposed technique. $\zeta$ can be represented by

$$\zeta = \Psi P_D + (1 - \Psi)P_{FA}. \tag{12}$$

Note that the first and second terms of eq. (12) are the probabilities that the SU can detect the OFDM signals and the false alarm probability at the SUs, respectively. Based on $\zeta$, we show the effect of the proposed technique. We let $\lambda_p(H_1|H_t)$ and $\lambda_p(H_t|H_0)$ denote the conditional probability whether the target signal is included in the CAF or not, respectively. $\lambda_p(H_1|H_t)$ and $\lambda_p(H_t|H_0)$ are given by

$$\lambda_p(H_1|H_t) = \frac{\Psi P_D}{\Psi P_D + (1 - \Psi)P_{FA}} \tag{13}$$

$$\lambda_p(H_t|H_0) = \frac{(1 - \Psi)P_{FA}}{\Psi P_D + (1 - \Psi)P_{FA}}. \tag{14}$$

Furthermore, we let $\lambda_C(H_t)$ and $\lambda_C(H_0)$ denote the probability where the target signal is included in the CAF or not in the conventional technique [5], respectively. Because the weight factor is always updated when the CAF is computed whether or not the target signal is included in the CAF, these can be written as

$$\lambda_C(H_t) = \Psi \tag{15}$$

$$\lambda_C(H_0) = 1 - \Psi. \tag{16}$$

Here, we compare $\lambda_p(H_1|H_t)$ and $\lambda_C(H_t)$, i.e., we derive $\lambda_p(H_1|H_t) - \lambda_C(H_t)$ as

$$\lambda_p(H_1|H_t) - \lambda_C(H_t) = (P_D - P_{FA}) \frac{(1 - \Psi)\Psi}{\Psi P_D + (1 - \Psi)P_{FA}}. \tag{17}$$

As $P_D \geq P_{FA}$, $\lambda_p(H_1|H_t) \geq \lambda_C(H_t)$ can always be achieved. Furthermore, we compare $\lambda_p(H_1|H_0)$ and $\lambda_C(H_0)$, i.e., we derive $\lambda_p(H_1|H_0) - \lambda_C(H_0)$ as
\[
\lambda_p(H_1|H_0) - \lambda_c(H_0) = -(P_D - P_{FA}) \frac{\Psi}{\Psi P_D + (1 - \Psi)P_{FA}}. \tag{18}
\]

Similar to eq. (17), \( \lambda_p(H_1|H_0) \leq \lambda_c(H_0) \) can always be achieved because of \( P_D \geq P_{FA} \). From these, it can be said that the weight factor of the proposed technique contains a lot of CAFs of target signals than that of the conventional one.

### 4 Numerical example

#### 4.1 Parameter setup

In order to validate the effectiveness of the proposed technique, some numerical examples are shown in this section. The target signal is OFDM, and on each subcarrier, data symbols are modulated with quadrature phase shift keying. The number of subcarriers (or the number of FFT points) is 64. The length of the CP is a quarter of the length of the OFDM symbols, i.e., 16\( \Delta t \). A Rayleigh flat fading channel model is employed. The target false alarm probability \( P_{FA} \) is set to 0.1, and the number of cyclic frequencies \( \beta_k \) for decision \( N_D \) is set to 9 to realize \( P_{FA} = 0.1 \). The number of samples \( N \) and \( N' \) for the CAF computation are 2560 and 268, respectively. The number of receive antennas \( N_R \) is 2, 4, and 8. We employ two-state Markov model to generate the traffic pattern. In the model, \( g_{ij} \) is a probability which transits from the state \( H_i \) to the state \( H_j \). It is known that \( g_{01} = g_{10}(1 - \Psi) \), \( g_{11} = 1 - g_{10} \) and \( g_{00} = 1 - g_{01} \). Further, we employ \( \Psi = 0.1, 0.2, 0.3 \) and \( g_{10} = 0.25 \). Results shown in this section are obtained after \( N_T \) CAFs with the decision \( H_1 \) are collected.

#### 4.2 Performance comparison

First, we evaluate the performance of false alarm probability for the proposed technique and conventional technique. Note that results of false alarm probability are obtained when only AWGN is included in the received signals for \( \Psi \neq 0 \). Table I shows the performance of false alarm probability for the proposed technique and conventional technique when \( N_R = 2, 4, 8 \) and \( \Psi = 0.2 \). As shown in Table I, the performances of both techniques are almost the same. Next, we evaluate the performance of signal detection probability for both techniques. Fig. 1 shows the performance of signal detection probability of the proposed technique and conventional technique for \( N_R = 2, 4, 8, N_T = 10, 20, 50 \) and \( \Psi = 0.1, 0.2, 0.3 \). As shown in Figs. 1a, 1b and 1c, it can be seen that the performance of the proposed technique outperforms that of the conventional technique.

| \( N_R \) | 2  | 4  | 8  |
|----------|----|----|----|
| \( N_T \) | Proposed | Conventional | Proposed | Conventional | Proposed | Conventional |
| 5  | 0.1003 | 0.1003 | 0.0998 | 0.0995 | 0.0998 | 0.0999 |
| 10 | 0.0999 | 0.0998 | 0.0997 | 0.0996 | 0.1002 | 0.1007 |
| 20 | 0.0994 | 0.0993 | 0.0999 | 0.1002 | 0.1003 | 0.1002 |
| 50 | 0.0992 | 0.0992 | 0.0994 | 0.0996 | 0.0991 | 0.0989 |

© IEICE 2020
DOI: 10.1587/comex.2019XBL0127
Received September 18, 2019
Accepted September 27, 2019
Publicized October 10, 2019
Copyedited January 1, 2020
technique as $N_T$ and $N_R$ increases. Further, as shown in Figs. 1c, 1d and 1e, it can be seen that the proposed technique is effective when $\Psi$ is low.

5 Conclusion

This paper proposed a weight updating technique for the statistics shared CAF diversity combining based spectrum sensing. In this paper, the time-averaged CAF is obtained by exclusively employing only the those CAFs when the PU is present. Further, this paper provided the theoretical analyses of the proposed technique. The proposed results showed that the performance of signal detection is improved as compared to that of the conventional technique.

Acknowledgment

This work was supported by JSPS KAKENHI Grant Number JP19K04374.
Traffic feature-based botnet detection scheme emphasizing the importance of long patterns

Yichen An\textsuperscript{a)}, Shuichiro Haruta, Sanghun Choi, and Iwao Sasase

Department of Information and Computer Science, Keio University,
3–14–1 Hiyoshi, Kohoku, Yokohama, Kanagawa 223–8522, Japan
\textsuperscript{a}) anyichen@sasase.ics.keio.ac.jp

Abstract: In this paper, we propose a traffic feature-based botnet detection scheme emphasizing the importance of long patterns. Since the communication sequences of bots are not easily changed, the long communication patterns of botnets are useful for detection. The proposed scheme emphasizes the long pattern’s importance by improving the feature extraction algorithms and giving weights to the long patterns with large occurrences. By the computer simulation with real dataset, we show the effectiveness of our scheme.

Keywords: botnet detection, feature extraction algorithms

Classification: Internet

References

[1] N. Hoque, D. K. Bhattacharyya, and J. K. Kalita, “Botnet in DDoS attacks: Trends and challenges,” IEEE Commun. Surveys Tuts., vol. 17, no. 4, pp. 2242–2270, 2015. DOI:10.1109/COMST.2015.2457491
[2] C. J. Dietrich, C. Rossow, F. C. Freiling, H. Bos, M. van Steen, and N. Pohlmann, “On botnets that use DNS for command and control,” IEEE Seventh European Conference on Computer Network Defense, pp. 9–16, 2011. DOI:10.1109/EC2ND.2011.16
[3] C. Li, W. Jiang, and X. Zou, “Botnet: Survey and case study,” IEEE Fourth International Conference on Innovative Computing, Information and Control (ICICIC), 2009. DOI:10.1109/ICICIC.2009.127
[4] C. Livadas, R. Walsh, D. Lapsley, and W. T. Strayer, “Using machine learning techniques to identify botnet traffic,” Local Computer Networks (LCN), pp. 967–974, 2006. DOI:10.1109/LCN.2006.322210
[5] Y.-H. Su, A. Rezapour, and W.-G. Tzeng, “The forward-backward string: A new robust feature for botnet detection,” IEEE Conference on Dependable and Secure Computing, 2017. DOI:10.1109/DESEC.2017.8073831
[6] E. B. Beigi, H. H. Jazi, N. Stakanova, and A. A. Ghorbani, “Towards effective feature selection in machine learning-based botnet detection approaches,” IEEE Conference on Communications and Network Security, 2014. DOI:10.1109/CNS.2014.6997492
[7] S. Saad, I. Traore, A. Ghorbani, B. Sayed, D. Zhao, W. Lu, J. Felix, and P. Hakimian, “Detecting P2P botnets through network behavior analysis and
1 Introduction

Recently, the computer networks are exposed to the crisis of the botnets. The attacks by botnets include spreading spams, DDoS (Distributed Denial of Service) [1], and so on. The botnet consists of two components called bots and C&C (Command and Control) servers [2]. The C&C server sends instructions to bots and the bots follow them. According to [3], about 40% of the 800 million computers connected to the Internet are botnets. For the secure network, botnet detection is imperative. To detect botnets, many approaches have been proposed.

In [4], Livadas et al. propose an approach which focuses on the fact that the botnets and ordinary users have different features such as size of packets and sending rate. However, the features mentioned above can be manipulated by attackers who try to avoid detection. In order to deal with this, Su et al. propose a scheme which uses the communication sequence as a feature [5]. The main idea behind that scheme is that the communication sequences of bots are not easily changed and represent special feature since they are controlled by programs which are not frequently updated. In that scheme, the communication sequence is tokenized to truncated sequences by \( n \)-gram. The occurrences of patterns appeared in the truncated sequences are used as a feature vector. The detection accuracy of that scheme is high. However, since the feature value of the previous scheme [5] is normalized by the total number of all patterns’ occurrences, the number of occurrences in larger \( n \) is less than that of smaller \( n \). That is, regardless of the value of \( n \), the previous scheme normalizes the feature values by the fixed number of all patterns’ occurrences. As a result, the values of normalized longer patterns’ features become smaller and are hidden by other features.

In this paper, we propose a traffic feature-based botnet detection scheme emphasizing the importance of long patterns. First, we normalize occurrences by the total number of occurrences in each \( n \), since the smaller occurrences in larger \( n \) are normalized by small sum and the feature becomes more balanced with a larger value. Second, we give weights to the features by calculating ranks of the normalized feature, since when longer pattern’s occurrence is very large, it is more useful to detect botnet. By computer simulation, we demonstrate that maximum improvement in our scheme is 12% compared with the previous scheme.

2 Previous scheme

The main idea of the previous scheme is that due to the control by the program, the directional information between bots and C&C servers can be used as a feature. The flow of creating the feature in the previous scheme is shown in Table I. As shown in Table I, the original source of feature is called “forward-backward string”. In order to identify the communications from botnet to C&C server (in) and from C&C server to botnet (out), they are calculated by XOR (exclusive OR) and the
result is called “corresponding direction less string (CDLS)”. CDLS is tokenized to truncated sequences by $n$-gram and the occurrences of patterns appeared in the truncated sequences are counted. However, the numbers of occurrences of each pattern are highly dependent on the length of CDLS. In order to mitigate this, these occurrences are normalized by the total number of all patterns’ occurrences and they are used as a feature vector.

### 2.1 Shortcomings of previous scheme

Although the feature value of the previous scheme is normalized by the total number of all patterns’ occurrences, the number of occurrences in larger $n$ is less than those of smaller $n$. As a result, normalized long patterns’ features become very small and are hidden by other features. The bottom table in Table I shows an example of the previous scheme’s normalization in the case of CDLS = 1010010 (the number of digit $L$ is 7). As shown in this table, when $n = 7$, the number of occurrence of “1010010” is 1. Although this is small compared to the case $n = 1$ where the numbers of occurrences of “0” and “1” are 4 and 3, respectively, those values are normalized by the same value of 28, total number of occurrences, in the previous scheme.

### 3 Proposed scheme

We argue the feature in the previous scheme can be improved by emphasizing importance of the long patterns. We realize that emphasizing by two ideas. The first idea is normalizing occurrences by total number of occurrences in each $n$ instead of the number of all patterns’ occurrences. By doing this, smaller occurrences in larger $n$ are normalized by smaller value and become more balanced with larger values. The second idea is giving weights to the normalized features according to the importance. In the condition where longer pattern’s occurrence is more frequent, it is useful feature for detecting botnet. Thus, we calculate ranks of the normalized features and create new feature according to the ranks.

**Table I. The feature creation in previous scheme**

| direction | forward-backward string | XOR operation | CDLS   | truncated sequences |
|-----------|--------------------------|---------------|--------|---------------------|
| out       | 0                        | >             | 1      | 1                   |
| in        | 1                        | >             | 0      | 0                   |
| in        | 1                        | >             | 0      | 0                   |
| out       | 0                        | >             | 0      | 0                   |
| out       | 0                        | >             | 0      | 0                   |
| in        | 1                        | >             | 0      | 0                   |

| $n$ | 1-gram | 2-gram | 3-gram | 4-gram | 5-gram | 6-gram | 7-gram |
|-----|--------|--------|--------|--------|--------|--------|--------|
| occurrences | 0 | 1 | 00 | 01 | 10 | ... | 1010010 |
| occurrences($n$) | 4 | 3 | 1 | 2 | 3 | ... | 1 | 1 | 1 |
| feature | 4/28= | 3/28= | 1/28= | 2/28= | 3/28= | ... | 1/28= | 1/28= | 1/28= | 1 |
| ($f$) | 0.142 | 0.107 | 0.035 | 0.071 | 0.107 | ... | 0.035 | 0.035 | 0.035 | 1 |
3.1 Normalizing procedure

Let \( x, L, N, f \), and \( F \) denote the number of occurrence of the pattern, the length of the CDLS, the maximum \( n \) in the \( n \)-gram, the feature value in the previous scheme, and the modified feature value calculated by normalizing in our proposed scheme, respectively. Since we normalize by total number of occurrences in each \( n \), we can describe \( F \) as

\[
F = \frac{x}{L - n + 1}
\]

(1)
on the condition \( L \geq N \). Compared with the previous scheme, the value of \( F \) is more balanced and larger than the feature \( f \) in the previous scheme because the occurrence \( x \) is smaller when \( n \) is larger. Table II shows the example modified feature in the proposed scheme. By comparing \( F \) in Table II with \( f \) in Table I, our scheme’s features have larger values than the previous ones. In particular, we focus on the patterns where “1” and “10” have the same occurrence. In this case, while the previous scheme has the same values of \( f, F \) of 2-gram is larger than that of 1-gram in our scheme. This indicates that the longer patterns are more emphasized in the proposed normalization.

3.2 Ranking procedure

The normalized feature vector is further weighted by ranking procedure. We first calculate ranks for each \( n \)-gram. The rank of the feature with smallest occurrence is one and that of largest is \( 2^n \). Note that the ranks become the same values if the occurrences are the same and they become one if the occurrence is zero. We weight the feature \( F \) by multiplying rank \( r \). Let \( F' \) denote the new feature weighted by ranking procedure. The new feature is represented as

\[
F' = F \ast r = \frac{rx}{L - n + 1}
\]

(2)
on the conditions \( 1 \leq r \leq 2^n \) and \( L > N \). From the former condition, as \( n \) is larger, the rank of larger occurrences become larger so that the value of the feature is emphasized. As we can see from Table II, the pattern “10” can be emphasized compared with “00” and “01” in 2-gram. If \( n \) is much larger, more effective emphasizing can be expected.

Table II. Example of modified feature in the proposed scheme

| \( n \) | 1-gram | 2-gram | ... | 6-gram | 7-gram |
|-------|--------|--------|-----|--------|--------|
| occurred patterns | 0 | 1 | 00 | 01 | 10 | ... | 101001 | 010010 | 1010010 |
| occurrences(\( x \)) | 4 | 3 | 1 | 2 | 3 | ... | 1 | 1 | 1 |
| modified feature(\( F \)) | \( \frac{4}{7} = 0.571 \) | \( \frac{3}{7} = 0.428 \) | \( \frac{1}{6} = 0.166 \) | \( \frac{2}{6} = 0.333 \) | \( \frac{3}{6} = 0.5 \) | ... | \( 1/2 = 0.5 \) | \( 1/2 = 0.5 \) | \( 1/1 = 1 \) |
| rank(\( r \)) | 2 | 1 | 2 | 3 | 4 | ... | 63 | 63 | 128 |
| weighted feature(\( F' \)) | 1.142 | 0.428 | 0.332 | 0.999 | 2 | ... | 31.5 | 31.5 | 128 |
In order to show the effectiveness of the proposed scheme, we evaluate the detection accuracy and FPR (False Positive Rate) calculated as

\[
\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]  
and

\[
FPR = \frac{FP}{TN + FP},
\]

where TP, TN, FP, and FN denote the number of True Positive, True Negative, False Positive, and False Negative, respectively. Each result is yielded by 10-fold cross validation. We use SVM (Support Vector Machine) as the machine learning classifier with a parameter \(\gamma\), which indicates how far the influence of each training samples reaches. Although the larger value of \(\gamma\) brings better result for SVM, that includes the risk of overlearning. In order to prove our idea, we test the effect of this parameter. We use ISCX [6] as a primary dataset and supplementally use ISOT dataset [7].

### 4.1 Overall tendency

Fig. 1(a) shows detection accuracy of the proposed and previous schemes versus \(N\) when the dataset ISCX and ISOT are used. The parameter \(\gamma\) is fixed to 10. As we can see from Fig. 1(a), the detection accuracy of the previous scheme [5] and the proposed scheme increases as \(N\) increases in both of dataset. This is because the number of patterns increases and longer patterns are more valuable. However, in the previous scheme, the increase of detection accuracy is slow. On the other hand, the proposed schemes achieve rapid increase in both of dataset. Especially in ISCX, when \(N = 4\), our normalizing and ranking procedures improve the performance compared to the previous scheme by 5% and 12%, respectively. In ISOT, those procedure improvements are by 3% and 4%, respectively. The reason why there is difference in the performance between two datasets is that ISOT includes fewer types of botnets. Thus, it is relatively easy to classify bots and ordinary users, and as a result, the difference of the accuracy between our schemes is small.
4.2 False-positive rate

Fig. 1(b) shows FPR of the proposed and previous schemes versus $N$ in ISCX dataset. As we can see from Fig. 1(b), FPR of both schemes decrease as $N$ increases. Comparing the proposed and previous scheme, the proposed scheme rapidly decreases FPR and it is close to zero. This is because the longer patterns’ features are effectively reflected.

4.3 Effectiveness of emphasizing longer pattern

Fig. 1(c) shows detection accuracy of the proposed and previous schemes versus $N$ with multiple $\gamma$ in ISCX dataset. We set the parameter $\gamma$ to 100, 10, and 0.0001. As we can see from Fig. 1(c), the proposed scheme improves the performance compared to the previous scheme in all $\gamma$ pairs. Focusing on the lines whose $\gamma = 0.0001$, the detection accuracy of the proposed scheme approaches 1.0, when $N \geq 4$.

5 Conclusion

We have proposed a traffic feature-based botnet detection scheme emphasizing the importance of long patterns by normalizing and ranking procedures. By the computer simulation with real dataset, we show the maximum improvement in our scheme is 12% compared with the previous scheme.

Acknowledgment

This work is partly supported by the Grant in Aid for Scientific Research (No. 17K06440) from Japan Society for Promotion of Science (JSPS).
Operational range increasement for STPA-BAA spectrum superposing using subcarrier modulation adaptation

Katsuya Senoo\textsuperscript{1a)}, Kazuki Maruta\textsuperscript{1}, Takatoshi Sugiyama\textsuperscript{2}, and Chang-Jun Ahn\textsuperscript{1}

\textsuperscript{1} Graduate School of Engineering, Chiba University, Chiba-shi, Japan
\textsuperscript{2} Faculty of Informatics, Kogakuin University, Shinjuku-ku, Japan
\textsuperscript{a}) aeka2327@chiba-u.jp

Abstract: In order to achieve high-speed and large-capacity communication, efficient use of frequency resources even over different wireless communication systems is an important issue. We previously proposed the spectrum superposing scheme using subcarrier transmission power assignment (STPA) and blind adaptive array (BAA). Even when multiple systems use the same frequency band, the secondary system enables the both receivers to mitigate inter-system interference by STPA-BAA. However, STPA-BAA has a problem that the operational region of the secondary system is limited due to low-level subcarriers. This paper attempts to resolve this issue by introducing subcarrier modulation adaptation. It can effectively expand the operational region of our proposed approach even in the low signal-to-noise-power-ratio (SNR) situation.

Keywords: blind adaptive array, subcarrier transmission power assignment, subcarrier adaptive modulation, spectrum superposing

Classification: Wireless Communication Technologies

References

[1] M. Labib, V. Marojevic, J. H. Reed, and A. I. Zaghoul, “Extending LTE into the unlicensed spectrum: Technical analysis of the proposed variants,” IEEE Commun. Standards Mag., vol. 1, no. 4, pp. 31–39, Dec. 2017. DOI:10.1109/MCOMSTD.2017.1700040

[2] K. Maruta, J. Mashino, and T. Sugiyama, “Blind interference suppression scheme by eigenvector beamspace CMA adaptive array with subcarrier transmission power assignment for spectrum superposing,” IEICE Trans. Commun., vol. E98-B, no. 6, pp. 1050–1057, June 2015. DOI:10.1587/transcom.E98.B.1050

[3] H. So, K. Maruta, and K. Suzuki, “Laboratory experiment of blind adaptive array with subcarrier transmission power assignment in spectrum superposing scenarios,” Electronics, vol. 7, no. 1, p. 7, Jan. 2018. DOI:10.3390/electronics7010007

[4] A. Agarwal and K. Agarwal, “Implementation and performance evaluation of
1 Introduction

Rapid spread of smartphones, tablets and wearable devices accelerate data traffic explosion. Since available frequency resources are exhausted, improving spectral efficiency is an essential issue. Spectrum sharing is in the process of becoming common sense emerged as licensed assisted access (LAA), long term evolution (LTE) in unlicensed spectrum (LTE-U) [1]. Addition to the above, we investigate a new concept as spectrum superposing in which multiple systems share spectral resource in spatial domain. It is assumed that the primary and secondary systems use the same frequency band without any interference from the secondary system to the primary system. The conceptual deployment scenario is shown in Fig. 1(a). This scheme is joint application of blind adaptive array (BAA) and subcarrier transmission power assignment (STPA) as shown in Fig. 1(b) [2, 3]. Interference signals are suppressed by BAA and the BAA is not required a priori information. However, BAA is limited to some operational throughput range at the situation that signal-to-interference-power-ratio (SIR) is nearly 0 dB. STPA changes the allocating power into high and low level deliberately for subcarriers. The STPA is also effective in reducing inter-system interference (ISI) to the primary system thanks to low-level subcarriers.

On the other hand, the applicability of this scheme is limited especially in low signal-to-noise-power-ratio (SNR) region. It is because the transmission power of

---

[5] K. SenooT, T. Akao, K. Maruta, and C.-J. Ahn, “Improvement and expansion of operational range for STPA-BAA spectrum superposing scheme using subcarrier adaptive modulation,” Proc. The 18th International Symposium on Communications and Information Technologies (ISCIT 2018), Bangkok, Thailand, Sept. 2018. DOI:10.1109/ISCIT.2018.8587852

[6] TGn Channel Models, IEEE Std. 802.11-03/940r4, May 2004.
the most low-level subcarriers is largely suppressed. Therefore, BAA weight optimization function is also limited. To overcome this issue, we extended our proposal by introducing a subcarrier modulation adaptation [4]. The transmitter provides QPSK to high-level subcarriers and BPSK to low-level ones. The modification is simple but it can improve throughput performance and operational SIR region compared to QPSK case in lower SNR situation [5]. This letter deepen the evaluation and discussion of our new approach in addition to [5] by examining various STPA parameters.

1.1 System model
The secondary system with STPA-BAA is laid over the primary one on the superposed spectrum under the situation of a multicarrier transmission system. Noted that there is no function of interference suppression in the primary system. On the same frequency resources, the secondary system basically must not give the interference to the primary system in the cognitive radio network. Therefore, interference from the primary transmitter must be suppressed by the secondary system concurrently with that the secondary system reduces interference to the primary receiver. SIR\(_k\) and SIR\(_{\text{total}}\) are denoted the SIR at the \(k\)-th \((1 \leq k \leq K)\) subcarrier and the total SIR among all subcarriers, respectively. Their relationship is expressed as

\[
\text{SIR}_k = \frac{S_k}{I_k},
\]

\[
\text{SIR}_{\text{total}} = \sum_{k=1}^{K} \frac{S_k}{I_k},
\]

where \(S_k\) and \(I_k\) indicate the power of desired and interference signals at the \(k\)-th subcarrier, respectively.

2 Blind adaptive array with subcarrier transmission power assignment (STPA-BAA)
In the spectrum superposing scenario, we cannot obtain a priori information such as an interference signal or direction of arrival. The main feature of our proposal is to exploit two BAA schemes as constant module algorithm (CMA) and Eigenvector Beamspace Adaptive Array (EBAA) [2]; initial weight of CMA is provided by the 1st or 2nd eigenvectors. This combined scheme is defined as E-BSCMA which can enhance interference suppression performance of CMA. Originally CMA has a limitation in its operational region that the initial input SIR must be larger than 0 dB. E-BSCMA can alleviate its limitation, i.e. CMA initialized by the 2nd eigenvector can effectively work to suppress interference even at SIR\(_k < 0\) dB.

Unfortunately, as stated above, input SIR\(_k\) cannot be available in the spectrum superposing scenario. As shown in Fig. 1(b), our original proposal deliberately assigned two levels of power density to each subcarriers: high-level or low-level at the transmitter. Receiver then assigns the 1st eigenvector-based E-BSCMA weight to high-level subcarriers and the 2nd one to low-level subcarriers. In the figure, \(G\) dB is the power difference of two levels subcarriers. \(F\) is the ratio of the number of
low-level subcarriers to high-level one. The power of total transmission is controlled so as to equal that of the conventional one. Exploiting such STPA strategy as a priori information, it enables the interference suppression when SIR_{total} is nearly 0 dB and its effectiveness was clarified through computer simulation [2] and experiment [3]. Remaining issue is that operational region provided by STPA-BAA reduces in lower SNR region; non-negligible bit error is caused due to low-level subcarriers.

3 Proposed scheme: Subcarrier modulation adaptation

Power density of low-level subcarriers at STPA-BAA should be suppressed to about 10 dB or more than the uniform power assignment so that the proposed scheme could be effective. Therefore, BER performance of low-level subcarriers is degraded due to their weak noise immunity as well as weight optimization failure, especially in lower SNR region. This issue affects overall performance of STPA-BAA and may limits its effectiveness in terms of SNR and operational SIR_{total} region where secondary system successfully obtain good throughput. The new proposed approach introduces subcarrier modulation adaptation where the transmitter provides QPSK to high-level subcarriers and BPSK to low-level ones. The conceptual illustration of this approach is shown in Fig. 1(b). Although BPSK has only a half information bit to QPSK, it exhibits a better BER performance than QPSK, and thus the throughput performance and operational region of STPA-BAA can be maintained even in lower SNR region. Applicability of higher order modulation should be further investigated, for example, applying a modified version of CMA known as multi modulus algorithm (MMA). It should be noted that the above modification can be implemented only to the secondary system. Interference reduction effect to the primary system can be guaranteed as it is.

4 Computer simulation

4.1 Simulation parameters

This letter assumes two pairs of transmitter and receiver communicates in a same frequency channel, respectively. Simulation parameters are listed in Table I. Spatially uncorrelated channels between a plurality of antennas are assumed. Our previously proposed STBA-BAA scheme is defined as the conventional.

4.2 Simulation results

Fig. 2(a) shows the operational region of the secondary system which is defined as the SIR_{total} range exceeding 4 Mbps throughput when SNR is 18 dB. Here we compare our new proposal with the conventional scheme in the various power difference of high and low levels subcarriers G. When G is lower than 14 dB, the operational range of the proposed scheme is narrower than the conventional one. Increasing G is effective in enlarging the operational SIR_{total} region of the proposed scheme with well covering around SIR_{total} = 0 dB. Larger G, over the 24 dB, cannot maintain the operational SIR region. As the result, we can conclude that the optimal G is from 16 dB to 20 dB and obtain the maximal 7.5 dB range at G = 18 dB. Fig. 2(b) shows throughput performance of secondary system versus SNR at
SIR\(_{\text{total}}\) = 0 dB and \(G = 18\) dB. The proposed scheme shows the better throughput performance than the scheme with fixed QPSK at lower SNR region from 10 dB to 17.2 dB. This result verified that using BPSK at low-level subcarrier can improve the noise immunity under the environment of high-level noise. If modulation order is optimally chosen based on the measured SNR, throughput performance can be maximized in any SNR conditions.

### 5 Conclusion

This letter improved the operational region in STPA-BAA spectrum superposing scheme by introducing subcarrier modulation adaptation. As a modification, the secondary transmitter provides BPSK to low-level subcarriers in order to improve the noise immunity of the secondary receiver. Computer simulation verified its effectiveness in terms of throughput and operational SIR\(_{\text{total}}\) region especially at lower SNR situation. We can conclude the proposed approach is quite essential to stabilize advantages of our spectrum superposing approach. Our future work includes more sophisticated adaptive modulation and coding with respect to the reception SNR.

| Table 1. Simulation parameters |
|-------------------------------|
| Parameters                     | Values                      |
| Number of Tx antenna, \(N_t\)  | 1                           |
| Number of Rx antenna, \(N_r\)  | 2                           |
| Modulation                     | BPSK, QPSK                  |
| FFT point                      | 64                          |
| Number of data subcarriers, \(K\) | 52                          |
| Number of data symbols, \(N_d\)| 128                         |
| Number of pilot symbol         | 2                           |
| Guard Interval                 | 16                          |
| Packets size                   | 576 bytes                   |
| Channel model                  | IEEE 802.11 TGn             |
| FFT windowing                  | Channel model D [6]         |
| Intra-system CSI estimation    | Least square                |
| Transmission bandwidth         | 20 MHz                      |
| Error correcting code          | Convolutional Coding, \(R = 1/2\) |
| Subcarrier Tx power ratio, \(G\) | 10, 12, 14, \ldots, 22 dB  |
| Subcarrier number ratio, \(F\) | 7                           |
Acknowledgements

This work was supported in part by JSPS KAKENHI Grant Number 17H06562 and the KDDI Foundation.

Fig. 2. Performances on the secondary system.
Screening of mild cognitive impairment in elderly via Doppler radar gait measurement

Kenshi Saho1a), Kazuki Uemura1, and Michito Matsumoto2
1 Faculty of Engineering, Toyama Prefectural University, 5180 Kurokawa, Imizu, Toyama 939–0398, Japan
2 Department of Social Welfare, Toyama College of Welfare Science, 579 Sanga, Imizu, Toyama 939–0341, Japan
a) saho@pu-toyama.ac.jp

Abstract: This letter presents a screening technique for elderly adults with mild cognitive impairment towards the early detection of dementia based on daily gait measurement using a Doppler radar. The gait parameters corresponding to walking speed, gait cycle, and leg velocities were remotely extracted using a simple Doppler radar system for elderly participants aged 65 years and above. The screening capabilities of the participants with mild cognitive impairment were investigated by using the extracted gait parameters. The results verified that our Doppler radar technique achieved mild cognitive impairment screening with approximately 94% sensitivity and 69% specificity.

Keywords: mild cognitive impairment, dementia, Doppler radar, elderly people, gait analysis

Classification: Sensing

References

[1] J. Verghese, M. Robbins, R. Holtzer, M. Zimmerman, C. Wang, X. Xue, and R. B. Lipton, “Gait dysfunction in mild cognitive impairment syndromes,” J. Am. Geriatr. Soc., vol. 56, no. 7, pp. 1244–1251, July 2008. DOI:10.1111/j.1532-5415.2008.01758.x
[2] J. W. Kim, D. Y. Lee, E. H. Seo, B. K. Sohn, Y. M. Choe, S. G. Kim, S. Y. Park, I. H. Choo, J. C. Youn, J. H. Jhoo, K. W. Kim, and J. I. Woo, “Improvement of screening accuracy of mini-mental state examination for mild cognitive impairment and non-Alzheimer disease dementia by supplementation of verbal fluency performance,” Psychiatry Investig., vol. 11, no. 1, pp. 44–51, Jan. 2014. DOI:10.4306/pi.2014.11.1.44
[3] T. Buracchio, H. H. Dodge, D. Howieson, D. Wasserman, and J. Kaye, “The trajectory of gait speed preceding mild cognitive impairment,” Arch. Neurol., vol. 67, no. 8, pp. 980–986, Aug. 2010. DOI:10.1001/archneurol.2010.159
[4] M. Lussier, M. Lavoie, S. Giroux, C. Consel, M. Guay, J. Macoir, C. Hudon, D. Lorrain, L. Talbot, F. Langlois, H. Pigot, and N. Bier, “Early detection of mild cognitive impairment with in-home monitoring sensor technologies using
functional measures: A systematic review,” *IEEE J. Biomed. Health Inform.*, vol. 23, no. 2, pp. 838–847, Mar. 2019. DOI:10.1109/JBHI.2018.2834317

[5] M. Gwak, E. Woo, and M. Sarrafzadeh, “The role of accelerometer and gyroscope sensors in identification of mild cognitive impairment,” Proc. IEEE Global Conf. on Sign. and Inform. Proc., Anaheim, CA, USA, pp. 434–438, Nov. 2018. DOI:10.1109/GlobalSIP.2018.8646622

[6] K. Saho, K. Uemura, K. Sugano, and M. Matsumoto, “Using micro-Doppler radar to measure gait features associated with cognitive functions in elderly adults,” *IEEE Access*, vol. 7, pp. 24122–24131, Mar. 2019. DOI:10.1109/ACCESS.2019.2900303

[7] C. Karabacak, S. Z. Gurbuz, A. C. Gurbuz, M. B. Guldogan, G. Hendeby, and F. Gustafsson, “Knowledge exploitation for human micro-Doppler classification,” *IEEE Geosci. Remote Sens. Lett.*, vol. 12, pp. 2125–2129, July 2015. DOI:10.1109/LGRS.2015.2452311

[8] J. M. Hilbe, *Logistic Regression Models*, CRC Press, City, FL, USA, 2009.

[9] T. Saito and M. Rehmsmeier, “The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets,” *PLoS One*, vol. 10, no. 3, p. e0118432, Mar. 2015. DOI:10.1371/journal.pone.0118432

1 Introduction

Mild cognitive impairment (MCI) is known as the pre-dementia stage, i.e., the transitional state between cognitive decline due to normal aging and serious decline due to dementia [1, 2, 3]. Daily screening of MCI strongly aids in early detection of dementia. Question/interview-based MCI screening tests have been widely used and validated [2, 3]. For example, Ref. [2] proposed a simple screening test for the MCI by combining two well-used cognitive tests: mini-mental state examination (MMSE) and verbal fluency test (VFT). However, conventional MCI screening tests require a questioner/ grader, which makes daily use difficult.

To solve this problem, gait sensing techniques based on relationships between walking ability and cognitive function [1, 3] are applicable for the MCI screening. Because a traditional walk test timed by stopwatch [3] is unsuitable for daily monitoring, some recent studies have used infrared motion sensors to automatically measure gait speed and its association with MCI [4]. However, this technique can measure only gait speed, and detailed gait information such as leg velocities are not obtained. Accelerometery-based detailed gait measurement techniques have been proposed, and the effectiveness for the MCI screening is shown in [5]; however, these are unsuitable for daily use because the study participants must wear accelerometers.

Doppler radar technique is a promising candidate for avoiding the above problems because it can measure various gait parameters remotely without constraints of participants and this letter presents a MCI screening via gait sensing using a Doppler radar. Our previous study [6] revealed that the cognitive impairment can be identified via micro-Doppler radar gait measurement. Although this previous study assumed the detection of relatively serious cognitive impairment, we hypothesize that our technique can also be applicable for the screening of the milder...
decline observed in MCI. We verify the screening capability of elderly participants with MCI using the gait parameters measured with our Doppler radar system.

2 Experimental protocol

The study participants were 178 elderly adults aged 65 years and above. They performed the MMSE/VFT-based MCI screening test [2] and we classified the participants using this test score into the MCI group (18 people: 9 men and 9 women, mean age 78.4 ± 6.82 years, mean height 154.8 ± 10.2 cm, mean mass 57.1 ± 9.39 kg, mean muscle mass 17.4 ± 4.18 kg) and the healthy group (160 people: 62 men and 98 women, mean age 73.4 ± 4.89 years, mean height 157.3 ± 8.70 cm, mean mass 55.1 ± 9.29 kg, mean muscle mass 17.0 ± 4.02 kg).

The participants then performed an unconstrained walk test using the Doppler radar measurement described in the next section. They also performed the conventional 5-m walk test timed by a stopwatch [3] and the gait speed $v_{5m}$ was measured as a result of the conventional method. We investigated the effective gait parameters acquired with the Doppler radar for the screening of the participants in the MCI group.

The experimental protocol was approved by the local ethics committee (Toyama Prefectural University, approval number H29-1).

3 Doppler radar gait measurement

A Doppler radar measurement system similar to that in [6] was used for this study. Fig. 1 shows the gait measurement situation and the representative spectrogram obtained from the received signal. A single Doppler radar was installed in front of the participant at a height of 0.86 m. The radar transmitted a sinusoidal wave at a frequency of 24 GHz and an effective isotropic radiated power of 40 mW to the participant. The sampling frequency of the received signal was set to 600 Hz. The participants walked toward the radar along a 10-m straight walkway at a self-selected comfortable pace.

For a received signal processing to acquire the gait parameters, the similar procedure indicated in Ref. [6] was conducted to extract the time-velocity distribution, and its feature envelopes are shown in Fig. 1. The length of the data extracted from each participant was one walking cycle and our used data correspond to walk of approximately 2 m. The Hamming window function with a length of 213 ms was empirically used for the short time Fourier transform of the received signals. Mean, upper, and lower envelopes were extracted as $V_m(t)$, $V_u(t)$, and $V_l(t)$, which correspond to body motion, forward motion of the legs, and motion of the legs in contact with the floor, respectively, as indicated in Fig. 1. (these physical interpretations of the envelopes have been validated by [7] using motion capture data). The following gait parameters were extracted using these envelopes. Although the single Doppler radar measures radial velocity and the measured velocities of the arms and legs depend on the distance between the participant and radar, we confirmed that this effect was negligible in the estimation of the following parameters in our radar setup because of the sufficiently far distance from the participants.
The gait cycle \( t_{\text{walk}} \) was estimated based on interpolated maximum peaks as indicated in the spectrogram of Fig. 1.

Mean body velocity \( v_{\text{m,mean}} \) was extracted as \( E[V_{\text{m}}(t)] \), where \( E[\ ] \) denotes the mean with respect to time.

\( v_{\text{u,mean}} \) was extracted as \( E[V_{\text{u}}(t)] \). This corresponds to the mean velocity of forward motions of the legs.

\( v_{\text{l,mean}} \) was extracted as \( E[V_{\text{l}}(t)] \). This corresponds to the mean velocity of the motions of legs in contact with the floor.

Degree of variation of body velocity \( v_{\text{m,std}} \) was extracted as \( \text{STD}[V_{\text{m}}(t)] \), where \( \text{STD}[\ ] \) denotes the standard deviation with respect to time.

\( v_{\text{u,std}} \) was extracted as \( \text{STD}[V_{\text{u}}(t)] \). This corresponds to degree of variation of the forward motions of the legs.

\( v_{\text{l,std}} \) was extracted as \( \text{STD}[V_{\text{l}}(t)] \). This corresponds to degree of variation of the motions of legs in contact with the floor.

\[ \begin{align*}
\text{Fig. 1.} & \quad \text{Fundamental information of our radar measurement: Experimental site (left) and an example of spectrogram for one walking cycle (right).}
\end{align*} \]

### 4 Screening of MCI and its accuracy evaluation

We constructed a logistic regression model [8] for the MCI screening by combining the gait parameters extracted using the Doppler radar, which is expressed as:

\[
\ln \frac{p_{\text{mci}}}{1 - p_{\text{mci}}} = \beta_0 + \beta_1 x_{\text{gait,1}} + \beta_2 x_{\text{gait,2}} + \cdots,
\]

where \( p_{\text{mci}} \) is a probability that the participant is in the MCI group, \( \beta_i \) is \( i \)-th coefficient of the model, and \( x_{\text{gait},i} \) is \( i \)-th predictor. We selected the predictors that achieved the lowest Akaike information criterion (AIC) for the model [8] from all combinations of the gait parameters explained in the previous section.

The screening of the participants with the MCI is conducted with a cut-off value \( p_{\text{cut}} \) of \( p_{\text{mci}} \); i.e., the participants with \( p_{\text{mci}} > p_{\text{cut}} \) are judged to person with the MCI. To determine \( p_{\text{cut}} \) and an evaluation of the screening accuracy, receiver operating characteristic (ROC) curve and precision-recall (PR) curve analyses [9] were performed for the constructed model. The area under the ROC Curve (AUC) was also calculated to evaluate the screening capability. The ROC and PR curves...
and their AUCs were calculated and compared with those of the results of the conventional walk test of \( v_{5m} \).

## 5 Results and discussion

We first show the results for the gait parameter extraction and model construction for \( p_{mci} \). The parameters of the model of Eq. (1) constructed by the logistic regression and the minimum AIC criterion were:

\[
(x_{\text{gait},1}, x_{\text{gait},2}, x_{\text{gait},3}, x_{\text{gait},4}) = (t_{\text{walk}}, v_{\text{m,mean}}, v_{\text{l,mean}}, v_{\text{l, std}}), \quad (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4) = (16.2, -7.38, -20.2, 17.7, 29.0).
\]

All parameters were significant (\( p \)-values in \( t \)-tests \cite{8} were smaller than 0.05). Fig. 2 shows the examples of plots for the gait parameters selected in the constructed model. This figure indicates that although the clear boundary to completely classify the two groups were not confirmed, the participants in the MCI group in the feature space composed of the variables in the model can be screened because of significantly large differences between the two groups.

We evaluated the screening capability for the constructed model. Fig. 3 depicts the ROC and PR curves with \( p_{mci} \) and \( v_{5m} \), and their AUCs of the ROC curves were estimated as 0.869 and 0.692, respectively. Their AUCs of the PR curves were estimated as 0.645 and 0.312. These results for both curves verify that the screening capability of the constructed model is clearly larger than that of the conventional 5-m walk test. For \( p_{\text{cut}} = 0.742 \), the screening using \( p_{mci} \) achieved 94.4% sensitivity with 68.8% specificity as indicated in the ROC curve. This study used imbalanced data between the two groups, the results of the PR curve are relatively high \cite{9} and this curve also indicates that there was a better MCI screening accuracy using the Doppler radar parameters than the 5-m walk test. Thus, these results verified the accurate screening capability of the extracted gait parameters.

Finally, we discuss the results above. The reason for MCI screening capability using the extracted gait parameters is that the gait dysfunction due to cognitive decline was detectable even though the decline is mild. In our previous study \cite{6}, the participants with larger cognitive declines in various cognitive domains were classified with the radar gait parameters. Although the MCI corresponds to a milder cognitive decline compared to our previous study, Ref. \cite{1} reported that the MCI is also associated with gait speed and stride length. The stride length is closely related
to not only gait speed, but also leg velocities corresponding to $V_l(t)$. In addition, gait speed was closely related to the parameters of the mean envelope, as shown in Fig. 1, corresponding to body motion. Thus, the MCI screening was achieved using the gait parameters. However, the parameters extracted from $V_u(t)$ were not selected for the logistic regression model despite our previous findings [6] of the efficacy of these parameters in leg forward motion for the evaluation of various cognitive functions. The mechanism of our results including the reason for the ineffectiveness of $V_u(t)$ could be investigated using a larger dataset in future studies.

6 Conclusion

In this study, we verified the screening capability for participants with MCI using the gait parameters obtained with the Doppler radar. This study can lead to the development of a daily unconstrained MCI detection system that contributes to the prevention and early detection of dementia.

Acknowledgments

This work was supported in part by the Ministry of Internal Affairs and Communications of Japan and JSPS KAKENHI (Grant no. 16K16093).