Machine-Learning Approach to Binary Classification of Uplink-Channel States for Secure Body-Coupled Communication

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SUMMARY Body-coupled communication (BCC) is a short-range wireless technology that can link communication devices with the human body. The BCC channel is formed by a capacitive coupling between the body, devices, and earth. When another person approaches the BCC system, the person becomes inevitably involved in the system because of the coupling. In this situation, eavesdropping and accidental data transmission can occur. A feasible solution to this security problem is to detect the existence of the undesirable person based on the information of received signals. We emphasize that fiber-optic EO-OE converters are indispensable for correctly evaluating the received signals in BCC uplink channels because they are affected by electronic apparatuses. We demonstrated that an undesirable person can be detected with an accuracy of 96% by using machine learning.
keywords: *body-coupled communication, channel gain, classification, EO-OE converter; machine learning.*

1. Introduction

The concept of body-coupled communication (BCC) was proposed in 1996 to realize smart communication among multiple wearable devices [1]. The basic concept of BCC is that a human body can be utilized as a data transmission channel similar to cables. This novel idea can also be applied to communication between fixed and mobile devices [2]. BCC is also considered for realizing smart certification systems such as walk-through gates. At present, BCC technologies are being studied by many researchers because of their excellent abilities to link multiple devices [3]–[17].

A limitation of BCC is that eavesdropping and accidental data transmission can easily occur. We recently proposed a method to address this security problem [18]. The basic concept of this method is that the existence of an undesirable person involved in eavesdropping or accidental data transmission can be detected by analyzing the received signals. If undesirable persons are correctly detected, the security problem can be avoided by using system-level measures. From a practical viewpoint, it is preferable to analyze signals received by fixed devices instead of mobile devices. In other words, the signals received by the uplink channels should be analyzed. Although the proposed method worked well in downlink channels [18], its effectiveness has not yet been investigated in uplink channels.

Based on these reasons, we investigated the feasibility of detecting an undesirable person in BCC uplink channels. We emphasized that photonic techniques play an important role in correctly evaluating the received signals. The process of detecting an undesirable person is equivalent to binary classification problems. We demonstrated that machine learning can effectively solve our classification problem.

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2. Concepts and Models of BCC Uplink Channels

A conceptual image of a BCC uplink channel is presented in Fig. 1. We refer to the situation shown in Fig. 1 as an “ordinary state.” Data signals generated by a mobile transmitter (M-TX) are applied between a pair of electrodes (M+ and M–). The human body is regarded as a conductor covered by insulators, such as skin, clothes, and shoes. When an M-TX exists in the vicinity of the human body, conduction currents flow inside the body. A fixed receiver (F-RX) is connected to a pair of electrodes (F+ and F–). When Person 1 equipped with the M-TX rides on F+, received currents are induced inside the F-RX. After passing through the F-RX, the currents flow within the earth. Because M– and the earth form a capacitor, the currents return from the earth to M– in the form of electric fields, and these are called displacement currents. The BCC uplink channel in this ordinary state is expressed by a simple RC circuit model, as shown in Fig. 2. Note that the electric fields are represented by the capacitors.

Figure 3 shows a conceptual image of the BCC uplink channel when an undesirable person (Person 2) is involved. Let us refer to the situation shown in Fig. 3 as an “extraordinary state.” In this state, Person 1 without an M-TX stands on F+, and Person 2 equipped with an M-TX exists in the vicinity of Person 1. Although Person 2 does not stand on F+, Person 2 can communicate with the F-RX via Person 1. From a communication security perspective, this is an undesirable situation because eavesdropping and accidental data transmission can occur. The BCC uplink channel in this extraordinary state can be represented by an RC circuit model shown in Fig. 4.

We define the channel gain, $G(f)$, of the BCC channels as

$$G(f) \triangleq \left|\frac{V_{\mathrm{out}}(f)}{V_{\mathrm{in}}(f)}\right|, \qquad (1)$$

where $V_{\mathrm{in}}(f)$ and $V_{\mathrm{out}}(f)$ are input and output voltages, respectively, as shown in Figs. 2 or 4. Note that $G(f)$ is equivalent to $V_{\mathrm{out}}(f)$ because $V_{\mathrm{in}}(f)$ is known in advance. Furthermore, we denote the channel gains under

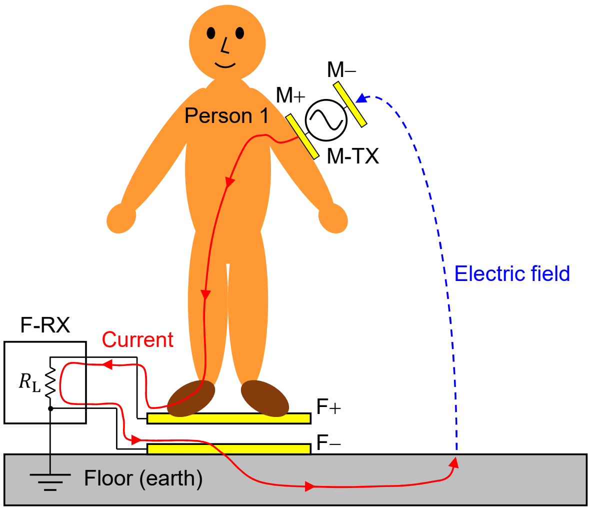

Fig. 1 Conceptual image of a BCC uplink channel in an ordinary state.

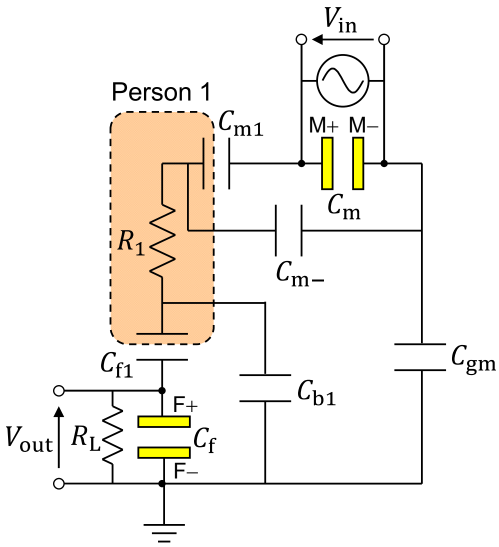

Fig. 2 Equivalent circuit model of a BCC uplink channel in an ordinary state.

ordinary and extraordinary states by $G_o(f)$ and $G_e(f)$, respectively. Note that $G_o(f)$ and $G_e(f)$ depend on the parameters shown in Figs. 2 and 4, respectively. They are formally written as

$$G_o(f) = G_o\big(f; R_L, R_1, C_{b1}, C_f, C_{f1}, C_{m-}, C_{m1}, C_{gm}\big), \quad (2)$$

$$G_e(f) = G_e\big(f; R_L, R_1, C_{b1}, C_f, C_{f1}, C_{m-}, C_{m1}, C_{gm} ; R_2, C_{m+}, C_{m2}\big). \quad (3)$$

Equations (2) and (3) indicate that $G_o(f)$ and $G_e(f)$ hold traces of the ordinary and extraordinary states, respectively. This suggests that we can predict the unknown state (ordinary or extraordinary) by analyzing the $G(f)$ obtained by the F-RX. This is a binary classification problem of detecting the undesirable person, which is the objective of this study.

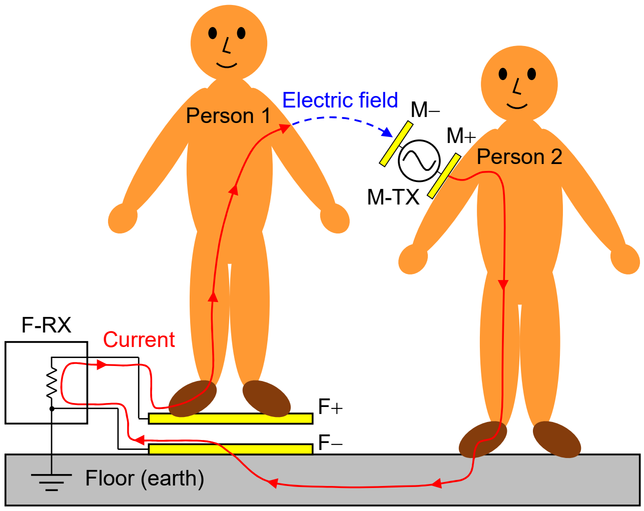

Fig. 3 Conceptual image of a BCC uplink channel in an extraordinary state.

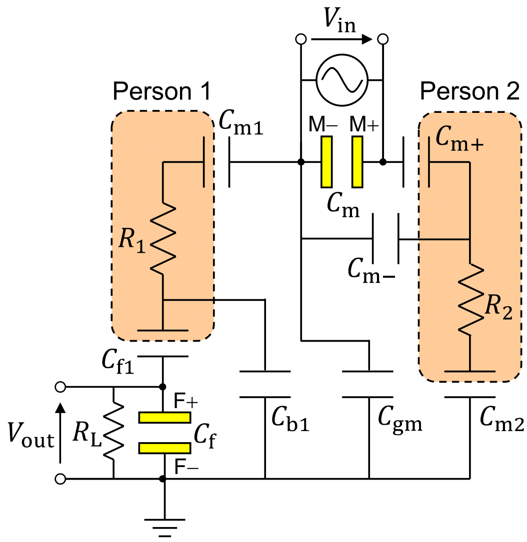

Fig. 4 Equivalent circuit model of a BCC uplink channel in an extraordinary state.

3. Setup for Channel Gain Measurements

To investigate the feasibility of binary classification, $G(f)$ must be experimentally obtained under various conditions. Before measuring $G(f)$, we must determine the influence of electronic apparatuses on BCC channels. Figure 5 shows the setup for measuring $G(f)$ by using purely electronic apparatuses. In this setup, M– is inevitably earthed because the ground of a function generator (FG) is connected to M–. However, in real situations, M– is electrically isolated from the earth because mobile devices are powered by batteries and not by AC power supplies. Therefore, the setup shown in Fig. 5 is invalid. To correctly evaluate BCC channels, measurements must be performed while keeping M– isolated from the earth.

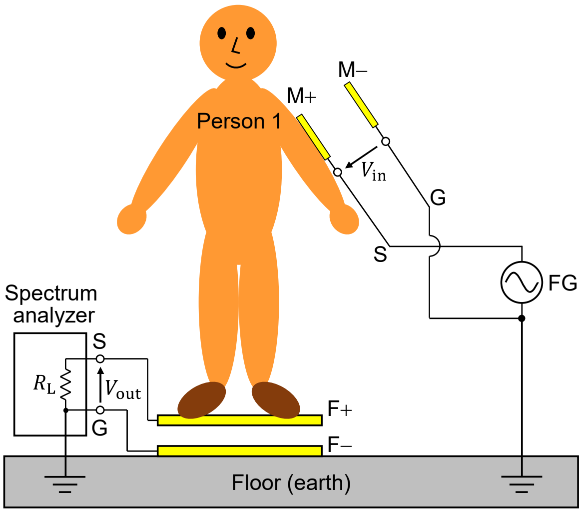

Fig. 5 Setup for measuring BCC uplink channel gain by using purely electronic apparatuses.

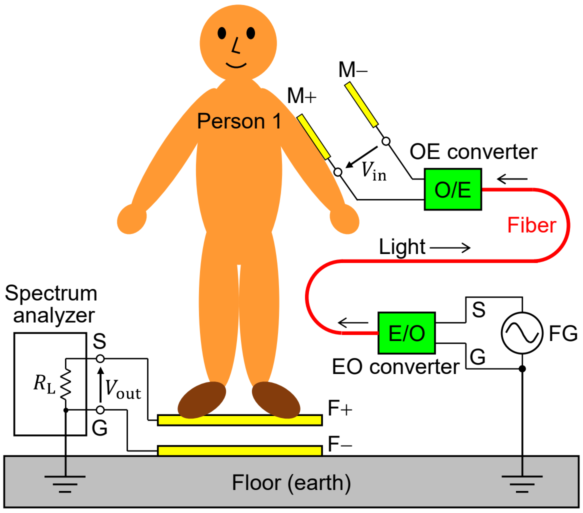

Fig. 6 Setup for measuring BCC uplink channel gain by using EO-OE converters.

An effective approach for achieving isolation is to use photonic techniques. In this case, it is suitable to feed the input signals by using the electrical-to-optical (EO) converter and optical-to-electrical (OE) converter. The setup for measuring $G(f)$ by using the EO-OE converters is shown in Fig. 6. The electrical signals generated by the FG are input to the EO converter (E/O). A semiconductor laser diode installed in the EO converter is modulated by the electrical signals. The intensity-modulated light emitted from the laser diode is delivered to the OE converter (O/E) by an optical-fiber cable. Finally, the modulated light is converted into electrical signals by a photodiode inside the OE converter. Consequently, the OE converter replicates the signals generated by the FG. The replicated signals are applied between M+ and M–. Because of the nature of the optical-fiber cable, M– is electrically isolated from the ground of the FG. Therefore, $G(f)$ can be correctly evaluated while keeping M– isolated from the earth owing to the EO-OE converters.

4. Binary Classification of BCC Channel States

We measured $G(f)$ by using the system shown in Fig. 6 under various conditions. Examples of the measured $G(f)$ values are shown in Fig. 7. The black curves indicate $G_o(f)$. Other colored curves show $G_e(f)$, and d represents the distance between Person 1 and the M-TX attached to Person 2. We observe that $G_o(f)$ is smooth and $G_e(f)$ undulates significantly. It is easy to correctly classify $G(f)$ into $G_o(f)$ or $G_e(f)$ as long as these general features are reflected in $G(f)$. Figure 8 shows $G(f)$ values measured under various conditions. Although most of $G_o(f)$ and $G_e(f)$ exhibit these general features, some do not seem to possess them. Therefore, it is not always easy to correctly classify $G(f)$ into $G_o(f)$ or $G_e(f)$.

It is well-known that machine learning can effectively solve classification problems. Therefore, we applied machine learning to predict the ordinary/extraordinary states based on the measured $G(f)$. In this study, we used Mathematica 12 as the machine-learning tool. Various learning algorithms can be used with this tool. As shown in Fig. 8, the numbers of measured $G_o(f)$ and $G_e(f)$ samples are 48 and 64, respectively. We used half of the measured data for the training. The other half was used to validate the prediction accuracy of the machine-learning method. To effectively increase the number of samples, a 2-fold cross-validation was performed.

The prediction accuracies obtained by using several machine-learning algorithms are summarized in Table 1. The results obtained in this study are listed in the "Uplink" column. For reference, results reported in [18] are shown in the "Downlink" column. The maximum prediction accuracy is 96% with logistic regression and neural network algorithms. However, several other algorithms exhibit a prediction accuracy of approximately 90%. This indicates that the prediction accuracy does not depend significantly on the learning algorithms. These results show the effectiveness of our proposed method for detecting an undesirable person.

5. Conclusion

We proposed a method for detecting the existence of an undesirable person in BCC uplink channels. The key concept of our method is the detection of an undesirable person based on the information contained in the signals received by fixed devices. The detection of an undesirable person is equivalent to binary classification problems: classifying the measured $G(f)$ into $G_o(f)$ or $G_e(f)$. An important feature of BCC systems is that mobile devices are electrically isolated from the earth in real situations because they are powered by batteries. We emphasized that EO-OE converters play an important role in correctly evaluating

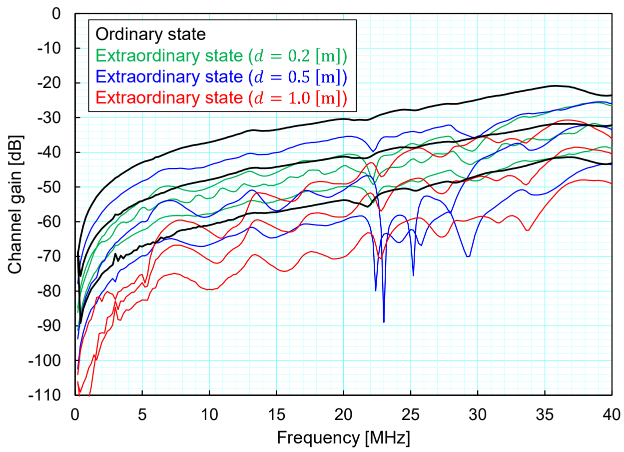

Fig. 7 Examples of BCC uplink channel gain measured under ordinary and extraordinary states.

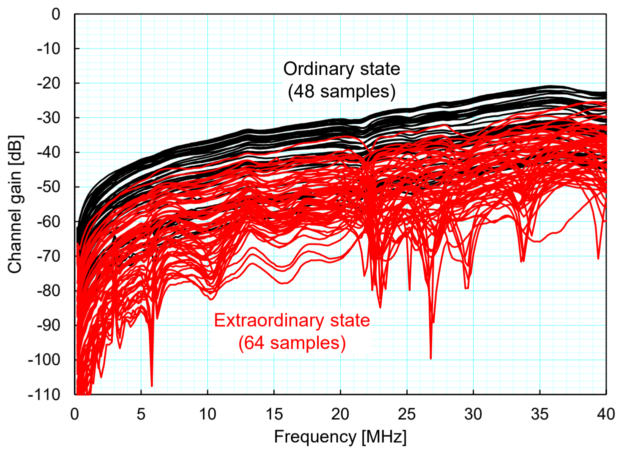

Fig. 8 BCC uplink channel gain measured under various conditions.

Table 1 Prediction accuracy obtained by using machine learning.

Algorithm	Prediction Accuracy	
	Uplink (this study)	**Downlink** [18]
Logistic regression	96%	94%
Neural network	96%	89%
Support vector machine	82%	89%
Decision tree	91%	86%
Nearest neighbors	93%	84%

$G(f)$ because it facilitates the evaluation of systems while keeping the mobile devices isolated. As demonstrated in our study, photonic techniques are effective in measurements of not only microwave-frequency ranges but also lower-frequency ranges. We applied machine learning for binary classification and achieved a prediction accuracy of 96% in BCC uplink channels. The experimental results showed the validity of our proposed method for establishing secure BCC systems.

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