A study on detection of rotary LED transmitter for image sensor communication

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Abstract: This study focuses on a rotary LED transmitter (RLT) for image sensor communication (ISC). RLT is a device that improves the transmission rate by utilizing the afterimages generated by moving the LEDs while blinking. When RLT is used in a real environment, the receiver needs to detect the position of the transmitter and the afterimages of lights on the captured image before data demodulation. This paper proposes a method for detecting the position of RLT and the coordinates of afterimages for ISC using RLT. Experimental results show that the proposed method operates correctly without false detection of them in the range of short distances.

Keywords: visible light communication, image sensor communication, optical camera communication, rotary LED transmitter

Classification: Wireless Communication Technologies

References


1 Introduction

This study focuses on visible light communication using light-emitting diodes (LEDs) as the transmitter and a camera as the receiver (i.e., image sensor communication: ISC) [1]. In ISC, the camera captures LED lights as an image. Because the optical signals and noise can be separated by image processing, ISC has excellent noise immunity [2, 3]. However, the communication speed of ISC depends on the camera shooting speed. Currently, commercial cameras only take several tens of frames per second (fps). When using these cameras as receivers, it is difficult to achieve the sufficient communication speed of ISC.

Fig. 1. Image sensor communication using the rotary LED transmitter.
To solve this problem, we developed a rotary LED transmitter (RLT) (see Fig. 1) [4]. RLT generates afterimages\(^1\) of light by moving the LED light of the transmitting signal while blinking. The receiver can acquire a large amount of data at a time, thus improving the speed of ISC. Thanks to the cylindrical rotation of RLT, we can send information 360° in all directions. We believe that RLT can be attached to devices with rotating mechanisms, such as persistence of vision displays and rotating lights. Although the effectiveness of the communication speed improvement was confirmed by an experiment using RLT in [4], we conducted this experiment assuming that the position of RLT on the image and the coordinates of afterimages were known. In a real environment, the receiver needs to detect the position of RLT and the coordinates of afterimages before data demodulation.

This study proposes a method for detecting the position of RLT and the coordinates of afterimages for ISC using RLT by sending known lighting patterns as a header of data. We evaluate the proposed method by experiments of the ISC using RLT.

2 ISC system model using RLT

Figure 1 shows the system model. The configuration and operation of RLT can be referred to [4]. The transmitter has 9-chip LEDs and changes the blinking pattern every \(\Delta \theta \) [°] of rotation. The data are sent in a packet format composed of a header part and a data part. For the data part, we use ON–OFF keying (OOK) for the modulation of transmitting data. RLT sends data by dividing the range of the rotation angle during one rotation. We define this angular range as \(\alpha \) [°] and set its value to 60° based on the results of [4]. We set the center of \(\alpha\) as 0° and the left end as \(+(\alpha/2 - 1)\) [°] and the right end as \(-\alpha/2\) [°]. All LEDs are lit every \(\alpha\), which is called “border.” In addition, all LED lights are turned off at the \(\pm(\alpha/2 - 1)\) [°] positions to the light of the border from interfering with the data section. Hence, the actual data range is \((\alpha - 3)\) [°] between \(\pm(\alpha/2 - 2)\) [°] positions.

The receiver camera first captures afterimages as an image. Next, the image processing unit detects the position of RLT and extracts the pixel values of the afterimages using the proposed method. Finally, the decoder recovers data based on extracted pixel values.

3 Proposed position and coordinate detection methods for RLT

The proposed method consists of four components: RLT position detection, data range detection, coordinate detection of afterimages, and threshold calculation for recovering signals modulated by OOK. Since RLT changes all the lighting patterns every one rotation, we express the length of the header and data parts as the number of rotations. The header part is divided into three sections. The 1st header is used to detect the RLT position and to calculate the threshold for OOK. The 2nd header is used for data range detection. The 3rd header is used for coordinate detection of afterimages.

\(^1\)This paper uses the term “afterimage” to refer to the afterimage of the LED light.
3.1 RLT position detection
As the 1st header, we send a grid pattern for two rotations by alternately blinking each LED according to odd and even rotation angles. The pattern of the 1st rotation is inverted as the pattern of the 2nd rotation. The receiver captures the header patterns of the 1st rotation and the 2nd rotation as the 1st frame and the 2nd frame, respectively. Here, the frame represents an image captured when the transmitter rotation speed is equal to the camera shooting speed. We create the image that takes the absolute value of the difference between two frames. Next, we binarize the image using a threshold value obtained by applying the discriminant analysis method to the created image and obtain the image with all the LEDs lit at all angles. The receiver uses the created image as the mask image to extract the RLT position.

3.2 Data range detection
In the 2nd header, only the border is lit. The receiver captures this pattern as 3rd frame and detects the data position. Figure 2(a) shows the process flow of the data range detection. Here, $\Delta \theta$ is the angle at which the LED lighting pattern is switched, and the LED light corresponding to $\Delta \theta$ is captured in the received image with a width of several pixels. We adopt labeling processing to detect the border to determine the data range. From the labeled image, we extract the center-of-gravity coordinate of
afterimage of LED\(_n,\theta\) when the LED in row \(n\) rotates from angle \(\theta\) to \((\theta + 1)\). We determine the border using the extracted coordinates. Since the blinking patterns are captured by 180° rotations on the image, more than three borders appear on the image in the data range of \(\alpha = 60°\). The receiver calculates and compares the distances in the image between the extracted borders, and selects the one with the longer border as the data range.

### 3.3 Coordinate detection of afterimages

After detecting the data range, the receiver performs the coordinate detection of the afterimages using the 3rd header. We send the 3rd header in a pattern of 10 rotations with all LEDs lighting up at the same time for every 10° of rotation angle, and each rotation shifts the lighting position by 1°. The receiver captures the 10 rotations of the 3rd header into 10 frames from the 4th frame to the 13th frame. Figure 2(b) shows an example of the lighting pattern of the 4th and 5th frames. By performing the same processing as in Sec. 3.2 on these frames, we can extract all afterimages within the data range.

### 3.4 Threshold calculation for data demodulation

Finally, the receiver calculates the threshold value \(T_{n,\theta}\) using the extracted coordinates of afterimages and the 1st header. We calculate \(T_{n,\theta}\) as \(\frac{l_{F_1,n,\theta} + l_{F_2,n,\theta}}{2}\). Here, \(l_{F_1,n,\theta}\) and \(l_{F_2,n,\theta}\) represent the pixel values of LED\(_n,\theta\) in the 1st and 2nd frames, respectively. The decoder recovers data based on the calculated threshold value and the extracted coordinates.

### 4 Experimental results

We experimentally evaluate the proposed method by measuring the bit error rate (BER) for each communication distance. The components and specifications of the equipment used in the experiment are shown in Fig. 1. We also show some experimental parameters in Fig. 3(a). We generated the data randomly and sent it modulated by OOK. The length of the data part of the packet was set to 60 rotations. Thus, the total number of transmitting data in the data part was 30,780 (= 9 \(\times\) 57 \(\times\) 60) bits. The RLT was set in front of the camera lens. To prevent saturation of the received LED light, an ND8 filter was attached to the camera lens. The experiment was conducted indoors with the lights off. We set the communication distance from 1.0 to 4.0 m and measured the BER every 0.5 m. The focus of the camera lens was adjusted for each distance.

Figure 3(a) shows the BER against the communication distance. As one can see, the proposed method achieved the error-free transmission up to 2.0 m. This means the coordinate detection of afterimages worked correctly. However, the number of errors increases rapidly from 2.5 m, and the BER reaches about 0.5 after 3.0 m. We consider that the cause was the distance on the image between the coordinates of the detected afterimages, and measured the distance \(p_0\) [pixel] between \(\theta\) and \((\theta + 1)\) from the captured image. Figure 3(b) shows the measured \(p_0\) for each distance. In this study, \(\theta\) are 0°, 14°, 28°, and the distances are \(p_0\), \(p_{14}\), \(p_{28}\), respectively. Comparing Fig. 3(b) with Fig. 3(a), we can see that at the longest distance of 2.0 m,
where the error-free transmission was achieved, $p_0$ is 4 pixels, and $p_{14}$ and $p_{28}$ are 2 pixels. At 2.5 m, where errors occur, $p_0$ and $p_{14}$ are 2 pixels and $p_{28}$ is 1 pixel. In the case of the experimental parameters, if $p_0$ is more than 2 pixels, the interfering light from the neighboring LEDs has little effect on the data demodulation. On the other hand, when $p_0$ is less than 1 pixel, the interfering light has a significant impact on the demodulation. These results show that the interference light of the neighboring angle LEDs causes demodulation errors when $p_0$ is less than one pixel even if the coordinates of afterimages can be detected correctly.
5 Conclusion

This study proposed the detection method of the position of RLT and the coordinates of afterimages for ISC using RLT. Experimental results show that the proposed method detects both the position of the transmitter and the coordinates of afterimages correctly, and achieves error-free transmission at short distances. However, with increasing the communication distance, the interference of the afterimages at adjacent angles affects the data demodulation performance even if the coordinates are detected correctly. Our future task is to devise a method for accurate RLT position and coordinate detection while preventing interference between afterimages. Studying the relationship between the border width of RLT, transmission range, and transmission efficiency is also future work.

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Overfitting characteristics of four-layer-deep-neural-network-based nonlinear equalizer for optical communication systems

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Abstract: We compared the characteristics of overfitting in nonlinear equalizers based on a three-layer artificial neural network (ANN) and a four-layer deep neural network (DNN) for nonlinearity compensation in optical-fiber transmission systems. The characteristics were investigated using training data of a pseudo-random bit sequence (PRBS) and a finite-length repeated random sequence, with a varying number of input- and hidden-layer units in the ANN and DNN. The results showed that the DNN-based nonlinear equalizer had stronger overfitting characteristics for both the PRBS and random sequence, compared to the three-layer ANN-based nonlinear equalizer.

Keywords: optical communications, optical nonlinearity, digital signal processing, artificial neural network, deep neural network

Classification: Fiber-Optic Transmission for Communications

References
1 Introduction

Nonlinear equalizers based on artificial neural networks (ANNs) are attracting attention as a novel nonlinear compensation scheme for optical communication systems [1, 2, 3, 4]. Some other nonlinear compensation schemes using digital signal processing (DSP) have been studied, including digital back-propagation (DBP) and the Volterra series transfer function (VSTF) [5, 6]. However, these methods require an enormous amount of calculations, which increases the delay time and power consumption at the receiver. An ANN can potentially improve the computational complexity of the DSP for nonlinear compensation [7]. ANN-based nonlinear equalizers using not only ANNs with three layers but also ANNs with more than three layers, namely, deep neural networks (DNNs), have been investigated [8, 9]. However, a detailed performance comparison between three-layer-ANN-based nonlinear...
equalizers and DNN-based ones has not been carried out. Here, we compare the characteristics of overfitting in these two types of nonlinear equalizers for optical communication systems [10, 11]. In our previous studies, we investigated the overfitting characteristics using training data of pseudorandom bit sequences (PRBSs) and a finite-length repeated random sequence, with a varying number of input- and hidden-layer units in the ANN and DNN [12]. We previously proposed a comparison scheme based on the criterion of computational complexity [13]. In this paper, additionally, we investigated the overfitting characteristics using a repeated random sequence with a varying number of multiplications in the nonlinear equalizer. The results showed that the DNN-based nonlinear equalizer had stronger overfitting characteristics.

2 Overfitting of ANN- and DNN-based nonlinear equalizers

Figures 1(a) and (b) respectively show the constructions of the three-layer-ANN- and four-layer-DNN-based nonlinear equalizers for optical nonlinearity compensation. The received data sequence is fed to the input layers of the ANN and DNN through feedforward tapped delay lines. The tap length, \( L \), is the same as the number of input-layer units. The output of each unit is described as

\[
y = f\left(\sum_k w_k x_k + b\right),
\]

where \( x_k \) is the input from the \( k \)-th unit, \( w_k \) is the weight, \( b \) is the bias, and \( f \) is the activation function of the unit. The input-layer units and output-layer units have linear activation functions. The hidden-layer units have sigmoid activation functions. Here, we assumed that the two hidden layers of the DNN have the same number of units. We calculate the computational complexity of the equalizers by the number of multiplications in the ANN and DNN:

\[
M_{\text{ANN}} = L \times S_{\text{hidden}} + S_{\text{hidden}},
\]

Fig. 1. ANN- and DNN-based nonlinear equalizers and system setup for overfitting evaluation.
\[ M_{\text{DNN}} = L \times S_{\text{hidden1}} + S_{\text{hidden1}} \times S_{\text{hidden2}} + S_{\text{hidden2}}. \]  

(3)

where \( L \) is the number of delay taps, \( S_{\text{hidden}} \) is the number of hidden-layer units in the ANN, and \( S_{\text{hidden1}} \) and \( S_{\text{hidden2}} \) are the numbers of units in the first and second hidden layers in the DNN. We neglected the calculations of the activation functions of the units, assuming that lookup tables are employed.

When PRBS is used as training data for the ANN- or DNN-based nonlinear equalizer, overfitting possibly occurs depending on the construction of the equalizer [10, 11]. PRBS is commonly used to evaluate the performance of optical communication systems in numerical simulations and experiments. The PRBS generator is composed of a shift register and some exclusive-OR (XOR) circuits, which are expressed by a primitive polynomial. The length of the PRBS is expressed as \( 2^M - 1 \), where \( M \) is the order of the PRBS. When \( M = 7 \), the primitive polynomial is described as

\[ B_{\text{PRBS7}} = x^7 + x^6 + 1. \]  

(4)

In the condition of overfitting, the shift register and the XOR circuits of the PRBS generator are imitated by a tapped delay line and the ANN of the nonlinear equalizer, respectively. In this condition, the ANN-based nonlinear equalizer can predict the incoming data sequence. Consequently, the performance of the nonlinear equalizer is overestimated. Furthermore, it is known that a similar kind of overfitting possibly occurs even when a finite-length repeated random sequence is used as the training data [10].

3 System setup for overfitting evaluation

Figure 1(c) shows the system setup employed to evaluate the overfitting; this setup had been used in the previous studies [10, 11, 12, 13]. A binary signal was generated using PRBS \( 2^7 - 1 \) data or a repeated random sequence with a finite length of \( 2^7 - 1 \). The repeated random sequence was generated by a Mersenne Twister (MT). White Gaussian noise (WGN) was added to it so that the signal-to-noise ratio (SNR) became 4 dB. Here, we do not need to include any nonlinear component in the setup, because we evaluate only the overfitting characteristics. The nonlinear equalizers were trained using a least mean squares (LMS) algorithm, to attempt to “compensate” for the noise. We did not employ batch or mini-batch techniques. The learning rate was 0.005. We did not use a preprocessing method, data augmentation, or initialization method to evaluate the overfitting characteristics in the simple condition. We did not use any overfitting avoidance techniques for both the ANN and DNN to ensure a fair comparison. The signal quality was evaluated using the error vector magnitude (EVM).

4 Results and discussion

First, we evaluated the overfitting with PRBS7. Figures 2(a) and (b) show the EVM characteristics after the ANN- and DNN-based nonlinear equalizers, respectively. The EVM values were plotted while varying the tap length and the number of units per hidden layer in the equalizers. We plotted the average of ten training trials, changing the initial values of the weights and biases of the ANN and DNN with the same
conditions. The error bars represent the standard deviation. In the case of the ANN, the equalizer started to predict the pattern of PRBS7 when the number of hidden-layer units was larger than or equal to 3 and the number of taps was larger than or equal to 13, resulting in overestimation of the EVM performance, as shown in Fig. 2(a). In the case of the DNN, overfitting also occurred when the number of taps was larger than or equal to 13. However, the required number of units per hidden layer was as small as 2. Figures 2(c) and (d) show the EVM versus the number of units per hidden layer in the ANN and DNN, respectively. When the number of taps was smaller than 13, large overfitting was not observed even when we increased the number of units per hidden layer in both the ANN and DNN. However, when the number of taps was 13, overfitting occurred with 3 units per hidden layer in the case of the ANN and with 2 units in the case of the DNN. Here, it should be noted that the DNN-based nonlinear equalizer showed stronger overfitting characteristics, having lower EVM values.

Next, we evaluated the overfitting with a repeated random sequence. Figures 2(e) and (f) show the EVM characteristics versus the number of taps in the ANN and DNN-based nonlinear equalizers with a repeated random sequence. Here again, the DNN showed stronger overfitting characteristics than the ANN. However, the DNN had twice as many total hidden-layer units as the ANN, because the DNN had two hidden layers. Therefore, we employed the criterion of computational complexity of
We compared the overfitting characteristics between the ANN and DNN based on the required number of multiplications expressed by Eqs. (2) and (3). Figures 3(a) and (b) respectively show the EVM characteristics after the ANN- and DNN-based nonlinear equalizers when PRBS7 was used as the data sequence. Figures 3(c) and (d) respectively show the EVM characteristics of the ANN and DNN when the repeated random sequence was employed. In these comparisons, the DNN showed stronger overfitting characteristics than the ANN as well. When the tap length and the number of hidden-layer units is increased, the equalization capability of the ANN- and DNN-based nonlinear equalizers is improved [14]. However, this makes the ANN and DNN more prone to overfitting. In particular, it should be noted that the DNN-based nonlinear equalizer showed stronger overfitting characteristics than the ANN.

5 Conclusions

We compared overfitting characteristics between three-layer-ANN- and four-layer-DNN-based nonlinear equalizers for optical communication systems. The DNN-based nonlinear equalizer had stronger overfitting characteristics for both PRBS and a repeated random sequence. Next, we will attempt to compare the nonlinear equalization performance. The comparison should be performed on the balance of the merits and drawbacks of the equalization capability and the overfitting characteristics. The study reported in this paper is an important step towards achieving this goal.

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User data selection using CNN-feature extractor for fingerprint localization

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Abstract: This paper examines a method for fingerprint indoor localization that employs CNN. CNN is trained using AP information. The estimation accuracy of CNN improves as the number of AP information increases. However, gathering AP information is expensive. The problem can be solved using UD (User Data). The UD is unlabeled data because the measuring method does not know the exact location of the user. As a result, we can perform semi-supervised learning with the estimation result as the correct label. In this paper, we propose a method for selecting UD using a CNN-feature extractor.

Keywords: fingerprint, indoor localization, CNN, semi-supervised learning

Classification: Navigation, Guidance and Control Systems

References


1 Introduction
The importance of location information has recently grown. Navigation systems based on mobile devices such as smartphones have become increasingly popular. Because the satellite signal is blocked, the GPS method cannot estimate the exact location in indoor facilities.

As an indoor location estimation method, fingerprint localization based on RSSI (Received Signal Strength Indicator) of Wi-Fi has been proposed. Machine Learning methods, particularly CNN, are used to fingerprint localization with high accuracy [1, 2, 3]. CNN is trained using AP information with correct labels. The AP information consists of the AP identifier and RSSI of the observed AP at the map coordinates. In general, the more training data with correct labels is used for machine learning, the higher the estimation accuracy. However, measuring a large amount of AP information with correct labels is expensive. The problem can be solved using UD (AP information users measured) [4]. The UD is unlabeled data because the UD measuring method does not know the exact location of the user. We use semi-supervised learning with estimated UD result as the correct label. The estimated result, however, may be incorrect. As a result, it is necessary to select UD that is estimated correctly and use it for CNN training. In this study, we propose a UD selection method for CNN training, and the effect is demonstrated using data collected in a building.

2 Fingerprint localization
2.1 Indoor fingerprint localization using CNN
This section describes the use of CNN for indoor fingerprint localization. CNN is primarily used to classify images. First, the coordinates in the location estimation area are arbitrarily set. The coordinates are referred to as preset coordinates from now on. The following step is to measure the AP information, also known as preset-AP information. The AP information measured at the preset coordinates is referred to as the preset-AP information. Then, using preset information, input images for CNN are generated. The observed AP is first arranged on a 2D image. To create the input image, the RSSI values obtained from the AP are treated as pixel values. The image that is created is used as training data for CNN [5]. When performing the indoor localization, a user’s terminal measures AP information as UD (User Data) and feeds the resulting image to CNN. The number of neurons in CNN’s output layer is equal to the number of preset coordinates in this study. The final layer, which employs the Softmax function, returns the user’s existence probability for each coordinate. Finally, the coordinate with the greatest probability is chosen as the estimated result.

2.2 Semi-supervised learning using UD
The more preset-AP information measured in a CNN-based localization method, the better the estimation accuracy. However, measuring a large amount of preset-AP information is expensive. On the other hand, if there are enough navigation system users, it is possible to collect a large amount of UD. To estimate the user’s location, a CNN trained with the preset-AP information is used. The estimated
result is assumed to be the correct UD label and UD can be used to train CNN. Using both preset-AP information and the UD, the proposed method can perform semi-supervised learning. Semi-supervised learning is a training method that uses both labeled and unlabeled data. However, the labels assumed for the UD could be incorrect. As a result, if all the UD are used, the estimation accuracy of the CNN may not be improved. At the preset coordinate, the preset-AP information is measured. UD, on the other hand, is measured at any point where the user is present. As a result, if the user is far from the preset coordinates, the estimated results are more likely to be incorrect.

As a result, it is critical to select UD that is correctly estimated. The chosen UD is used for semi-supervised learning. Semi-supervised learning with the chosen UD is referred to as UD-learning from now on.

3 UD selection for semi-supervised learning

3.1 Feature value extracted from CNN

CNN is employed in order to extract the feature value of input images. The trained CNN is fed an image. As the feature value of the input image, the output values of each neuron in the middle layer are extracted. If the feature values of the two input images are similar, they are close [6]. UD is chosen in a proposed scheme if the feature values of UD and preset-AP information are close.

Figure 1(a) depicts the CNN configuration used in this study. The output values in the middle layer before the output layer of the CNN were used as feature values of the input image to select the UD.

3.2 UD selection using CNN-feature extractor

The UD closest to the preset coordinates should be added to the CNN’s training data. In contrast, if the measured position is significantly different from the estimated coordinates, the UD should not be included in the training data. The feature value extracted from the preset-AP information is similar to the feature value of the UD measured near the preset coordinate. The feature value of the UD measured away from the preset coordinates, on the other hand, is different.

First, as described in Section 2.1, preset-AP information is measured. CNN is trained using images generated from the preset-AP information. Following the training of CNN, the feature values are extracted from all of the training data. The extracted feature values of all preset coordinates are then gathered as illustrated in Fig. 1(b), and the average value is used as the feature value for each preset coordinate.

The location estimation for the UD using CNN selects a coordinate. At that point, the UD feature value is extracted from CNN. The feature value of UD is then compared to the preset coordinate selected by location estimation, as shown in Fig. 1(c). If the two feature values are similar, the UD is used as CNN training data. In [7], Euclidean distance was used to calculate the similarity between two feature values, as shown in Eq. (1). The feature values are x and y, and the Euclidean distance is d. The smaller the Euclidean distance value, the closer the two feature values are. In this study, Cosine similarity is also used to calculate the similarity, as shown in Eq. (2), as shown in Eq. (2). As Cosine similarity approaches one, the two feature values are more
Fig. 1. Method of UD selection

\[
\begin{align*}
    d(x, y) &= \sqrt{(x_1 - y_1)^2 + \cdots + (x_n - y_n)^2} \\
    \cos(x, y) &= \frac{x \cdot y}{\|x\|\|y\|}
\end{align*}
\]  

(1) 

(2)

3.3 Verification of UD-learning

In the verification environment as shown in Fig. 2, UD-learning was implemented. TensorFlow is used to implement this verification and the estimation result is slightly altered because initial values of CNN’s weights are determined randomly. As a result, this verification was carried out ten times with the average value of each estimation result shown below.
Figure 3(a) depicts the average error with respect to the Euclidean distance and Cosine similarity thresholds. The CNN trained solely with preset-AP information is depicted as “only preset” in Fig. 3(a). As shown in Fig. 3(a), UD-learning improves estimation accuracy over “only preset.” In this verification, the average error was 1.74m when the Euclidean distance threshold was set to 6.5. Furthermore, the average error was 1.69 m when the Cosine similarity threshold was set to 0.95. As a result, using Cosine similarity to select UD is slightly better than using Euclidean distance. The number of chosen UD increases as the threshold of Euclidean distance is set larger or that of Cosine similarity is smaller. However, the average error value is not significantly lower than only preset. The reason for this is most likely that by setting a high threshold, many UD far from the preset coordinates are used for UD-learning.

Figure 3(b) depicts the CDF of the estimation error for the test data with a Euclidean distance threshold of 6.5 and a threshold of Cosine similarity set to 0.95. Fig. 3(b) shows that the estimation error of UD-learning is smaller than “only preset”. Furthermore, UD-learning estimation accuracy using Cosine similarity is slightly better than using Euclidean distance. The effectiveness of the proposed UD selection method based on Euclidean distance or Cosine similarity was confirmed by these experimental results. Furthermore, as shown in Fig. 3, Cosine similarity outperforms Euclidean distance.

### 4 Conclusion

The more preset-AP information measured in fingerprint localization using CNN, the better the estimation accuracy. However, measuring a large amount of preset-AP information is expensive. We proposed a method for selecting UD for semi-supervised learning using an extracted feature value from CNN in this study. The similarity of feature values between preset-AP information and UD was calculated.
Fig. 3. Verification result using Euclidean distance and Cosine similarity. UD-learning can improve estimation accuracy more than CNN trained solely with preset-AP information. Furthermore, based on these experimental results, we confirmed that using Cosine similarity is superior to using Euclidean distance in UD selection.

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Effectiveness of simulation data on walking in Wi-Fi fingerprints using RNN

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Abstract: This study focuses on Wi-Fi fingerprint localization using RNN. Walking survey is a method used for collecting fingerprint datasets. This method can collect continuous walking data while the measurer is walking. However, multiple walking patterns must be measured to accommodate users with different walking speeds and routes. We propose a method for generating simulation data with different walking patterns. The simulation data were created using the coordinate adjacency of the measurement data. Further, we evaluated the model trained with and without the simulation data. Results demonstrate that the accuracy of the proposed method shows its effectiveness.

Keywords: Wi-Fi, localization, fingerprint, RNN

Classification: Navigation, Guidance and Control Systems

References


1 Introduction

This study focuses on localization using a fingerprint-based Wi-Fi received signal strength indicator (RSSI). Wi-Fi fingerprints can use existing Wi-Fi access points (APs) and allow localization without knowing the location of those APs. RSSI values are temporally correlated because users move with certain ranges of speeds. Previous studies [1, 2] confirmed improvements in localization performance by learning its temporal characteristics with recurrent neural network (RNN). However, users move
with various speeds and paths. The patterns in previous studies have been restricted because measuring all the walking patterns is difficult.

We consider various walking patterns of users in localization using an RNN. Here, a tradeoff exists between the number of walking patterns and measurement cost (time). Therefore, we propose generating simulation data with various walking patterns using the adjacency of observation positions (reference coordinates). We aim to reduce the cost and improve the localization performance by training the RNN using the simulation data. The experimental results show the effectiveness of the proposal.

2 Conventional method

The Wi-Fi fingerprinting method is an indoor localization method, which comprises two phases: offline training and online testing. In offline training, a machine learning-based model is trained from the sets of RSSI and its reference coordinate (fingerprinting dataset) is collected in advance. In an online test, the RSSI values are collected in real-time and its location is estimated using the trained model. Point-by-point and walking survey [1] are two methods for collecting fingerprinting data.

In the point-by-point, the RSSI values are measured for a specified number of times at each reference coordinate to obtain static fingerprints. In the walking survey, the measurer specifies the route to move and collects time-series RSSI while walking along the route. Position information between two points cannot be obtained because this method measures by determining only the start and endpoints. Thus, we can obtain the information by calculating the walking speed as a constant speed.

Our proposal can create simulation data for the datasets of both methods. However, the walking survey method is similar to the radio environment received when the user is walking. Thus, we used the walking survey method in this experiment.

As mentioned above, the walking survey has the advantage of obtaining time-series data. However, measuring walking patterns comprising all possible walking speeds and paths is challenging because increasing the number of walking patterns requires a longer measurement time. Thus, we address this problem by generating simulation data that simulates user walking.

3 Methodology

This chapter describes the proposal of generating the simulation data and RNN model for learning time-series data.

3.1 Generating simulation data

We propose a method for generating simulation data with different walking patterns from data measured with a limited number of walking patterns. The following steps describe the process of creating the simulation data (Fig. 1):

(A) Conversion to Static Fingerprint

Extract static fingerprints obtained at each time from the time-series fingerprints, which are collected using walking survey (Fig. 1 (a)), and obtain the point-by-point datasets. However, the reference coordinates are converted from the start
Fig. 1. Generating simulation data

and end time of the measurement as if the measurer was walking at a constant speed.

(B) Generating Simulation Data

(B1) Select P0 (Selected Coordinate) from the list of static fingerprints. Find \( n \) (\( n \geq 0 \)) neighbor coordinates P1 within a predefined distance from P0 (Fig. 1 (b)). Further, we can obtain \( n \) time-series coordinate data, which consist only of coordinates with the series length of two by combining P0 and P1; perform this process for all coordinates.

(B2) Calculate the vector \( \text{Vec}_{P0 \rightarrow P1} \) from P0 to P1 (Fig. 1 (b)).

(B3) Find neighbor coordinates P2 of P1 and the vector \( \text{Vec}_{P1 \rightarrow P2} \) from P1 to P2.

(B4) Calculate the difference vector \( V_d = \text{Vec}_{P0 \rightarrow P1} - \text{Vec}_{P1 \rightarrow P2} \) and combine only the coordinates where \( |V_d| \) is below a certain value among P2 with time-series coordinate data (Fig. 1 (c)). Set the newly merged coordinate to the selected coordinate.

This process generates data where users do not walk irregularly but move at a constant speed.

(B5) With the number of timesteps \( T \), (B2)–(B4) are repeated \( (T - 2) \) times to create the time-series coordinate data of lengths \( T \). The time-series RSSI data are created by combining the RSSI values observed at each coordinate in the time-series coordinate data that have been created.

As described above, we can expect to improve the performance for unknown walking patterns by creating the simulation data as described above. However, performance may be reduced by different movement directions of the data to be combined because there is an effect of shielding by the human body. We will experimentally confirm effectiveness of the simulation data, including this negative influence.
In the following, the data before simulation data is generated is called the original data.

3.2 RNN-based method

3.2.1 Applying RNN

To study time-series data, we use RNN and long short-term memory (LSTM) as estimation methods. LSTM is introduced to solve the gradient vanishing problem of RNN [3].

We preprocess data, making it suitable for training the model. First, considering that the range of the RSSI values is $-100$ to $0$ dBm, we set the missing Wi-Fi signals to $-100$ dBm. Further, we use min–max normalization to normalize RSSI values from zero to one.

3.2.2 RNN structure

The input data of RNN is $\text{RSSI}_{t_x + T}$ from $t = t_x$ to $t = t_x + T$, and the output is the value of the coordinate $e_{t_x + T}$ at $t = t_x + T$. Here, the number of timesteps $T$ determines series length from $t_x$ to $t_x + T$, and the greater the $T$ value, the more information from the past can be incorporated. Further, we employed a stacked RNN structure, which comprises multiple RNN layers. Stacked RNN structures allow deeper structures to be created using the RNN’s hidden state as input to another RNN [4]. The loss function uses MSE, which comprises the error distance between the estimated coordinate $\hat{e}_t$ and correct coordinate $e_t$.

4 Experiments

In this chapter, we conducted several experiments to confirm the effectiveness of the simulation data.

4.1 Data collection

We measured time-series fingerprints in a building hallway while walking holding a device in hand (Fig. 2). Further, we measured the training data by making four round-trips of three straight lines at a constant speed (= approx. 1 m/s) on both sides (Fig. 2 (a)). For the test data, we measured not only the walking pattern of the training data but also different walking patterns, such as clockwise or zigzagging (Fig. 2 (b)), and increased the speed to approx. 1.5 m/s. The difference between these walking patterns is that the effectiveness of the simulation data is experimentally confirmed. The coordinates of the measured training and test data were 837 and

![Fig. 2. Measurement environment](image-url)
130, respectively. The number of APs observed in all coordinates was 147, which were used for model training.

Further, we generated the simulation data with an arbitrary length $T$ from the measured data. The distance that defines neighbor coordinates described in Section 3.1 was set to approximately 3 m. This distance was calculated as $1.5 \text{ m/s} \times 2 \text{ s} = 3 \text{ m}$, considering that the maximum speed of users is approximately 1.5 m/s and the reception interval of the device is approximately 2 s. The number of samples of the original and simulation data obtained from 837 points was 789 and 76651 samples, respectively, at $T = 3$. Note that the original data were obtained by slicing the measured time-series fingerprints by specified timesteps.

4.2 Performance of our proposed algorithm

We built each RNN (LSTM) model-trained simulation and original data. Further, we varied the number of RNN layers and timesteps $T$ from one to two and three to five, respectively, and examined the estimation performance on the test data. We compared the highest performance at each $T$ using average and maximum errors as evaluation indicators.

The model’s performance using the simulation data improves at each $T$ for the average and maximum errors (Fig. 3 (a)). Further, the model’s performance using the simulation data improves as $T$ value increases, whereas the performance of the model using the original data decreases. This may be because of the differences in walking patterns, particularly the walking speed, between the training and test data.

Next, we experimented with different conditions to determine the effects of

![Comparison of the original and simulation model](image-url)
different walking speeds. The test data were classified into two types of walking speeds, which are normal (approximately 1 m/s) and fast (approximately 1.5 m/s), and we evaluated four models. The four models are two RNN and two LSTM models, which were evaluated using the original and simulation data. Each model is the one at the highest performance obtained in the above experiment.

Figures 3 (b) and (c) show the CDF of localization errors for normal and fast speeds, respectively. Figure 3 (b) shows that the RNN model trained with the original data has the highest performance for the test data with normal. This is because there is no difference in speed between the training and test data. However, Fig. 3 (c) shows that the two models using the simulation data provide higher performance for the fast speed. These results show that the model using the simulation data provided high performance even for data with walking patterns that were not measured.

5 Conclusion
This study proposed methods for generating simulation data that simulate the changes in Wi-Fi signals caused by various users’ walking for fingerprint localization using RNN. Simulation data were created with different walking patterns by processing the measured data using the adjacency of the reference coordinates, thereby reducing the measurement cost. By training the RNN model using the simulation data, we obtained a high performance for the test data with various walking patterns.

Acknowledgments
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Model-based software design of a large-scale Butler matrix beamformer for hybrid 5G subsystems

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Abstract: With 4G networks reaching their practical limits due to the ever-increasing demand for seamless connectivity, it has been clear that 5G is the future of communications. Millimetre-waves (mmWaves) is considered as a way forward with momentous research being carried out to provide cost-effective and easy-to-implement solutions, which can increase the data rate, provide low latency, and reliable radio connection. Inspired by this, a Butler matrix (BM) structure was considered in this work, due to its potential role in implementing large-scale beamforming networks (BFNs) for 5G systems. This would facilitate their deployment in both practical and analytical hybrid beamforming scenarios. Thus, a system-level model of large-scale BMs was realised in software to demonstrate its integrated structures and outputs. The proposed model can be significantly instrumental in the design of large-scale and hybrid wireless infrastructures at both sub-6 GHz and mmWave bands.

Keywords: BFN, Butler matrix, hybrid modelling, large-scale subsystem

Classification: Wireless Communication Technologies

References

1 Introduction

According to the new Cisco Annual Internet Report that provides a global forecast of digital transformation across various business segments, there will be 5.3 billion total Internet users (66% of the global population) by 2023 [1]. This increase in traffic is in part due to the ever-increasing use of ‘data-hungry devices’, including mobile phones, laptops, and other smart devices. Considering this growing demand for high-quality mobile or multimedia applications, a paradigm shift through 5G is envisaged as the way forward, to effectively realise future communications [1, 2]. Moreover, due to the scarcity of frequencies available for mobile/wireless systems, mmWave bands were proved to be a viable substitute, especially within the 20 to 90 GHz range, to increase channel bandwidth, thus, resulting in higher throughput and data rates. The utilisation of these mmWaves as a possible solution has been predicted to achieve a tremendous capacity increase in comparison to current LTE networks [2]. However, using mmWaves proved to be more complex compared to currently deployed frequency bands, due to higher propagation losses, i.e., is a key factor in determining insertion loss (IL) of a device; with IL being defined as loss measured between a given source and receiver in dB. From this initial analysis, it quickly became clear that using these bands with current infrastructure could not provide needed low latency and high enough data rates. Consequently, the existing communication infrastructure was deemed not suitable and required to be updated [3]. As a result of reduced wavelengths at mmWave frequencies, antenna systems can have smaller physical dimensions compared to radio devices and subsystems used at current standards. This allows for beamforming (i.e., the concentration of power in a thin beam in a certain direction to increase signal power and to suppress interference) to be utilised as a possible solution to mitigate higher path loss and absorption at higher frequency bands. At these frequencies, systems can harbour a larger number of radiating elements, thus allowing beamforming arrays to play a vital part in the practical implementation of 5G. This would also provide a higher directive gain that improves signal-to-interference ratio (SIR), thus, increasing the capacity of the network. Also, levels of interference are reduced in the propagation environment, due to the provision of narrow beams, and the increasing possibility of sustaining adequate power in rural areas at the receiver terminal [3]. Therefore, to ensure optimal system-level design using numerical and simulation techniques, mainly in terms of implementation complexity, component count, and other figures
of merit, the proposed large-scale BM was thoroughly developed. This structure can be significantly advantageous to the area of hybrid wireless design. It can be incorporated into core transceiver architectures and construct a suitable platform for the accurate assessment of real-world scenarios based on wireless beamforming. The proposed software-based model can reproduce integrated BFN front-ends, and exhibit output characteristics for system modelling and performance evaluation.

2 Array beamforming techniques

Amplitude and phase are two primary variables used for beamforming processing, being able to be applied in both analogue and digital baseband frameworks. Their crucial properties can be simultaneously utilised in hybrid beamforming, in which a switched-beam microwave-digital system enables the beam to adapt and alter per channel and propagation conditions [4]. Hence, generated patterns through BFNs can be adaptively interchanged from one beam to another, depending on the user’s location, to efficiently realise cost-effective solutions for 5G systems. Thus, due to excessive cost and complex deployment of digital infrastructures at sub-6 GHz and mmWaves, core system design based on BFN was considered, to not only propose a new standalone theoretical BM-BFN structure, but to substantially facilitate the potential realisation of large-scale and hybrid multibeam front-ends [5]. Within analogue beamforming techniques, there are mainly two network types, lens-based devices and circuit-based systems [6]. This work was conducted based on the latter, in which networks are made by using various interconnected circuit components, including transmission lines (TLs), hybrid couplers; such as branch-line couplers (BLCs); splitters, and phase shifters (PSs); i.e., to provide a predefined phase shift to signal. Lengths of TLs are used to obtain phase shifts required to generate beam steering, while splitter ratios are used to regulate constant amplitude distributions [5, 6]. Also, BM has been established as one of the most commonly used BFNs in modern wireless communications [5]. A conventional BM typically is a symmetric $N \times N$ network, with $N$ being a power of two in most implementations. This matrix is made up of TL, BLC, and PS components, with $N$ input (i.e., beam) and $N$ output (i.e., array) ports. A BLC can produce two signals that are 90° out of phase at array outputs with the same amplitude. The signal can be equally divided with varying phases into $N$ outputs, by exciting each input beam port one by one, to dynamically perform beam scanning [4, 5, 6]. Also, BM, as the feeding of an array, generates $N$ orthogonally spaced beams and provides desired input voltage standing wave ratio (VSWR) and beam port isolation, to ensure high-performance operation required for next-generation communications. Moreover, there has been considerable works reported on hardware aspects of microwave BM-BFNs, which has been thoroughly reviewed in [5]. However, there have been a few works focusing on the analytical and system-level aspects of BMs. Thus, inspired by seminal papers given in [7, 8], this work reports on the first software-based development of a 32-element BM.

3 Design and modelling of a large-scale 32 × 32 BM-BFN

The proposed 32-element BM structure was systematically modelled in MATLAB and Simulink, based on conventional BM equations (i.e., not provided for sake of
Fig. 1. Zoomable model-based MATLAB/Simulink design of the proposed large-scale BM-BFN for hybrid 5G multibeam communication subsystems: (a) complete implementation of the $32 \times 32$ BFN with $p = 5$, BLCs = 80, and PSs = 64; (b) a segment of the developed structure in (a), comprising its constituent components and interconnections; i.e., ports, BLCs, and PSs, to facilitate its software reproducibility.
Fig. 2. Output characteristics of the proposed 32 × 32 BM-BFN, in terms of normalised AF plots (i.e., the main figure of merit) for 5G electronic beam steering applications.

This module was comprised of three subsystems, including switch, BFN, and post-processing units, with the latter containing magnitude, phase, and array factor (AF) elements. Figure 1 presents a developed BM model, thoroughly depicting its internal network of constituent system components and interconnections across the central BFN subsystem unit in the proposed hybrid communication framework. The post-processing unit transformed complex signals generated by this BFN unit into their corresponding magnitude and angle values. These resultant phase values (i.e., converted to degrees) were then passed to the AF submodule where they were stored and sent to MATLAB, to generate output characteristics of the large-scale model, in terms of normalised narrow-beam patterns; depicted in Fig. 2. These AF plots also aided to validate the correct operation of BM structures according to key figures of merit and to validate the performance of the software-based BM design. Besides, the overall purpose of the switch unit was to send a random signal to each of the beam ports in the BFN unit, one by one, to fully excite each port individually; hence, generating required phase differences. When implementing this 32-element unit, it was important to calculate the number of constituent components needed in each N-by-N iteration. BLCs were also implemented in $p$ rows and $N/2$ BLCs per row. It should be noted that the large-scale BM-BFN was originally scaled up from conventional 4-element BM and its associated equations applicable to upscaling of the designed network. As one of the key building blocks of this subsystem, BLCs were effectively utilised in conjunction with PSs according to calculated and given values in Fig. 1, to provide predefined phase shifts to signals across the front-end. Within switching units, several blocks were essential to the consistent operation of BM. The switches were designed to output discrete-time sequences (i.e., repeated over a set duration) and to control generated outputs being fed to the BFN as inputs.
4 Conclusion

Model-based software design and implementation of a large-scale BM-BFN was thoroughly conducted in this work. This subsystem was able to effectively control phase and amplitude at each element of the array front-end and to generate narrow-beam patterns, to fully realise electronic beam steering for 5G hybrid beamforming applications. This investigation was the first of its kind in terms of software-based development of a large-scale BM-BFN, and as interdisciplinary research, it was conducted based on different elements from the broad areas of software systems, microwave technology, and 5G communications. Outputs based on the key figures of merit (i.e., circuit layout and patterns) were provided, to validate the operation and deployability of the model. This is of crucial importance for initial evaluations of this complex structure before its physical implementation. Lastly, a zoomable vector figure, given below, will enable its reproducibility and will enable its design enhancements by providing all circuit, connection, and component details, which can also be realised in other software environments (e.g., full-wave EM simulators).
Interference-free AP identification and shared information reduction for tabular Q-learning-based WLAN coordinated spatial reuse

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Abstract: Access point (AP) coordinated spatial reuse with Q-learning enables efficient spectrum utilization [1]. Although sharing of transmission schedules among APs is necessary for coordination, there is no mechanism to identify the APs with which the schedules are to be shared, resulting in excess information being shared among APs. In this study, we propose a scheme to identify the interference-free APs that are not required for sharing of information by comparing Q-values. A simple simulation demonstrates that this scheme successfully reduces shared information without throughput degradation.

Keywords: WLAN, coordinated spatial reuse, reinforcement learning, dimensionality reduction

Classification: Wireless Communication Technologies

References


1 Introduction

With the widespread prevalence of wireless local area networks (WLANs), there is increasing competition for the limited transmission opportunities. To identify the factors responsible for frame loss under the situation, in our previous study, we focused on the application of access point (AP) coordination for spatial reuse [1]. In the proposed framework, APs share their transmission schedules beforehand (e.g., via backhaul links). By utilizing the transmission schedules and transmission results, the AP can identify the factors responsible for frame losses, specifically, the interference from other transmitters or low received-signal power. Depending on these factors, the AP determines its own transmission schedules and transmission data rate using Q-learning. As a result, high spectrum efficiency is achieved.

However, since the APs do not know which APs the transmission schedules should be shared with, the APs may unnecessarily share the schedules with all surrounding APs. If the shared schedules contain information that is redundant for AP coordination, the traffic for information sharing is needlessly large, which should be avoided for efficient operation of coordinated spatial reuse. This problem was not discussed in [1].

To solve this problem, we propose a method to reduce the amount of shared information. In this method, we focus on the fact that the transmissions from interference-free APs have almost no impact on the Q-values. This method identifies the interference-free APs by examining the Q-table and subsequently stops sharing the transmission schedules with those APs. As a result, the traffic for information sharing is reduced.

2 System model

The system model is almost the same as in our previous study [1], i.e., there are coordinated \( N + 1 \) basic service sets (BSSs) and each of them consists of an AP and a station (STA) with only downlink traffic. Note that this assumption can be easily extended to multi-STA scenarios. The BSSs perform coordinated time-division resource assignment in the same frequency band in periods for multi-AP coordination, which is under discussion for the IEEE 802.11be standard [2]. In this study, the unit of resource assignment is called a slot. Each BSS is numbered from \( n = 0, 1, \ldots, N \), and the AP and STA in the BSS \( n \) are named AP \( n \) and STA \( n \), respectively. The other APs randomly decide in advance whether or not to transmit for each slot and share the transmission schedules with AP 0. Note that we only consider slots for multi-AP coordination and the details have been discussed in [1].

AP 0 determines whether to transmit a frame as well as the transmission data rate (i.e., a modulation and coding scheme (MCS) index), according to the information on the transmission schedules of the other APs.
3 Determination of transmission timing by reinforcement learning

This section describes how AP 0 determines its transmission schedule and data rate. In this scheme, the agent uses Q-learning to decide its action as in [1]. At each learning step, AP 0 observes a state that is determined by whether each surrounding AP is going to transmit or not. The state space is given as follows:

$$S := S_1 \times S_2 \times \cdots \times S_N, \quad S_i := \{0, 1\}, \ i \in N := \{1, \ldots, N\}. \quad (1)$$

Here, $S_i$ represents the set of each AP’s condition. The state is set to be zero if the AP is going to transmit; otherwise, the state is set to be one. It is assumed that the conditions of APs are shared via backhaul link.

The agent decides whether or not to transmit; if so, it selects an MCS index. The action space of AP 0 is given as follows:

$$\mathcal{A} := \{0\} \cup M,$$

where $M := \{1, \ldots, M\}$ denotes a set of MCS indices and 0 denotes an action of not transmitting a frame. The respective number denotes which MCS index AP 0 selects when transmitting a frame, and $M$ represents the number of the MCS indices.

If AP 0 successfully transmits a frame at $x$ Mbit/slot, the agent receives a reward of $x$. Otherwise, the agent is given a negative reward of $-1$ for a frame loss. Owing to this penalty, the agent attempts to avoid collisions with other transmissions. The agent selects actions by the $\epsilon$-greedy method.

4 Shared information reduction

Because the observation of state (1) requires exhaustive information sharing, this section describes how to reduce the volume of transmission schedules to be shared with other APs. This reduction is achieved by avoiding redundant information sharing with some of the APs.

The agent identifies the APs that can be excluded from the information sharing by examining the values of the Q-table during the learning process as follows. After some learning, the agent extracts the parts of the Q-table for a state with only one 1 in the state vector, for example, $s = (0, \ldots, 0, 1), (0, \ldots, 1, 0), \ldots, (1, 0, \ldots, 0)$. Here, we define $s_i$ as the vector whose $i$th element is 1 and the others are 0 ($i \in N_i$). Among them, the agent focuses on the states whose Q-values are close to the values of $s_0 := (0, 0, \ldots, 0)$. The fact that the Q-values are close for $s_0$ and $s_i$ implies that the transmissions of AP $i$ have almost no impact on the communication of AP 0. Because the information from these APs is not necessary for efficient management, the agent can ask these APs to stop sharing information and reduce the number of dimensions of the state space.

In this study, AP 0 stops sharing information with AP $i$ upon satisfying the following inequality:

$$\frac{|Q(s_i, a) - Q(s_0, a)|}{Q(s_0, a)} \leq \beta, \ \forall a \in \mathcal{A}, \quad (3)$$

where $Q(s, a), s \in S$ and $a \in \mathcal{A}$, denotes the Q-value, and $\beta \geq 0$ denotes a parameter. Then, we redefine $S$ by removing $S_i$ from (1). As a result, this method can reduce
the shared information that AP 0 has to receive. In addition, the size of Q-table can be reduced by decreasing the dimensionality of the state space. This results in faster learning and less data storage.

To comply with reduced state space, the Q-table is downsized by repeatedly averaging over the axis. First, if \( i \) satisfies (3), the Q-table is reduced by the following operation:

\[
Q(s_{\text{after}}, a) := \frac{1}{2} (Q(s_{\text{before} 0}, a) + Q(s_{\text{before} 1}, a)) \quad \forall a \in \mathcal{A},
\]

where \( s_{\text{before} 0} \) and \( s_{\text{before} 1} \) denote the states before the reduction. They are defined as follows:

\[
s_{\text{before} 0} := (e_1, e_2, \ldots, e_{i-1}, 0, e_{i+1}, \ldots, e_{N-1})
\]

\[
s_{\text{before} 1} := (e_1, e_2, \ldots, e_{i-1}, 1, e_{i+1}, \ldots, e_{N-1}) \quad e_f \in \{0, 1\}, \quad j \in \mathcal{N}_i \setminus \{i\},
\]

where \( s_{\text{after}} \) denotes the state after the reduction and is represented as follows:

\[
s_{\text{after}} := (e_1, e_2, \ldots, e_{i-1}, e_{i+1}, \ldots, e_{N-1}) \quad e_j \in \{0, 1\}, \quad j \in \mathcal{N}_i \setminus \{i\}.
\]

Note that \( s_{\text{after}} \) has one less dimension than \( s_{\text{before} 0} \) and \( s_{\text{before} 1} \). By repeating the same operation, the size of Q-table is reduced in size. If information sharing with \( n \) APs is stopped, the size of the Q-table is reduced by a factor of \( 2^n \).

5 Evaluation

To facilitate understanding, we simplify the relationship between the transmission data rate and the distance between APs. A set of MCS indices is denoted as \( \mathcal{M} = \{1, 2, 3\} \), where 1, 2, and 3 denote transmissions at 1, 2, and 3 Mbit/slot. The distances between APs are assumed to be of four levels: 1, 2, 3, and “no interference”. Distance \( d \) is the distance at which transmission fails at a transmission rate of \( d \) Mbit/slot or higher when the other AP is transmitting. Additionally, “no interference” means that these communications have no effect on each other. The distance between AP 0 and the surrounding six APs (i.e., \( N = 6 \)) are shown in Table I.

**Table I.** Setting of distance of APs and the result of interference-free AP identification; values below \( \beta \) are shown in bold, meaning they were identified as interference-free APs.

<table>
<thead>
<tr>
<th>Index of APs</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance from AP 0</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>(Interfering)</td>
<td>(Interference-free)</td>
<td></td>
</tr>
<tr>
<td>At 100,000th slot LHS in (3)</td>
<td>1.5</td>
<td>1.3</td>
<td>1.3</td>
<td>0.0007</td>
<td>0.0009</td>
<td>0.0002</td>
</tr>
<tr>
<td>Decision</td>
<td>Interfering</td>
<td>Interference-free</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We compare the proposed scheme with the following two baselines. **W/o reduction scheme** continues to share transmission schedules from all APs forever. This
scheme does not reduce the shared information. *W/o sharing scheme* does not share the transmission schedules with other APs. This scheme corresponds to the case of not sharing transmission schedules. As in the proposed scheme, this scheme uses Q-learning with \( \epsilon \)-greedy action selection rules.

**Fig. 1.** Maximum value of LHS in (3) of AP 0 for all actions.

Figure 1 shows the maximum values of LHS in (3) of AP 0 for all actions. We can see that the values for \( s_4, s_5, \) and \( s_6 \) converge to zero. In this evaluation, identification of interference-free APs and consequent shared information reduction are conducted at 100,000th slot with \( \beta = 1/3 \). As summarized in Table I, from six APs, three interference-free APs 4, 5, and 6 are successfully identified. Thus, the amount of information-shared APs and the shared information are reduced by half.

**Fig. 2.** Learning curves of the proposed and comparison schemes for the throughput. Proposed scheme reduces shared information at 100,000th slot.
information reduction, we can see that there is no performance gap between the proposed scheme and w/o reduction scheme, thus the proposed scheme does not reduce the throughput. Note that how much the shared information can be reduced depends on radio environment and BSS density. According to Fig. 2, the throughput of w/o sharing scheme is lower than that of the other two schemes. This indicates that the information sharing with surrounding APs contributes to the improvement of the throughput.

6 Conclusion

We successfully identified the interference-free APs. By excluding these APs, this method can achieve a reduction in the shared information for coordinated spatial reuse.

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Asymmetric autoencoder for PAPR reduction of OFDM signals

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Abstract: Orthogonal frequency division multiplexing (OFDM) signals have a high peak-to-average power ratio (PAPR). Although a method using an autoencoder for PAPR reduction has been proposed, it requires a huge amount of computation for both the transmitter and the receiver. In this paper, we propose a method to reduce the computational complexity of the autoencoder. The proposed method is called an asymmetric autoencoder and is an extension of the conventional method. Numerical experiments show that the proposed method can reduce the computational complexity of the receiver.

Keywords: OFDM, deep learning, autoencoder, PAPR, PRNet

Classification: Wireless Communication Technologies

References


1 Introduction

Because of its high frequency-utilization efficiency, orthogonal frequency division multiplexing (OFDM) has been widely adopted for wireless local area network (LAN) and mobile communications that require high-speed and high-capacity transmission. Although OFDM has many distinctive features, its high peak-to-average
power ratio (PAPR) is considered its main drawback. The high PAPR causes the OFDM system to suffer in-band distortion and out-of-band radiation. One of general PAPR reduction methods is clipping and filtering, where the amplitude of the signal is limited to a certain value (clipping) and then the high-frequency components are removed by a filter [1]. However, careful clipping is necessary to suppress deterioration of the bit error rate (BER) because the orthogonality of the signal is not retained. Selective mapping (SLM), which randomly rotates the phase of data symbols, does not cause error-rate degradation but is computationally expensive [2].

Substantial advances in the field of deep learning have been reported in recent years, and a method to use this technology for PAPR reduction has been proposed [3]. In reference [3], the researchers proposed an autoencoder that inputs the transmitting information bit and outputs a transmitting data symbol with a low PAPR. However, the autoencoder is symmetric and the encoder in the transmitter and the decoder in the receiver each have five fully connected layers, resulting a huge amount of computation at both the transmitter and the receiver.

In the present paper, we propose an asymmetric autoencoder as an extension of the conventional autoencoder for PAPR reduction. In the proposed method, either the transmitter or the receiver will bear a huge computational load but the load of the other will be reduced. We conduct numerical experiments to evaluate this system.

2 Proposed system

2.1 System overview

Figure 1(a) shows a block diagram of the proposed system for PAPR reduction of the OFDM signals. AE-ENC and AE-DEC in the figure denote the encoder and the decoder of the autoencoder, respectively. At the transmitter, the $QK$ transmitted data bits are mapped to the $K$-dimensional complex data symbol vector $\mathbf{d} = [d_0, \ldots, d_{K-1}]^T$ with a $2^Q$-QAM modulator\(^1\). The data symbol $\mathbf{d}$ is transformed to $\mathbf{d}'$ by the AE-ENC, and $N$-point IFFT ($N = \lceil \log_2 K \rceil$) generates an OFDM symbol $\mathbf{s}$ from $\mathbf{d}'$.

At the receiver, the received symbol is input into the FFT and the AE-DEC generates $\hat{\mathbf{d}}$ from the output of the FFT. Finally, $\hat{\mathbf{d}}$ is demapped into $QK$ received bits by a $2^Q$-QAM demodulator.

2.2 Asymmetric autoencoder

The structures of the AE-ENC and AE-DEC are shown in Fig. 1(b). The proposed system has the same structure as the conventional one except that the encoder and the decoder are not the same size. FC in this figure denotes a fully connected layer, and the input and output of each layer can be expressed as follows:

$$y^f_i = \phi^f_i((W^f_i x^f_i + b^f_i)_{\text{norm}}),$$

$$y^g_i = \phi^g_i((W^g_i x^g_i + b^g_i)_{\text{norm}})$$

where superscripts $f$ and $g$ of all variables indicate the layered neural networks labeled AE-ENC and AE-DEC in Fig. 1(b), respectively (these superscripts are

\(^1\)It is a QPSK if $Q = 2$.\n
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Fig. 1. Proposed system.

omitted in the following equations). \( \mathbf{x}_l = [\ldots, x_{l,i}, \ldots]^T \), \( \mathbf{y}_l = [\ldots, y_{l,i}, \ldots]^T \), \( \mathbf{W}_l \), and \( \mathbf{b}_l = [\ldots, b_{l,i}, \ldots]^T \) are the input, output, weights, and bias of the \( l \)-th layer \((l = 1, \ldots, L)\), and \( L \) is the number of layers. Because the first layers of the AE-ENC and AE-DEC are fed with a \( K \)-dimensional complex vector, the size of the vector \( x_1 \) is \( 2K \) and \( (x_{1,i}, x_{1,i+k}) = (\text{Re}(d_i), \text{Im}(d_i)) \), where \( d_i \) is the \( i \)-th element of the complex vector. Similarly, the size of the vector \( y_L \) at the final layer is \( 2K \) and the \( i \)-th element of the complex vector at the output side of the AE-ENC and AE-DEC is constructed as, for example, \( y_{L,i} + j y_{L,i+k} \), where \( j \) is an imaginary unit. The number of neurons in each layer is \( U \) except in the final layer.

If the encoder and/or the decoder has only one layer \((L = 1)\), then the dimension of both the input and output of the layer is \( 2K \) (As an example, a one-layer decoder is depicted in the lower-right corner of Fig. 1(b)). The model also includes no nonlinear output function such as Eq.(3) defined later; thus, this model is just a simple linear transformation.

\[
\phi_l(u) = [\ldots, \phi_l(u_i), \ldots]^T, \text{ called ‘relu,’ is the output function of the } l \text{-th layer and is defined as follows:}
\]

\[
\phi_l(u) = \begin{cases} 
  u & (u > 0) \\
  0 & (u \leq 0) 
\end{cases} \quad (l < L). \tag{3}
\]

The output function of the final layer is defined as

\[
\phi_L(u) = u. \tag{4}
\]
(x)_{norm} refers to the batch normalization mathematically expressed as

\[(x)_{norm} = \gamma \frac{x - E[x]}{\sqrt{Var[x]} + \nu} + \beta \quad (5)\]

where \(\gamma\) and \(\beta\) are a scaling and shift factor, respectively, \(\nu\) is a small positive constant that prevents division by zero, and \(E[\cdot]\) and \(Var[\cdot]\) are the expectation and variance, respectively. Note that the batch normalization is performed at the time of learning only.

### 2.3 Learning

The learning of the proposed system is performed as follows. First, we generate \(M\) data symbols randomly. The \(m\)-th data symbol \(d_m = [\ldots, d_{m,i}, \ldots]^T\) \((m = 1, \ldots, M)\) is passed through the AE-ENC, and then the IFFT generates an OFDM symbol \(s_m = [\ldots, s_{m,n}, \ldots]^T\).

After a certain amount of noise is superimposed on \(s_m\), it is passed through the FFT and AE-DEC to obtain the output \(\hat{d}_m = [\ldots, \hat{d}_{m,i}, \ldots]^T\). Finally, the loss function of the following equation is considered, and the total weights and bias are updated by back-propagation based on the stochastic gradient descent (SGD) method.

\[L_1 = \frac{1}{2K} \sum_m ||d_m - \hat{d}_m||^2. \quad (6)\]

Let us refer to the aforementioned training as Phase I. In this phase, the model grows into a system with a low BER.

After the loss function \(L_1\) is sufficiently reduced, the PAPR calculation defined by the following equation is introduced into the training:

\[\text{PAPR} = 10 \log_{10} \frac{\max_{0 \leq n < N} \{s_{m,n}^2\}}{E[s_{m,n}^2]} \quad (7)\]

The loss function defined as the following equation is considered, and the total weights and bias are updated by the SGD.

\[L_2 = L_1 + \lambda \text{PAPR} \quad (8)\]

where \(\lambda\) is a parameter for balancing the BER and PAPR performance. This learning is referred to as Phase II and is carried out after Phase I. In this phase, the model grows into a system that allows the generation of signals with low BER and low PAPR.

### 3 Performance evaluation

#### 3.1 Performance

We conducted numerical experiments to evaluate the performance of the proposed method.

First, the experimental conditions were as follows: QPSK modulation was used, the OFDM duration \(T_s\) was 3.2\(\mu\)s, the guard interval \(T_g\) was \(T_s/4\), \(K = 52\), and \(N = 64\). The oversampling rate used to evaluate the PAPR was 4.
autoencoder. \( U = 1,024 \) \(^2\), \( M \) was 500,000, the size of the mini-batch was 400, and Phases I and II were both set to 1000 epochs.

We set \( \lambda \) to 0.01 and measured the BER and PAPR in models with \((L^f, L^g) = (1, 9), (3, 7), (5, 5), (7, 3), \) and \((9, 1)\). Here, the encoder of \((1, 9)\) and the decoder of \((9, 1)\) are a simple linear transformation.

Figure 2(a) and (b) show the experimental results of the BER and the PAPR. The black line in the figures shows the performance of the original OFDM signal, where \( p + q \) represents a model with \((L^f, L^g) = (p, q)\); thus, \(5 + 5\) refers to the conventional method. The figures show that the BER of the model \(9 + 1\) is saturated where \(Eb/N_0\) is large, but its level is less than \(10^{-4}\). In addition, where \(Eb/N_0\) is small, the performance of the \(9 + 1\) is the most similar to that of the original OFDM. However, with the other models, including the model \(5 + 5\), the BER performances

\[^2\]The researchers in [3] set \( U \) to 2,048; however, in [4], we confirmed that \( U = 1,024 \) is sufficient.
Table I. Number of multiplications of each method.

<table>
<thead>
<tr>
<th></th>
<th>5 + 5</th>
<th>9 + 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>encoder, decoder</td>
<td>$2KU \times 2 + 3U^2$</td>
<td>$2KU \times 2 + 7U^2$</td>
</tr>
<tr>
<td>$(K, U) = (52, 1024)$</td>
<td>3,358,720 (100%)</td>
<td>7,553,024 (225%)</td>
</tr>
</tbody>
</table>

are considerably worse than that of the original OFDM.

The PAPR of the proposed method, with the exception of that of the model $9 + 1$, is substantially improved. However, the model $9 + 1$ also improves the PAPR by more than 5 dB compared with the original OFDM.

Next, we measured the BER and PAPR for each model using $(L^f, L^g) = (1, 9), (2, 8), \ldots, (9, 1)$ for $\lambda$ of 0.001, 0.01, and 0.02. Figure 2(d), (e) and (f) show the $E_b/N_0$ such that the BER is $10^{-3}$ and the PAPR such that the CCDF (Complementary Cumulative Distribution Function) is $10^{-3}$. The figures show that all the proposed methods have the same or better PAPR performance as the original OFDM.

In the case of $\lambda = 0.001$, the models $8 + 2$ and $9 + 1$ demonstrate the same performance as the original OFDM; however, the other models are worse with respect to the BER although the PAPR is improved. In the case of $\lambda = 0.01$, the model $9 + 1$ demonstrates the best performance among the investigated models, as indicated by it exhibiting the same BER and better PAPR performance than the original OFDM. By contrast, the other models show an inferior BER. In the case of $\lambda = 0.02$, the BERs of all the models are worse than that of the original OFDM.

Finally, we compared the BER of the models $9 + 1$ and $5 + 5$ in a multipath fading channel for which the conditions are described in [5]. The results are shown in Fig. 2(c). The figure shows that the model $9 + 1$ demonstrates superior performance compared with the model $5 + 5$.

### 3.2 Computational complexity

Lastly, we compare the computational complexity of the models $5 + 5$ and $9 + 1$. The decoder of the model $9 + 1$ is a one layer and it has an input of $2K$ and output of $2K$; thus, the number of multiplications is $2K \times 2K$ (see the lower-right corner of Fig. 1(b)). For the encoders ($5 + 5$ and $9 + 1$) and the decoder ($5 + 5$), the number of multiplications of the first, middle and final layer are $2K \times U$, $U \times U$, and $U \times 2K$, respectively.

The computational complexity of the models $5 + 5$ and $9 + 1$, which is based on the aforementioned estimations, is shown in Table I. The complexity of the encoder of the proposed method is 2.3 times that of the conventional symmetric method ($5 + 5$). However, that of the decoder is only 0.32%. Thus, the proposed method is suitable for the downlink of a mobile communication system with severe battery constraints at the mobile station.

### 4 Conclusion

In this paper, we proposed an asymmetric autoencoder, which is a natural extension of the conventional autoencoder for PAPR reduction. The experimental results show that the model with a 9-layer encoder and a 1-layer decoder is superior to the
conventional symmetric autoencoder; that is, compared with the original OFDM, it can improve the PAPR by 5 dB. The complexity of the encoder is more than twice that of the conventional method; however, the decoder complexity is drastically reduced to only 0.3%. Thus, the proposed method is suitable for the downlink of a mobile communication system.
Reactive route construction for UAV delivery considering travel time and safety using wireless multi-hop network

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Abstract: For the automatic operation of UAV delivery, a route construction method using smart meter radio devices has been studied. We could construct a delivery route that avoids densely populated areas and prevents excessive travel distance based on AODV. However, it is necessary to guarantee arrival time in the delivery service. We propose a route construction method that optimally evaluates traveling time and safety (Proposed Method 1). When multiple UAVs are constructing routes, there are risks of collision between the UAVs due to the use of the same node or links. We propose two methods to construct a route without using the same node and the same link, respectively (Proposed Method 2). The proposed method and the conventional method are evaluated by computer simulation.

Keywords: wireless multi-hop network, UAV delivery, ad-hoc network

Classification: Navigation, Guidance and Control Systems

References

1 Introduction

Recently, radio devices known as “Smart Next Generation Electricity Meters” [1] have been installed in each home in Japan. These radio devices use an energy-efficient multi-hop radio (920 MHz) network.

We considered that the smart meter network could be used for a route navigation service basis using wireless multi-hop network in addition to the information transfer. As service examples, we suppose route navigation in the home delivery service by Unmanned Aerial Vehicle (UAV).

Conventional mobile ad hoc network (MANET) routing protocols include the reactive Ad hoc On-Demand Distance Vector (AODV) [2] and the proactive Optimized Link State Routing (OSLR) [3]. However, conventional routing protocols do not provide optimal routes for UAV home delivery which requires safer and shorter routes.

For safer navigation, it is desirable to avoid high density populated areas in order to avoid damage to people and houses due to UAV possibly crashing. As a result, a two layered network model has been adopted; a network of nodes in a scattered residential area (relay node), which is a safer navigation route (relay network), and an access network of nodes in a densely populated area. An overview of the network topology is presented in Fig. 1. Because no single delivery route is reused within a short period time for home delivery purposes, we investigated our routing protocol based on AODV which is a masterpiece of the reactive type, that creates a routing table on demand.

We propose an optimal route construction method for UAV home delivery that is safe and reduces the travel time of UAV.

2 Related works

2.1 AODV-based route construction [1, 4, 5]

At first, information about the densely populated or the scattered residential area is set in all nodes. A parameter counting the distance of the route that a UAV takes is added to Route Request (RREQ) header of AODV. The node which receives RREQ
adds the distance in the passage area counter of RREQ. At the same time, the node records and sends the best RREQ from equation (1). The destination node transmits Route Reply (RREP) through the best route. This is how a route avoiding densely populated area is established.

\[ R = \min\{\alpha \times \text{Densely} + \beta \times \text{Total}, \text{Total} = \text{Densely} + \text{Scatter} \]  

Here, \( R \) is the optimal route, \( \alpha \) is a factor to avoid densely populated areas in route evaluation from the viewpoint of safety, \( \beta \) is a factor to shorten the total distance, \( \text{Densely} \) is the distance of the route that a UAV takes and is included in a densely populated area, \( \text{Scatter} \) is the distance of the route that a UAV takes and is included in a scattered residential area and \( \text{Total} \) is the total distance of the route.

2.2 Issue

We did not know if the routes were constructed to meet the requirement of delivery time. Therefore, we propose to change the evaluation criterion from distance to time that balances high safety with short delivery time.

3 Proposed method 1

We propose the fastest route selection method in consideration of safety. The speed of the UAV heading to the densely populated area \( v_1 \) and heading to the scattered residential area \( v_2 \) are set in all nodes. A node that receives an RREQ via multiple routes chooses, records and sends the optimal RREQ from equation (2).

By weighting for the travel time of each node and taking the minimum value, both the safety and the time perspectives are comprehensively determined.

\[ R = \min\{\alpha \times \frac{\text{Densely}}{v_1} + \beta \times \left( \frac{\text{Densely}}{v_1} + \frac{\text{Scatter}}{v_2} \right) \} \]  

3.1 Evaluation

We created a simulator using Excel VBA, and compared the total time, total distance (\( \text{Total} \)), and distance travelling through the densely populated area (\( \text{Densely} \)). We compared three methods, the shortest physical distance without considering safety (Shortest distance method), the method of previous studies (Conventional method), and the Proposed method 1. Conventional method is the one whose optimal route evaluation formula is based on equation (1). Figure 2 (A) shows the simulation environment model, the nodes are randomly placed. The area of the simulation experiment is 1,800m \( \times \) 1,800m for one cell and 5,400m \( \times \) 5,400m for 9 cells. The source and destination are arbitrarily selected from the nodes placed in the scattered residential areas. Fig. 2 (B) shows the experiments conditions. The speed of \( v_1 \) and \( v_2 \) are set to 10m/s and 30m/s, respectively.

3.2 Evaluation results

Figure 2 (C) shows \( \text{Total}, \text{Densely}, \) and Total time. Compared with Shortest distance method, both Conventional method and Proposed method 1 construct the route avoiding the densely populated area. Both Conventional method and Proposed method 1 have a longer total distance but shorter total travelling time. However, there is no difference between Conventional method and Proposed method 1.
3.3 Consideration
We established a method of route construction based on the evaluation of optimality in the time axis. We could reflect that the speed in the safe scattered residential areas would be high and the dangerous densely populated areas would be low. In the optimality evaluation function, the $\alpha$ and $\beta$ coefficients were added to the safety evaluation function, and the difference in speed was added to the evaluation function, making it a more safety-oriented evaluation function.

The reason why there is no difference between Conventional method and Proposed method 1 is because both methods take the minimum value.

3.4 Issue
When multiple UA Vs are constructing routes, there are risks of collision between the UA Vs due to the use of the same node or links. We propose two methods to construct a route without using the same node and the same link, respectively.

4 Proposed method 2
We propose a route construction method (node-lock) that prevents multiple UA Vs from using the same node. A node usage flag is added to each node information,
and the flag is initially set to “0”. When a route is established, the nodes in the route are set to be in use, the flag is set to “1”.

We propose another method in which each node checks its own routing table and does not send an RREQ to a node that has already sent RREQ. Each node checks its own routing table and does not receive RREQ from a node that has already received RREQ (link-lock).

4.1 Evaluation
We created a simulator using Excel VBA, and examined the conventional method, the node-lock method, and the link-lock method by changing the number of UAVs requesting routes using the equation (1). The number of times the same node was used (collisions), the probability of route constructing failure are measured. We also measured the probability of constructing a route including a densely populate area and $Densely$ are measured. The simulation environment model and experiments conditions are same as the Sect. 3.1.

4.2 Evaluation results
In Fig. 3 (A) left shows the number of UAVs requesting a route using the same node, for the conventional method, node-lock method and link-lock method. The number of times the same node is used for multiple UAVs route increases as the number of UAVs increases. The node-lock method constructed routes without using the same node, but compared to the other methods, route construction tends to fail as the number of UAVs increases as shown in right figure. Compared to the node-lock method, the link-lock method does not fail in route construction, and the number of times the same node is used is reduced. In the conventional method, the route construction never fails because it does not have lock control method.

Figure 3 (B) show the results by the order of route requests. In the node-lock method, the later the route request order is, the more routes are created that include the densely populated areas, and $Densely$ tends to increase. In the link-lock method, the probability that an established route includes densely populated area and the $Densely$ are lower than node-lock method.

4.3 Consideration
With node-lock method, the node is occupied by first UAV route and other UAVs cannot use it. Therefore, node-lock method can be used depend on the number of nodes. On the other hand, link-lock method provides fewer failures in route construction, and superior safety than node-lock method. However, when the number of UAVs is small, node-lock method is safer. So, the methods should be used properly according to the number of UAVs.

All methods failed to construct a route for the first UAV. This was due to the random placement of nodes, which placed them in positions where communication was not possible. Since smart meters are always placed in positions where multi-hop communication is possible, the node placement in the simulation experiments needs to be revised.
5 Conclusion

We proposed a route construction method that considers travel time and safety in the proposed method 1. It is necessary to arrange the weighting $\alpha$ and $\beta$ according to the delivery service requirement.

We confirmed the effectiveness of both nodes-lock and link-lock in the proposed method 2. We defined collision as routes overlapped on a node, but since links itself cross each other, we consider more about the risk.

Acknowledgments

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Proactive route construction for UAV delivery considering distance and safety using wireless multi-hop network

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Abstract: A method of constructing a route using “Smart meter” radio devices has been studied for the automatic operation of home delivery by small Unmanned Aerial Vehicle (UAV). Each smart meter node was given information about its own densely populated or scattered residential area, the source node should construct a delivery route to the destination node to avoid the densely populated area. In this study, we adopt OLSR-based route construction because the smart meter network is stable. We propose a method using Dijkstra’s method, which uses the distance between nodes and the density of nodes as costs for selecting the optimal route. The effectiveness and characteristics of the proposed method are evaluated by computer simulation.

Keywords: wireless multi-hop network, UAV delivery, OLSR

Classification: Navigation, Guidance and Control Systems

References


1 Introduction

Recently, radio devices known as “Smart Next Generation Electricity Meters” have been installed in each home in Japan. These radio devices use an energy-efficient multi-hop radio (920 MHz) network. RPL [1] is used in smart meter networks to transfer electricity usage information.

We considered that the smart meter network could be used for a route navigation service basis using wireless multi-hop network in addition to the electricity usage information transfer. As service examples, we suppose route navigation in the home delivery service by Unmanned Aerial Vehicle (UAV) [2].

RPL is the protocol that forwards information from each node to the concentrator. We need other routing protocols to build communication routes between nodes. Conventional mobile ad hoc network routing protocols include the reactive AODV [3] and the proactive OLSR [4]. However, conventional routing protocols do not provide optimal routes for UAV home delivery which requires safer and shorter routes.

For safer navigation, it is desirable to avoid high density populated areas in order to avoid damage to people and houses due to UAV possibly crashing. As a result, a two layered network model has been adopted; a network of nodes in a scattered residential area (relay node), which is a safer navigation route (relay network), and an access network of nodes in a densely populated area. An overview of the network topology is presented in Fig. 1 (B).

Smart meter network is a stable ad hoc network with no node movement and few deletions and additions of smart meters. Therefore, in this research, we establish a routing method based on the proactive OLSR.

![Fig. 1. UAV navigation network based on multi-hop wireless networks.](image-url)
2 Related works

2.1 UAV navigation in avoidance from no-fly zone
A new UAV navigation with considering the no-fly zone and efficient selection of the charging station are proposed [5]. It considered only avoidance of no-fly zones for safety, and the architecture is centrally managed by the UAV traffic control center, which has problems with scalability in terms of area and number of nodes scale. It is necessary to consider dangerous and safe areas within the area where UAVs can fly, and an autonomous decentralized network approach is needed.

2.2 AODV-based UAV route construction
We established the method constructing UAV route based on AODV, which is a typical example of reactive type [2]. First, all nodes are given information about the area, “scattered residential area” where UAV can move safely, or “densely populated area” where is dangerous. The source node sends a RouteRequest (RREQ) to the destination node in order to create a routing table. The destination node receives the RREQ via multiple routes and sends a RouteReply (RREP) to the route that minimizes the number of hops in the densely populated area [2].

2.3 OLSR
HELLO message serves to advertise its own existence and to exchange information about neighboring nodes, and it sends its own address to neighboring nodes. By sending and receiving multiple messages, it obtains and updates the information of neighboring nodes, which is called local link information.

Topology Control (TC) message serves to advertise topology information to the entire network. It is periodically sent based on local link information.

2.4 Dijkstra method
Dijkstra method [6] is one of the shortest paths finding algorithms, which can determine the route to minimize the cost between specific nodes based on the link cost between nodes.

3 Proposed method
In conventional OLSR, the route is selected based on the number of hops, which is not optimal for home delivery. We propose to use the Dijkstra method to construct a route that consider the distance traveled by the UAV. In addition, we introduce the weight of safety between links to the distance. We propose a route construction method that can establish a safe route with a short travel distance. The basic part of this method, the flow of sending and receiving messages and route generation, is based on the conventional OLSR.

3.1 Information sharing between nodes
We propose method that each node exchanges whether it is in a densely populated area or a scattered residential area, the distance between neighboring nodes by HELLO message. We add the information to the HELLO message header to the sender’s district information corresponding to the neighboring interface address (Fig. 2 (A)).
In the TC message, the distance between nodes will be advertised, so that to share distance between nodes corresponding to the TC message sender. The area information and the neighbor main address are also added in TC message header to be advertised (Fig. 2 (B)).

### 3.2 Weighting for link cost

We refer to the conventional method that determines the route based on the number of hops as “OLSR” and the Dijkstra method with distance as the cost (“Dijkstra method”). The proposed method (“Weighted Dijkstra method”) weights the distances based on the safety level between links in the shortest path search of the Dijkstra method. The weighting pattern is changed according to the link states of four moving area: from the densely populated area (A) to the densely populated area (A-A), from the scattered residential area (B) to the densely populated area (B-A), (A-B) and (B-B).

Each method has its own weighting pattern (Fig. 2 (C)). Since the Dijkstra method does not consider safety, only the distance traveled is used as the link cost for the shortest path search. In the “Weighted Dijkstra method”, links to densely populated area (A-A, B-A) are weighted by 3.0, and links to scattered residential area (A-B, B-B) are weighted by 0.6. With this weighting, the safest route is given priority.

![Fig. 2](image-url)  
(A) Proposed method HELLO message  
(B) Proposed method TC message  
(C) Patterns of weighting

**Fig. 2.** Message headers and weighting of proposed method.

### 4 Evaluation

We compare the distance between source node and destination node (Total distance) by the conventional “OLSR”, “Dijkstra method”, and “Weighted Dijkstra method”, and the distance over the densely populated area (Densely distance), to see if we...
can construct a safe and short route. The results were compared with AODV-based methods in previous studies.

4.1 Evaluation methods
In order to experiment with a model close to the real environment, a simulation was created using NS-3. The radio was simulated with wifi802.11b, which can be used with NS-3 instead of 920MHz specific power-saving radio. The communication distance is 120m. The nodes are arranged in 9 cells (3×3), and the densely populated area is placed in the center. The cells outside the center are scattered residential area (Fig. 1). In this paper, we assume a small town with a population of thousands and a cell size of 333m×333m. A cluster consists of approximately 100 houses, with one node per cluster having a relay function. The number of nodes in each cell is randomly arranged with 50 nodes in densely populated area and 20 nodes in scattered residential area, and the source and destination nodes are selected that are sufficiently far apart. Since the experiment assumes a “Smart meter” network, nodes are not moved, added, or deleted. The weighting used is the same as in Table 1. The experiment is repeated 10 times.

As Experiment 1, the source and destination are selected from the scattered residential area nodes so that it is verified whether a route that bypasses the densely populated area can be constructed. As Experiment 2, the source and destination are selected from the nodes in the densely populated area, and it is verified whether a safe route can be selected even it is long distance.

4.2 Evaluation results
4.2.1 Experiment 1
Fig. 3 (A) show the results of the total distance and the distance over the densely populated area for the three methods. It can be confirmed that the total distance of the “Weighted Dijkstra method” is about 20.3% higher than that of the conventional “OLSR” method. The distance over the densely populated area improved by about 98.3%. As a result of constructing a route that avoided the densely populated area nodes, navigation in the danger zone was significantly reduced, although the total distance increased.

The reason why the improvement rate of the “Weighted Dijkstra method” did not reach 100% is because there were cases in which the total distance increased significantly when the densely populated areas were avoided.

The total distance was 2,070 for the AODV-based method, while the proposed method was able to shorten it to 1,326.8. The densely distance was 10 for the AODV-based method, while the proposed method performed slightly better at 7.4.

4.2.2 Experiment 2
The results of Experiment 2 are shown in Fig. 3 (B). In the “Weighted Dijkstra method”, we were able to construct a route that leaves the densely populated area once and goes through the scattered residential area. As a result, the total distance increased, but the distance over the densely populated area improved by about 67%.
Although it is possible to reach the nodes in the densely populated area in a short distance, it is considered dangerous to proceed through the densely populated area by weighting.

The total distance was 511 for the AODV-based method, but 950.4 for the proposed method, which is longer. The densely distance was 224.5 for the AODV-based method and 143.6 for the proposed method, showing good performance.

![Fig. 3. Experiment results.](image)

5 Conclusion

We proposed a route construction method that considers the safety and physical distance of UAV. From the experiments, it is confirmed that the safety is improved by calculating the route using Dijkstra method and safety weighting the link cost.

As future issues, we will verify the characteristics of the method by examining differences in size such as large cities and regional cities.

Acknowledgments

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Secrecy rate optimization for ISAC-UAV system via joint trajectory and power control

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Abstract: This letter investigates a secrecy rate maximum optimization problem of unmanned aerial vehicle (UAV) system with integrated sensing and communication (ISAC) function. To ensure the security of the ISAC-UAV system, we formulate a joint UAV trajectory and transmit power optimization problem to maximize the secrecy rate under the constraints of mobility restrictions, power budgets and sensing requirement. The block coordinate descent (BCD) method is employed to divide the original problem into two sub-problems. Then, the non-convex sub-problems are transformed to convex by the appropriate constraints relaxation and fractional programming method. Eventually, the simulation results verify the effectiveness of our proposed algorithm and demonstrate the trade-off performance between the secrecy and sensing.

Keywords: integrated sensing and communication (ISAC), unmanned aerial vehicle (UAV), secrecy rate, joint trajectory and power optimization

Classification: Wireless Communication Technologies

References
1 Introduction

Recently, unmanned aerial vehicle (UAV) has attracted a great deal of research interests because of the flexible deployment and dominant line-of-sight (LoS) air-ground channel. The UAV can be leveraged as aerial sensing platforms to collect information on the ground as well as provide high-performance wireless communications [1]. Fortunately, the functionality of integrated sensing and communication (ISAC) system can perfectly match the UAV’s task, which motivates the researchers to develop ISAC-UAV system. However, the security of the information is overlooked in the current works on ISAC-UAV, which is important to ensure that the illegal receivers are blocked from the communication information.

In traditional UAV systems, the communication security can be guaranteed by optimizing the power allocation or the UAV’s trajectory [2]. Moreover, the work in [3] proposed to enhance the security by jointly optimizing the trajectory and power allocation of the UAV, whose performance outperforms the trajectory or power optimization method in both UAV-to-ground and ground-to-UAV cases. However, this approach is inapplicable for ISAC-UAV system. When the eavesdropper (Eve) is close to the sensing filed interested (FI), there is a performance trade-off between sensing and secrecy rate. Specifically, the better sensing performance is achieved when the UAV fly closer to the FI (Eve), but the more information will be leaked. Therefore, security design problem in the ISAC-UAV is quite different from the traditional joint trajectory and power optimization problem for providing communication service only.

To fill the aforementioned research gap, we consider a ISAC-UAV system simultaneously senses the FI and communicates with the information receiver (IR) on the ground, while guaranteeing the information security under threat of the Eve around the FI. We formulate an average secrecy rate maximum problem with respect to trajectory and power, under the constraints of mobility restrictions, power budgets and sensing requirement. To solve the non-convex problem, we apply block coordinate descent (BCD) method to divide the original problem into two sub-problems. Then, the fractional programming (FP) method and Taylor expansion are employed to transform the sub-problem into convex. Finally, the simulation results verify the effectiveness of our proposed iterative algorithm and demonstrate there is a trade-off between the performance of secrecy and sensing.

2 System model and problem formulation

2.1 Signal model

We consider a ISAC-UAV system where a UAV base station flies at a fixed altitude of $H$ above ground. The UAV transmits information to the IR and senses the FI on the ground, at the presence of a potential Eve. Without loss of generality, we consider a three-dimensional (3D) Cartesian coordinate system, where the IR, FI and Eve are located at $(x_B, y_B, 0)$, $(x_R, y_R, 0)$ and $(x_E, y_E, 0)$, respectively.

The UAV flies from the initial location $A(x_0, y_0, H)$ to the final location $B(x_F, y_F, H)$ within a given finite flight period $T$ seconds. For convenience, we divide the period $T$ into $N$ time slots with equal length, $T = N d_t$. Furthermore, we chose a sufficiently small value of $d_t$, the channels between the UAV and ground notes can
be regarded as unchanged within each time slot. As a result, the UAV’s horizontal coordinate in time slot \( n \) can be denoted as \((x[n], y[n])\) (next, we use \([n]\) denotes the time slot \( n \)). The maximum flying distance in each slot is \( D = Vd_t \) with the maximize speed of \( V \). Therefore, the mobility constraints of the UAV should be satisfied as

\[
\|w[1] - w_0\| \leq D, \quad \|w_F - w[N]\| \leq D, \\
\|w[n + 1] - w[n]\| \leq D, \quad n = 1, \ldots, N - 1,
\]

(1)

where \( w[n] \triangleq (x[n], y[n]) \), \( n = 1, \ldots, N \) represents horizontal coordinate of the UAV. Furthermore, \( w_0 \) and \( w_F \) are the horizontal coordinates of initial and final locations.

The channels between the UAV and ground nodes mainly consist of the LoS channels, where the channel gain follows the free-space path loss model, given by [3]

\[
g_{UG}[n] = \beta_0 d_G^{-1}[n],
\]

(2)

where the \( d_G \) denotes the square of the distance from the UAV to the ground notes \( G \), which represents the set of IR (\( B \)), Eve (\( E \)) and FI (\( R \)). \( \beta_0 \) denotes channel power gain at the reference distance \( d_0 = 1 \text{ m} \).

Let us denote \( p[n] \) as the transmit power, which subjects to the average and peak power limits, i.e.,

\[
\frac{1}{N} \sum_{n=1}^{N} p[n] \leq \bar{P}, \quad 0 \leq p[n] \leq P_{\text{peak}},
\]

(3)

where \( P_{\text{peak}} \) and \( \bar{P} \) denote the peak and average power. To make the power budgets non-trivial, we assume \( \bar{P} \leq P_{\text{peak}} \) in this paper.

Therefore, the achievable rate from the UAV to the G can be expressed as

\[
R_{UG}[n] = \log_2 \left( 1 + \frac{p[n]g_{UG}[n]}{\sigma^2} \right) = \log_2 \left( 1 + \frac{\gamma_0 p[n]}{d_G[n]} \right),
\]

(4)

where \( \sigma^2 \) is the additive white Gaussian noise (AWGN) power at the receiver and \( \gamma_0 = \beta_0/\sigma^2 \) is the reference signal-to-noise ratio (SNR). Then, we can formulate the average secrecy rate as [3]

\[
SR = \frac{1}{N} \sum_{n=1}^{N} \left( \log_2 \left( 1 + \frac{\gamma_0 p[n]}{d_B[n]} \right) - \log_2 \left( 1 + \frac{\gamma_0 p[n]}{d_E[n]} \right) \right)^+.
\]

(5)

In order to satisfy the sensing performance, the average SNR at the FI has to be greater than a certain threshold, which given by

\[
\frac{1}{N} \sum_{n=1}^{N} \frac{p[n] \gamma_0}{d_R[n]} \geq \eta.
\]

(6)

2.2 Problem formulation

In this letter, we aim to maximize the average secrecy rate by jointly optimizing the UAV’s transmit power \( p \in \mathbb{R}^N \) and trajectory in terms of its horizontal coordinates
\( x \in \mathbb{R}^N \) and \( y \in \mathbb{R}^N \) over all \( N \) time slots. The optimization problem can be formulated as

\[
\max_{x, y, p} \sum_{n=1}^{N} \left[ \log_2 \left( 1 + \frac{\gamma_0 p[n]}{d_B[n]} \right) - \log_2 \left( 1 + \frac{\gamma_0 p[n]}{d_E[n]} \right) \right]
\]

s.t. (1), (3), (6).

In (7), we ignore the operator \([·]^+\) to make the problem smooth without changing the optimal value [3]. However, the problem is still difficult to tackle since that the objective function and constraint (6) are non-convex with respect to either \( x, y \) or \( p \).

### 3 Proposed algorithm

In this section, we develop an iterative algorithm to obtain a suboptimal solution with good performance. We divide the problem (7) into two sub-problems and transform each sub-problem into solvable convex form. What’s more, we assume the FI and the Eve are in the same position, \( d_E[n] = d_R[n] \). On the one hand, this more practical situation can be regarded as that the Eve is close to the FI where our solution will be the lower bound of the system secrecy rate. On the other hand, this assumption can similarly represent the simultaneous wireless information and power transmission (SWIPT) system, where the Eve can be treated as the energy receiver [4].

#### 3.1 Transmit power optimization

For given UA trajectory \((x, y)\), sub-problem 1 can be expressed as

\[
\max_{p} \sum_{n=1}^{N} \left[ \log_2(1 + a_n p[n]) - \log_2(1 + b_n p[n]) \right]
\]

s.t. (3), (6),

where \( a_n = \gamma_0/d_B[n] \), \( b_n = \gamma_0/d_E[n] \). In order to deal with the non-convexity caused by the cost function, the Taylor expansion is used. We can transform the cost function into

\[
\sum_{n=1}^{N} \ln 2 \left[ \ln(1 + a_n p[n]) - \ln(1 + b_n p_{feed}[n]) - \frac{b_n}{1 + b_n p_{feed}[n]} (p[n] - p_{feed}[n]) \right]
\]

(9)

The problem becomes convex and can be solved by the CVX tool after the transform.

#### 3.2 UAV trajectory optimization

For given transmit power \( p \), by letting \( P_n = \gamma_0 p[n] \) and introducing slack variables \( t \in \mathbb{R}^N, u \in \mathbb{R}^N \) and \( \alpha \in \mathbb{R}^N \) over all \( N \) time slots, the problem can be reformulated as [3, 5]

\[
\max_{x, y, t, u} \sum_{n=1}^{N} \left[ \log_2 \left( 1 + \frac{P_n}{u[n]} \right) - \log_2 \left( 1 + \frac{P_n}{t[n]} \right) \right]
\]

s.t. \( H^2 \leq t[n] \leq d_E[n] \), \( \forall n \)

\( d_B[n] \leq u[n], \forall n, \) and (1)
where \( F(x[n], y[n], \alpha[n]) = 2\alpha[n]\sqrt{p[n]y_0} - \alpha^2[n]d_E[n] \) and the \( \alpha \) can be updated by setting \( \partial F / \partial \alpha = 0 \) [5].

With the given feasible initial points \( x_{\text{f ea}}, y_{\text{f ea}}, u_{\text{f ea}} \) and \( t_{\text{f ea}} \), we use the Taylor expansion to reformulate the non-convex terms. Then, we have

\[
H^2 \leq t[n] \leq -(x_{\text{f ea}}^2[n] - 2x_{\text{f ea}}[n]x[n] + 2x_E[n] - x_E^2) + y_{\text{f ea}}^2[n] - 2y_{\text{f ea}}[n]y[n] + 2y_E[n] - y_E^2, \forall n,
\]

\[
SR[n] = \log_2 \left( 1 + \frac{P_n}{u_{\text{f ea}}[n]} \right) - \frac{P_n(u[n] - u_{\text{f ea}}[n])}{\ln 2(u_{\text{f ea}}[n]^2 + P_nu_{\text{f ea}}[n])}
\]

Finally, the problem (10) is transformed into

\[
\max_{x, y, t, u} \sum_{n=1}^{N} SR[n] \quad \text{s.t. (10b), (10c), (11).}
\]

Problem (13) is a convex and can be solved through CVX tool. Since the problem is non-decreasing over iterations and the optimal value is upper-bounded by a finite value, the convergence is guaranteed.

### 4 Simulation results

In this section, we conduct simulations to verify the effectiveness of the proposed optimization algorithm, which is labelled as Proposed. Unless otherwise stated, we adopt all parameters in Fig. 1. Besides, for initial feasible UAV trajectory, we use the best-effort approach, which can be labelled as Baseline 1. Baseline 2 represents joint trajectory and power optimization algorithm without sensing requirement in [3].

Figure 2 shows the trajectories of the UAV by applying different algorithms with different flight periods. We use circle and square represent the IR and Eve, respectively. When \( T > 50 \text{ s} \), compared with the Baseline 1, the Baseline 2 shows that the UAV flies as close as possible to the IR and as farther as possible from Eve to achieve the best secrecy rate. What’s more, it can be seen in Fig. 2 that the increase of the sensing SNR threshold makes the UAV fly closer to the FI (Eve). It means that we have to sacrifice some secrecy performance to satisfy the sensing requirement.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( W_0 )</th>
<th>( W_F )</th>
<th>( W_\alpha )</th>
</tr>
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<tr>
<td>Value</td>
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<td>(50,50)</td>
<td>(0,0)</td>
</tr>
<tr>
<td>Parameter</td>
<td>( W_E )</td>
<td>( P_{\text{peak}} )</td>
<td>( \gamma_0 )</td>
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<tr>
<td>Value</td>
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<td>( P_{\text{peak}} = 4\hat{P} )</td>
<td>80dB</td>
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<tr>
<td>Parameter</td>
<td>( V )</td>
<td>( d_e )</td>
<td>( h )</td>
</tr>
<tr>
<td>Value</td>
<td>2m/s</td>
<td>1s</td>
<td>30m</td>
</tr>
</tbody>
</table>

**Fig. 1.** Simulation parameters
Figure 3 shows the SNR of FI versus time in different algorithms. Compared with the Baseline 1, Baseline 2 shows that the secrecy rate is increased and the SNR of FI is decreased. This is because the objective of [3] is maximizing the secrecy rate. However, in order to meet the sensing requirement in our study, we have to sacrifice the secrecy performance as the Proposed shows. Moreover, more power should be transmitted when the UAV is close to the FI for better sensing performance. Therefore, the SNR at the both ends is greater than the other time slots.

Figure 4 shows the average secrecy rate versus sensing SNR with different transmit power and fight period. Consistent with the above analysis, the increase of sensing SNR threshold decreases the secrecy rate. However, we can increase the transmit power or fight period to increase the secrecy rate.

5 Conclusion

In this letter, we have studied the secrecy rate maximization problem of ISAC-UAV system. Specifically, we maximize the average secrecy rate by jointly optimizing the UAV trajectory and transmit power under the mobility constraints, power budgets and sensing requirement. In order to solve the original problem, we divide it into two sub-problems, which are transformed into convex by using Taylor expansion and fractional programming. Simulation results verify the effectiveness of our proposed algorithm and demonstrate there is a compromise between the secrecy and sensing performance.
Optimal combination of forward error correction and selective state feedback for wireless feedback control systems

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Abstract: In wireless feedback control systems, loss of control packets due to unreliable wireless channels is one of the most important problems. To cope with this problem, we have proposed a novel concept that combines forward error correction (FEC) and selection of important state feedback while keeping a fixed packet length. In this paper, we provide its optimization based on a control layer’s theorem. Numerical results show that the proposed method can achieve the best control performance against communication channel errors.

Keywords: wireless control, feedback control, state feedback, forward error correction, error correction coding

Classification: Wireless Communication Technologies

References


1 Introduction

In factory automation, process monitoring, and so on, there is a growing interest in wireless control of machines because of its advantages such as reconfigurability, mobility, and no maintenance costs associated with cables. However, because of unreliability of wireless channels, there is disadvantage that the control performance deteriorates due to loss and delay of control packets. Therefore, it is very important how to suppress such deterioration of the control performance, and several approaches have been discussed from the viewpoint of control and communication layers [1]. In this study, we focus on suppressing the effects of packet loss and have proposed FEC methods [2, 3, 4] for wireless feedback control systems; [2, 3] focus on the error collection of control information packets for the forward channel, and [4] focus on the error collection of state information packets for the feedback channel. These methods have a common view point of adding redundancy to control/state information while keeping a fixed packet length to avoid lengthening the control period. Especially, the method of [4] selects important state information to shorten the packet length and adds error correction bits to the shortened state information to reduce the probability of packet loss. However, theoretical optimization of which state information to select and encode for the best control quality has not been provided.

The novelty of this paper is to propose an optimal combination of the code rate of FEC and the selective state feedback that minimizes the control cost based on a control layer’s theorem. We show that for the same packet length, the proposed method can achieve the best control performance against communication channel errors.

2 System model

Figure 1 shows the model of wireless feedback control with the proposed method. It consists of one controller and one controlled plant. The feedback channel from the plant side to the controller side is assumed to be noisy, but the forward channel is assumed to be ideal with no error in order to focus on the effect of errors in state feedback. The plant state is observed by sensors and fed back to the controller, and the plant state is estimated by a state estimator at the controller. In the proposed method, before the state feedback, state information to be fed back is selected and FEC coding is performed. The details are described in the next section.

![Fig. 1. Wireless feedback control system with the proposed method.](image-url)
The plant is assumed to be a linear time-invariant and its discrete-time state space representation is given as \( x[k+1] = Ax[k] + Bu[k] + w[k] \) and \( y[k] = Cx[k] + v[k] \), where \( u[k] \), \( x[k] \), and \( y[k] \) are a control input vector, a state vector, and an observed state vector at time \( kT \) (\( T \) is a control period), respectively; \( A, B, \) and \( C \) represent dynamics and observation matrices and are controllable and observable; \( w[k] \) and \( v[k] \) represent a system disturbance and an observation noise with zero mean and covariance matrices \( W \) and \( V \), respectively.

The controller calculates control information as \( u[k] = K(x_{\text{ref}}[k] - x_{\text{est}}[k]) \), where \( x_{\text{ref}}[k] \) is a reference vector, and estimated state vector \( x_{\text{est}}[k] \) is calculated from the previously received \( y_{d}[k-1] \) by a Kalman filter-based state estimator of [5]; due to space limitations, the formulas of the estimator are omitted here. The controller minimizes an infinite horizon linear quadratic cost of \( J = \lim_{K \to \infty} \frac{1}{K} \sum_{k=0}^{K} (x[k]^T Q x[k] + u[k]^T R u[k]) \) for zero reference, where \( Q \) and \( R \) are positive definite weight matrices, and the gain is given as \( K = (B^T XB + R)^{-1} B^T X A \), where \( X \) is the solution of \( X = A^T X A + Q - A^T X B (B^T XB + R)^{-1} B^T X A \).

### 2.1 Proposed method

The proposed method selects important state information to shorten the packet length and adds error correction bits to the shortened state information while keeping a fixed packet length. The selection of elements of \( y[k] \) can be represented as \( y_{s}[k] = S y[k] \), where \( S \) is a matrix with 1 for selected elements and 0 otherwise. A header is added to the selected state information and error correction coding is performed. Given that the \( N \) elements selected out of \( N_y \) elements of \( y[k] \) are represented by \( NB \) bytes, the number of error correction bits is \((N_y - N)B\) bytes. Given a \( B_h \)-byte header, the total length is \( B_h + N_y B \) bytes regardless of the selection, and the coding ratio is \((B_h + NB)/(B_h + N_y B)\) and is uniquely determined for the selection. The encoded packet passes through the noisy channel, and the received packet will be discarded (i.e., packet loss) if a bit error remains after error correction by the decoder.

This method has a tradeoff: the more state elements selected, the smaller the state estimation error, but the lower the tolerance to channel error, while the fewer state elements selected, the higher the tolerance to channel error, but the higher the state estimation error. Therefore, optimization of which state elements to select and encode for the best control quality is required. We propose to utilize the theorem of [5] to optimally select and encode the state feedback. The theorem states that the expected minimum cost can be bounded by \( J \leq \bar{J} \), and \( \bar{J} \) converges to the following value under the condition that the probability \( p \) of packet loss satisfies \( p < \bar{p} = 1/\prod_{i} |\lambda_i(A)|^2 \), where \( \lambda_i(A) \) are the unstable eigenvalues of \( A \).

\[
\bar{J} = \text{trace}((A^T X A + Q - X)(\bar{P} - (1 - p)\bar{P} \tilde{C}^T (\bar{C} \bar{P} \tilde{C}^T + V)^{-1} \bar{C} \bar{P})) + \text{trace}(SW),
\]

where \( \bar{P} = A \bar{P} A^T + W - (1 - p)A \bar{P} \tilde{C}^T (\bar{C} \bar{P} \tilde{C}^T + V)^{-1} \bar{C} \bar{P} A^T \). Note that \( \bar{C} \) represents an observation matrix and can be regarded as \( \bar{C} = SC \) in our system.

Utilizing this theorem, the optimization steps are described as follows.
I. From the possible $2^{N_y}$ selections, obtain the set of $S_i$ that satisfies the observability of $A$ and $S_iC$.

II. From the set obtained in the step I, obtain the set of $S_j$ that satisfies $p_j < \bar{p}$ for the packet loss rate $p_j$ at the coding rate $(B_h + N_jB)/(B_h + N_yB)$ corresponding to the number of selected elements $N_j$ of $S_j$.

III. From the set obtained in the step II, determine the optimal $S$ and corresponding coding rate that minimizes the cost of (1).

3 Performance evaluation

3.1 Numerical setup

A rotary inverted pendulum, which is a typical under-actuated object and widely used as a control performance measure, is employed as an example of the plant. Its control objective is to enable the arm angle to follow a reference while maintaining upright of the pendulum attached at the tip of the rotating arm. $u[k]$ is an one-dimensional vector consisting of the input voltage to the DC motor that drives the arm. $x[k]$ is a four-dimensional vector consisting of the arm angle, pendulum angle, arm angular velocity, and pendulum angular velocity. The physical parameters are based on Quanser Rotary Pendulum; $A$, $B$ at $T_s = 0.1$ s are given as follows, and $C$ is the identity matrix.

$$A = \begin{bmatrix} 1 & 0.201629 & 0.030517 & 0.00543252 \\ 0 & 1.422160 & -0.0687027 & 0.110059 \\ 0 & 3.147250 & -0.0303328 & 0.165601 \\ 0 & 7.840620 & -1.07239 & 1.33241 \end{bmatrix}, \quad B = \begin{bmatrix} 0.124943 \\ 0.12354 \\ 1.85272 \\ 1.92834 \end{bmatrix}, \quad (2)$$

The reference is a rectangular signal switching $\pm \pi/4$ rad every 10 s. For simplicity, $W$ is diagonal with diagonal elements are $10^{-6}$ for white Gaussian noises, and $V$ is diagonal with diagonal elements are $\delta/12$, where $\delta = 2\pi/2^{10}$ step size for 2-byte uniform quantization. The controller is designed with $Q = \text{diag}[10 10 1 1]$ and $R = [1]$ as simple values to avoid falling over of the pendulum due to the above noises in the simulation.

The noisy feedback channel is assumed to be a binary symmetric channel with bit error rate $p_b$. Polar codes and CRC-aided successive cancellation list decoding with 16 list size and 2-byte CRC are employed as a way to realize various coding rates and both error correction and error detection. The length of each state elements is $B = 2$ bytes and the header is $B_h = 6$ bytes, resulting in the coding rate of $(6 + 2N)/(6 + 8)$ excluding the CRC.

3.2 Numerical results

From the step I of the proposal, the following 8 selections satisfy the observability condition, and the number of selected state elements of each selection is $N_0 = 4$, $N_1 = N_2 = N_3 = 3$, $N_4 = N_5 = N_6 = 2$, and $N_7 = 1$, respectively.

$$S_0 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad S_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad S_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad S_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad S_4 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix},$$
\[
\begin{align*}
S_4 &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, \quad S_5 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad S_6 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, \quad S_7 = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}
\end{align*}
\]

Figure 2(a) shows the packet loss rate corresponding to each selection and the critical packet loss rate \( \bar{p} = 0.228 \). It shows that the fewer the number of the state feedback elements, i.e., the smaller the coding rate, the smaller the packet loss rate. In the step II of the proposal, \( S_0 \) satisfies \( p < \bar{p} \) at \( p_b \leq 10^{-3} \), \( S_1 \), \( S_2 \), and \( S_3 \) satisfy \( p < \bar{p} \) at \( p_b \leq 10^{-2} \), \( S_4 \), \( S_5 \), and \( S_6 \) satisfy \( p < \bar{p} \) at \( p_b \leq 2.5 \times 10^{-2} \), and \( S_7 \) satisfies \( p < \bar{p} \) at \( p_b \leq 5 \times 10^{-2} \). Figure 2(b) shows the optimization costs calculated in the step III of the proposal. It shows that the selection with lower packet loss rate does not necessarily result in lower cost. \( S_3 \) minimizes the cost at \( p_b \leq 10^{-2} \), \( S_6 \) minimizes the cost at \( p_b = 2.5 \times 10^{-2} \), and \( S_7 \) minimizes the cost at \( p_b = 5 \times 10^{-2} \) (and \( S_0 \) minimizes the cost at \( p_b < 10^{-4} \), but it does not appear in this graph).

![Figure 2. Criteria of the proposal.](image)

Figure 3 shows the simulation results of control performance versus bit error rate. It shows the root mean squared error (RMSE) of pendulum and arm angles against the ideal control case without errors and noises. We can see that the relationship of performance with each selection is similar to the relationship of cost in Fig. 2. The method of [4] provides well-balanced communication error tolerance and control.
performance, but does not achieve the best performance. The proposed method uses $S_3$ at $p_b \leq 10^{-2}$, $S_6$ at $p_b = 2.5 \times 10^{-2}$, $S_7$ at $p_b = 5 \times 10^{-2}$, and the corresponding coding rates, and thus achieves the best performance under various bit error rate.

4 Conclusion

We have proposed an optimal method of combining forward error correction and selection of important state feedback while keeping a fixed packet length. It has been shown that the proposed method can provide the best control performance against state feedback channel errors. Due to space limitations, we have only shown the results under certain conditions, but the differences in parameters do not impair the optimality. Our approach will lead to further discussions together with quantization methods by properly designing the cost function.

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A study on optimization of polling scheduling for in-vehicle UWB wireless networks*

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Abstract: This paper proposes a polling-scheduling for UWB-based in-vehicle networks. The proposed scheduling aims to reduce the preamble overhead by aggregating periodic data readout of the in-vehicle sensors. Experimental results show that the proposed scheduling successfully suppresses data loss rate compared to the cyclic scheduling.

Keywords: UWB, in-vehicle networks, polling-scheduling

Classification: Wireless Communication Technologies

References


*This paper is an extended version of [1] including new experimental results.
1 Introduction
To reduce greenhouse gas emission, demand for improving the fuel efficiency of vehicles has been increasing. One such way is to reduce vehicle weight by trimming the wire harnesses as much as possible. For this sake, we are developing an integrated in-vehicle network consisting of Power Line Communication (PLC) and Ultra Wideband (UWB) with DENSO TEN Limited and Advanced Telecommunications Research Institute International (ATR) [1]. The power line needs to remain for electronics devices. Thus, PLC can utilize it as a communication medium. Further, replacing a part of the wire harnesses with wireless networks reduces wire harnesses. Impulse Radio-UWB (IR-UWB, in short UWB hereafter) specified in IEEE 802.15.4a/z is one of the candidates. This is because of its excellent penetration of the signal and robustness in multipath environments.

This paper focuses on in-vehicle wireless networks and proposes a polling-scheduling for UWB-based in-vehicle networks. As literature related to this work, for example, Ref. [2] proposes a scheduler for in-vehicle UWB wireless sensor networks considering periodic data readout. However, it does not consider data aggregation, which will be explain in Section 3. Regarding data aggregations, Ref. [3] shows the effectiveness of frame aggregation for vital sensing by IEEE 802.15.4. However, it does not take scheduling into account. Unlike the above, our scheduling aims to reduce the preamble overhead by aggregating periodic data readout of the in-vehicle sensors.

In what follows, we will explain our scheduling algorithm and show some experimental results.

2 UWB/PLC integrated in-vehicle network
Figure 1(a) shows our developing UWB/PLC integrated in-vehicle network, which consists of one master terminal (MT) and five slave terminals (STs). Multiple sensors

<table>
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<th>Readout cycle (ms)</th>
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<tr>
<td>Slave terminal 5</td>
<td>4</td>
<td>10</td>
<td>16</td>
<td>14</td>
</tr>
</tbody>
</table>

(b) Number of sensors and readout cycles

Fig. 1. UWB/PLC integrated in-vehicle network
and actuators are connected to each ST. The Electronic Control Unit (ECU) reads data from the sensors connected to the ST via the MT. It also sends control data to each actuator as needed.

Each sensor has a specific readout cycle based on its type. The length of sensor data is 6 bytes that consist of the sensor ID of 2 bytes and the sensor reading of 4 bytes. Figure 1(b) shows an example of the number of sensors connected to each ST and their cycles. In this case, the data transfer load is about 250 kbit/s.

The ECU cannot always read out at the desired timing because it can only read from one ST at a time. Therefore, the delay until the ECU actually receives the data is regarded as the readout delay. From this viewpoint, communications are categorized into low latency for safety data related to driving operation and non-low latency for body-equipment data related to wiper operation. For these, we aim to satisfy the following qualities:

- Low latency: data load 250 kbit/s, allowable data loss rate $10^{-4}$, allowable readout delay 15 ms
- Non-low latency: data load 500 kbit/s, allowable data loss rate $10^{-3}$, allowable readout delay 25 ms

We assume that UWB conveys the load of 250 kbit/s for non-low latency data while PLC does the rest for non-low latency data and low delay data.

3 Data aggregation oriented polling type MAC

In IEEE 802.15.4a/z, the maximum length of Physical Service Data Unit (PSDU) is 127 octets by default. Moreover, the preamble symbol is about eight times longer than the payload symbol. This leads to much preamble overhead in physical frames. For example, the preamble length is 128 symbols in the Qorvo DWM3000 used in the experiments. In this case, the preamble and payload parts have almost the same length [4]. Therefore, conveying as much sensor data as possible in a Physical layer Protocol Data Unit (PPDU) is more efficient.

In IEEE 802.15.4a, Clear Channel Assessment (CCA) is enabled by periodically inserting preamble symbols into the data symbols [5]. It is optional and not implemented in NXP Semiconductors or Decawave (currently Qorvo) UWB modules. Therefore, this study employs polling-type media access control in which the MT controls the media access of STs.

3.1 Frame format

Figure 2(c) shows the format of the polling frame and response frame. The polling frame from the MT to an ST includes the IDs of sensors to be read and data toward actuators. The response frame from the ST includes the readout data of the sensor specified in the polling frame.

3.2 Polling transmission/retransmission

When and which the ST is polled is determined by off-line scheduling. The scheduling is generated on a slot basis. (See Section 4.) Each sensor has a unique read cycle in milliseconds. Its period is assumed to be an integral multiple of the slot time.
The MT sends a polling frame to the intended ST when the slot begins. If the MT receives no response frame, it judges that the polling has failed. Then, the MT repeats polling until it succeeds as long as possible within the slot. If every polling fails eventually, the MT backlogs the readouts that possibly satisfy delay constraints even in the following slots. On the other hand, if time remains within the slot thanks to successful polling, the MT utilizes it for backlogged re-polling.

4 Optimization of polling-scheduling

This section explains how to generate the schedule that aggregates readouts using integer programming to minimize the number of polling.

4.1 Variable definitions

The variables used in the formulation are defined below:

- $T$: Scheduling cycle (least common multiple of readout cycles)
- $\delta$: Slot duration in milliseconds
- $S$: Total number of slots in scheduling cycle $T$
- $D$: Allowable readout delay in milliseconds
- $M$: maximum readable data size in bytes in a polling
- $k$: Slot number ($0 \leq k < S + D/\delta$)
- $N$: Set of STs
- $J_n$: Set of readout data for ST $n$
- $J$: Set of readout data over all STs
- $a_j$: Desired readout time in milliseconds for readout data $j$
- $v_j$: Size of readout data $j$ in bytes
- $s_j$: Allocated slot number for the readout data $j$
- $x_{j,k}$: Binary variable, 1 if data $j$ is readout in the $k$th slot, otherwise 0
• $y_{n,k}$: Binary variable, 1 if the $k$th slot is assigned to ST $j$, otherwise 0

It is assumed that time starts from 0 ms and slots are numbered in ascending order from zero.

### 4.2 Objective function and constrains

A multi-objective function is formulated to reduce the total number of polls to STs and avoid unnecessary polling delays as shown below:

\[
\text{Minimize} \quad \alpha \sum_{k=0}^{S+D/\delta-1} \sum_{n \in N} y_{n,k} + (1 - \alpha) \sum_{j \in J} \{ s_j \delta - a_j \},
\]

subject to:

\[
0 \leq a_j < T = \delta S, \quad \forall j \in J, \tag{2}
\]

\[
s_j \delta - a_j \leq D - \delta, \quad \forall j \in J, \tag{3}
\]

\[
a_j \leq s_j \delta, \quad \forall j \in J, \tag{4}
\]

\[
\sum_{k=0}^{S+D/\delta-1} x_{j,k} = 1, \quad \forall j \in J, \tag{5}
\]

\[
s_j = \sum_{k=0}^{S+D/\delta-1} k x_{j,k}, \quad \forall j \in J, \tag{6}
\]

\[
y_{n,k} = \min \left\{ 1, \sum_{j \in J_n} x_{j,k} \right\}, \quad \forall n \in N, \tag{7}
\]

\[
\sum_{n \in N} y_{n,k} \leq 1, \quad 0 \leq k \leq S + D/\delta - 1, \tag{8}
\]

\[
\sum_{n \in N} (y_{n,k} + y_{n,k+S}) \leq 1, \quad 0 \leq k \leq D/\delta - 1, \tag{9}
\]

\[
\sum_{j \in J} v_j x_{j,k} \leq M, \quad 0 \leq k \leq S + D/\delta - 1. \tag{10}
\]

Equation (7) can be rewritten as follows by using the SOS2 (Special Ordered Set of Type 2) auxiliary variables $t_1$, $t_2$, and $t_3$ [6].

\[
\left( \sum_{j \in J_n} x_{j,k} \right) = t_1 \begin{pmatrix} 0 \\ 0 \end{pmatrix} + t_2 \begin{pmatrix} 1 \\ 1 \end{pmatrix} + t_3 \frac{|J_n|}{1}, \tag{11}
\]

\[
t_1 + t_2 + t_3 = 1, \quad t_1 \geq 0, \quad t_2 \geq 0, \quad t_3 \geq 0, \tag{12}
\]

\[
t_1 \leq z_1, \quad t_2 \leq z_1 + z_2, \quad t_3 \leq z_2, \tag{13}
\]

where $z_1$ and $z_2$ are auxiliary binary variables whose values are 0 or 1.

### 5 Experiments

Simple experiments were conducted in the Electromagnetic Compatibility (EMC) tent manufactured by Medical Aid Co., Ltd. to verify the effectiveness of the proposed scheduling. The target system consists of one MT and five STs as in Fig. 1. Interference systems consisted of one MT and one ST, they mimic the target system.
Qorvo DWM3000 was used as a UWB radio device. Its configurations were channel 9 (center frequency 7987.2 MHz, bandwidth 499.2 MHz), data rate 6.81 Mbit/s, and preamble length 128 symbol. For the load of about 250 kbit/s, the situation shown in Fig. 1(b) was assumed. By halving the number of sensors, the lower load of 125 kbit/s was generated. The slot duration $\delta$ was set to 4 ms. The weight $\alpha$ in Eq. (1) was set as $\alpha = 1000/1001$.

For comparison, cyclic scheduling was also evaluated. In this method, polling is scheduled in order from ST 1 to 5, repeatedly; that is, ST 1 is polled after ST 5. In case of no sensor data to be read out for the intended ST, polling is not performed in that slot, and the next ST will be polled in the next slot.

Data loss rates are shown in Fig. 3. Note that both the cyclic scheduling and the proposed scheduling satisfy the allowable readout delay of 25 ms. The proposed scheduling successfully suppresses the data loss rate compared to the cyclic scheduling. In the case of the load of 250 kbit/s, the cyclic scheduling could not satisfy the allowable data loss rate of $10^{-3}$. On the other hand, the proposed one could do when one interference system exists. In the case of the load 125 kbit/s, the proposed one provides a lower data loss rate than the allowable one of $10^{-3}$ even when three interference systems exist. From the above, the effectiveness of data aggregation is confirmed.

![Fig. 3. Experimental results](image)

**Acknowledgments**

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Analysis of digital pre-distortion with I/O interfaces for analog baseband signal over broadcasting satellites

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Abstract: Broadcasting satellite systems currently use multilevel modulation schemes, which are vulnerable to non-linear distortion, while their on-board amplifiers operate near the saturation point. We have developed a digital pre-distortion (DPD) embedded transmitter and demonstrated its effectiveness over a 12-GHz-band satellite transponder. To improve its versatility, we developed an external DPD adder, which enables existing transmitter to give an analog baseband signal its function. In this study, we confirm the effectiveness of the external DPD adder by evaluating the transmission performance of 64APSK over the satellite transponder.

Keywords: broadcasting satellite, non-linear distortion, external DPD adder, 64APSK

Classification: Satellite Communications

References

1 Introduction

The technical standard of the ISDB-S3 transmission system was developed with the aim of delivering 4K8K ultra high definition TV (UHDTV) via 12 GHz-band satellite broadcasting in Japan [1, 2]. ISDB-S3 specifies a symbol rate of 33.7561 Mbaud and a roll-off factor of 0.03, 16 and 32 amplitude and phase shift keying (APSK) modulations, and low density parity check (LDPC) for forward error correction (FEC). 16APSK (LDPC code rate: 7/9) enables a transmission capacity of about 100 Mbps per transponder channel and is currently used for the 4K8K broadcasting services.

We studied digital pre-distortion (DPD) based on error vector estimation [3] and developed a prototype ISDB-S3 transmitter embedding (internal) DPD function [4]. We have evaluated its effectiveness on 32APSK over a 12-GHz-band satellite transponder in laboratory experiments [4]. To improve its versatility, we developed an external DPD adder, which applies the DPD function to the analog baseband modulation signal. The external DPD adder can be used with ordinary transmitters when a central frequency of 140 MHz and bandwidth of less than 40 MHz for the transmitted signal are available [5].

Regarding the transmission capacity, we studied set-partitioning 64APSK coded modulation [6] and fabricated prototype modems [7]. 64APSK is more vulnerable to non-linear distortion than 32APSK, but the prototype 64APSK transmitter is not equipped with a DPD function.

In this study, we evaluated the transmission performance of 64APSK when an external DPD is used through computer simulations and hardware experiments. We also conducted a more detailed analysis of its function and performance than our previous study [5].
2 Transmission system

2.1 Experimental system

Figure 1 (a) shows the experimental block diagram. Except for the modulation scheme (64APSK), the main transmission parameters are the same as in ISDB-S3. The red plots in Fig. 1 (b) show the measured AM/AM and AM/PM characteristics of the analog linearized traveling wave tube amplifier (LTWTA).

2.2 External DPD

The external DPD adder within the blue line in Fig. 1 (a) consists of an A/D converter, digital amplifier, digital filter, and D/A converter. The digital amplifier and digital filter are implemented in the form of a look-up table (LUT) so that their characteristics can be arbitrarily controlled.

The digital amplifier works based on the AM/AM and AM/PM characteristics. These characteristics are set in 1-dB steps and are interpolated with a cubic spline. The functions $f_{db}$ and $f_{deg}$ are the AM/AM and AM/PM characteristics, respectively. The instantaneous power $y_{db}$ and phase $y_{deg}$ at the digital amplifier output can be derived from Eqs. (1) and (2), respectively, as follows:

\[
y_{db} = f_{db}(x_{db} + x_{op}) - x_{db}
\]

\[
y_{deg} = f_{deg}(x_{db} + x_{op}) - f_{deg}(x_{db}),
\]

where $x_{db}$ and $x_{op}$ are the instantaneous power and operating point (average power) at the digital amplifier input, respectively.

\[
y_{db} = f_{db}(x_{db} + x_{op}) - x_{db}
\]

\[
y_{deg} = f_{deg}(x_{db} + x_{op}) - f_{deg}(x_{db}),
\]
Fig. 1. System diagram and characteristics: (a) block diagram, (b) AM/AM and AM/PM characteristics of LTWTA in satellite transponder (red) and in external DPD (blue), (c) original 64APSK (4/5) constellation points, (d) analysis of distance between 3rd and 4th circles \(r_3 - r_4\) by AM/AMs, and (e) constellations through external DPD.

The blue plots in Fig. 1 (b) show the AM/AM and AM/PM characteristics of the digital amplifier. The characteristics in the external DPD can compensate for the non-linear distortion caused by the LTWTA (red plots in Fig. 1 (b)). Regarding the AM/AM in the external DPD, the gain increases by the amount of decrease in the gain of the LTWTA. The AM/PM in the external DPD sets horizontal symmetry to that of the LTWTA. In case the characteristics of the LTWTA cannot be obtained, the estimation technique reported in [8] would be applicable.

The digital filter works as the frequency versus amplitude response characteristics. The amplitude response characteristics are designed as a 35 MHz-band pass filter to compress spectrum re-growth due to the non-linearity of the digital amplifier in the system [9].

2.3 Analysis of 64APSK constellations

Figure 1 (c) shows the original constellation points of 64APSK (4/5). The radius ratios between the circles \(r_1 - r_4\) are \(2, 2.093, 4.05\), which are determined in a way that the channel capacity of the 64APSK constellation in additive white Gaussian noise (AWGN) is maximized through computer simulations [6].
Here, the amplitudes of each circle \( r_1, r_2, r_3, r_4 \) are \(-9.15 \, \text{dB}, -3.13 \, \text{dB}, 0.39 \, \text{dB}, 2.89 \, \text{dB}\) when the average power \( r_{\text{ave}} \) is 0 dB. Consequently, the Euclidean distances between the circles \((r_2-r_1), (r_3-r_2), (r_4-r_3)\) are \(6.02 \, \text{dB}, 3.52 \, \text{dB}, 2.50 \, \text{dB}\).

These constellation points are dominantly distorted through AM/AM characteristics of the LTWTA [10], and a compress of the distance between the 3rd and 4th circles \((r_4 - r_3)\) are especially occurred by the non-linearities in the high power range. Therefore, we analyzed the relation between the constellation distances and the AM/AM compression using Figs. 1 (c)–(e). Figure 1 (d) shows the AM/AM characteristics in the external DPD on the left and those of the LTWTA on the right. Here, the input back-off (IBO) for the external DPD and LTWTA was set to \(5.18 \, \text{dB} \) \(x_{\text{op}} = -5.18 \) in Eqs. (1) and (2)). The original constellations in Fig. 1 (c) generated from the transmitter go through the external DPD, and the external DPD causes the distance \((r_4 - r_3)\) along with the AM/AM curve to change from 2.50 to \(3.51 \, \text{dB}\) as shown in Fig. 1 (d) on the left. Furthermore, the average power, shown as the pink dashed lines, changes from \(-0.39\) to \(0.48 \, \text{dB}\) greater than the amplitude of the 3rd circle because of increase in the amplitude of the 4th circle. When the average power (operating point) at the input of LTWTA is \(-5.18 \, \text{dB}\) as shown in Fig. 1 (d), the amplitude of the 3rd circle at the input of LTWTA changes from \((-5.18) - (-0.39) = -4.79 \) to \((-5.18) - (0.48) = -5.66 \, \text{dB}\) and that of the 4th circle changes from \((-4.79) + (2.50) = -2.29 \) to \((-5.66) + (3.51) = -2.15 \, \text{dB}\). Correspondingly, the amplitude of the 3rd circle at the output of LTWTA changes from \(-1.73\) to \(-2.49 \, \text{dB}\) and that of the 4th circle changes \(-0.27\) to \(-0.23 \, \text{dB}\). The distance \((r_4 - r_3)\) is \(2.26 \, \text{dB}\) at the output of LTWTA, which compares with \(1.46 \, \text{dB}\) without DPD. Therefore, the actual received constellations can be expected that the distance \((r_4 - r_3)\) of their centroids gets closer to the original one when the external DPD is used.

### 3 Transmission performance

#### 3.1 Received constellations

Figure 2 (a) shows computer-simulated results of the received constellations for 64APSK (4/5) without DPD and Fig. 2 (b) shows those with the external DPD.

![Fig. 2. Received constellations: (a) without DPD [EVM: 8.53%], (b) with external DPD [EVM: 4.66%].](image-url)
The received constellations with the external DPD were more convergent to the original points. The error vector magnitude (EVM) [11] improved from 8.53% without DPD to 4.66% with the external DPD. Next, we compared the received constellation centroids. In the case without DPD, the centroid amplitudes (average of 18 centroids in each circle) was 0.71 dB in the 3rd and 2.51 dB in 4th circle as shown in Fig. 2 (a). The distance \(r_4 - r_3\) was 1.80 dB. In the case with the external DPD, those was 0.51 dB in the 3rd and 2.78 dB in the 4th as shown those in Fig. 2 (b). As a result, the distance \(r_4 - r_3\) with external DPD was increased to 2.27 dB compared to 1.80 dB without DPD, which is 0.47 dB closer to the original distance \(r_4 - r_3\) of 2.50 dB.

3.2 Required C/N + OBO

Table I shows the required C/N + OBO for 64APSK (4/5) as the overall transmission performance by the simulation and experiment. In this study, the required C/N is defined as the smallest C/N at a bit error rate (BER) of \(1 \times 10^{-11}\) or less after FEC [2]. OBO is defined as the logarithmic ratio between the OMUX filter output power of the CW signal at the peak point and that of the modulated signal at the operating point [2]. Here, the OBO with the external DPD was more increased than the one without DPD despite the IBO was the same. This indicates that the transmitter signal with the external DPD included higher instantaneous power than that without DPD under the same average power, however the higher instantaneous power was more compressed by the LTWTA.

Regarding the simulations, we compared the transmission performances for the external DPD and the existing internal DPD. Here, the internal DPD is located between the mapper and the root roll-off filter shown in Fig. 1 (a). The results show that the external DPD worked as well as the internal DPD because the differences in required C/N + OBO were only 0.09 dB.

Regarding the experiments, we verified the effectiveness by the external DPD in comparison with that without DPD. The required C/N + OBO was 22.01 dB with the external DPD, while it was 20.72 dB without DPD, for an improvement of 1.29 dB.

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4 Conclusion

To improve the versatility DPD, we developed an external DPD adder, which applies the DPD function to the analog baseband modulation signal. At first, we analyzed its detail operation in the AM/AM characteristics. Next, we evaluated its effectiveness by the transmission performance of 64APSK (4/5) and confirmed that the external DPD worked as well as the internal DPD in the simulations. At the end, we obtained a 1.29 dB improvement by the external DPD in the experiments.
Two-wavelength adaptive thresholding for uplink from smartphone’s low-luminance WDM/SDM screen to camera

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Abstract: Secure uplink from smartphone screen to camera communication (SCC) needs to increase the throughput and simultaneously reduce the screen luminance. To realize low-luminance wavelength division multiplexing/space division multiplexing (WDM/SDM) transmission, 2-wavelength adaptive thresholding that categorizes both inter-wavelength and spatial intersymbol interferences (ISIs) is proposed and experimentally verified. The camera images are categorized into $3 \times 3$ cells and the symbol of the center cell is determined. The inter-wavelength ISIs are categorized by the pixel value of the center cell of the other wavelength. The spatial ISIs are categorized by the outer 8-cell symbol pattern estimated at the same wavelength.

Keywords: visible light communication, optical camera communication, screen camera communication, space division multiplexing, wavelength division multiplexing, inter-symbol interference

Classification: Wireless Communication Technologies

References

1 Introduction

Indoor downlink optical camera communication (OCC) from LED lighting to smartphone cameras has been extensively studied. To enable the same full-duplex communication as radio-waves, uplink OCC needs to be developed. However, there have been few studies on the uplink. Short-range uplink from red, green, and blue (RGB) LEDs to smartphone cameras uses 4-pulse amplitude modulation per color to increase the data rate [1]. In short-range screen to camera communication (SCC) between smartphones, the smartphone screen transmits space-division-multiplexing (SDM) binary image and the opposite smartphone camera captures the image and determines the symbol based on the pixel value threshold [2]. Both are limited for short range applications.

On the other hand, we are proposing an uplink SCC with a relatively long distance of 3.5 m. Figure 1(a) shows the uplink SCC from a smartphone’s SDM-based screen to a video camera. Since small screen causes out-of-focus on the camera over long distances, spatial inter-symbol interference (ISI) due to the defocus blur increases. We have proposed adaptive thresholding that takes spatial ISI into account [3].

In this study, we will combine wavelength division multiplexing (WDM) and SDM to increase the throughput and reduce the luminance simultaneously. As for WDM, in the downlink RGB-LED based OCC, the camera can receive each wavelength independently based on multiple-input multiple-output (MIMO) [4]. Visual MIMO SCC has also been studied to reduce channel distortion due to pixel and color mixing [5]. Both are limited for short range applications.

In 3.5-m uplink, spatial ISI increases owing to the blur. As the number of cells and the transmission distance increases, it becomes more difficult to adopt MIMO for WDM/SDM because of the spatial ISI. We will propose and experimentally verify 2-wavelength adaptive thresholding that classifies both inter-wavelength and spatial ISIs.
2 Principle of 2-wavelength adaptive thresholding

Figure 1(b) shows a schematic diagram of numerical model for 2-wavelength adaptive thresholding. The screen transmits \( n \times m \)-cell binary image that consists of its color and black cells independently in each wavelength. The colored cell indicates symbol “1” and black cell indicates symbol “0.” The \( n \times m \)-cell smartphone screen and camera images are categorized into \( 3 \times 3 \) cells, where \( p_r \) and \( p_b \) shows the \( 3 \times 3 \) red and blue pixel value on the screen and \( P_r \) and \( P_b \) shows the \( 3 \times 3 \) red and blue pixel value on the camera image, respectively. The center pixel values of \( 3 \times 3 \) cells on the camera image, \( P_{r0} \) and \( P_{b0} \) are given by

\[
P_{r0} = \sum_{i=0}^{8} w_{rri} P_{ri} + \sum_{i=0}^{8} w_{rb} P_{bi}, \tag{1}
\]

\[
P_{b0} = \sum_{i=0}^{8} w_{bri} P_{ri} + \sum_{i=0}^{8} w_{br} P_{bi}, \tag{2}
\]

where \( w_{rri}, w_{rb}, w_{bri}, w_{br} \) shows the coupling coefficients between the screen pixel value, \( p_{ri} \), \( p_{bi} \), and the center pixel value on the camera image, \( P_{r0}, P_{b0} \). In the single-wavelength SDM, the optimal pixel value threshold for \( P_{r0} \) and \( P_{b0} \) is adaptively determined by the outer 8-cell symbol pattern, \( p_r \) and \( p_b \) (\( i = 1, \ldots, 8 \)), respectively [3]. The optimum threshold is adaptively determined by transmitting known symbols in the preamble before transmitting unknown symbols. The preamble needs to transmit at least \( 2^8 \) different types of symbols.

In 2-wavelength SDM, the inter-wavelength coupling coefficients, \( w_{r_0b_1}, w_{b_0r_1} \), are added. At least \( 2^{18} \) different types of binary data are required to categorize \( 3 \times 3 \) cells consisting of 2-wavelength SDM in the preamble. We focus on \( w_{r_0b_1} \) and \( w_{b_0r_1} \) to reduce the data size in the preamble. The inter-wavelength coupling coefficients, \( w_{r_0b_1}, w_{b_0r_1} \), are expressed by the same-wavelength spatial coupling coefficient, \( w_{rri}, w_{bri} \), as follows:

\[
w_{b0r1} = \alpha_{br} w_{r0r1} \quad (0 \leq \alpha_{br} \leq 1), \tag{3}
\]

\[
w_{r0b1} = \alpha_{rb} w_{b0b1} \quad (0 \leq \alpha_{rb} \leq 1), \tag{4}
\]

where \( \alpha_{br} \) and \( \alpha_{rb} \) is the ratio of the inter-wavelength coupling coefficient to the same-wavelength coupling coefficient. Since the inter-wavelength coupling is determined by the spectral overlap among RGB colors of the camera [4], the inter-wavelength coupling coefficient between the cells is proportional to the same-wavelength coupling coefficient between the cells. Therefore, \( \alpha_{br} \) and \( \alpha_{rb} \) are constant. By substituting Eqs. (3) and (4) into (1) and (2), \( P_{r0} \) and \( P_{b0} \) are given by

\[
P_{r0} = (1 - \alpha_{rb} \alpha_{br}) \sum_{i=0}^{8} w_{rri} P_{ri} + \alpha_{rb} P_{b0}, \tag{5}
\]

\[
P_{b0} = (1 - \alpha_{br} \alpha_{rb}) \sum_{i=0}^{8} w_{bri} P_{ri} + \alpha_{br} P_{r0}. \tag{6}
\]

The inter-wavelength couplings based on the screen pixel values, \( w_{r_0b_1} P_{b_1} \) and \( w_{b_0r_1} P_{r_1} \) are replaced by the couplings based on the center pixel values on the
camera image. Since \( \alpha_{rb} \alpha_{br} \ll 1 \), \( P_{r0} \) and \( P_{b0} \) are approximately given by

\[
P_{r0} \approx \sum_{i=0}^{8} w_{r0i} p_{ri} + \alpha_{rb} P_{b0}.
\]

\[
P_{b0} \approx \sum_{i=0}^{8} w_{b0i} p_{bi} + \alpha_{br} P_{r0}.
\]

The pattern categorization by Eqs. (7) and (8) reduces the number of known symbols required in the preamble to determine the optimal threshold. The number of symbols required for 2-wavelength thresholding is reduced to \( 2^{10} \) different types, much the same as for the single-wavelength thresholding.

### 3 Numerical analysis

Numerical analysis was conducted based on Eq. (7). Figure 2(a) shows an example of the red pixel value distribution, \( P_{r0} \), only categorized by the screen pixel value, \( p_{r0} \) and \( p_{b0} \), where, \( p_{r0} \) and \( p_{b0} \) are normalized to be 1 or 0, the spatial coupling coefficient, \( w_{r0i} \) and \( w_{r0i} \) \((i = 1, \cdots, 8)\) are assumed to 1 and 0.22, respectively, the center pixel value on the camera image, \( P_{b0} \) is 1 or 0, and the ratio, \( \alpha_{rb} \) is assumed to 0.22. The “R on,” “R off,” “B on,” and “B off” indicates the screen pixel value, \( p_{r0} = 1, p_{r0} = 0, p_{b0} = 1, \) and \( p_{b0} = 0 \), respectively. The “R on” and “R off” distributions overlap due to the spatial ISI and the inter-wavelength ISI. Even if the “B on” and “B off” distributions are categorized by \( P_{b0} \), it is difficult to correctly distinguish between “R on” and “R off.”

![Fig. 2. Calculated red pixel value distributions, \( P_{r0} \).](image)

On the other hand, Fig. 2(b) shows an example of the center red pixel value distributions categorized by the outer 8-cell symbol pattern in addition to \( p_{r0} \) and \( P_{b0} \), where the pixel value of the outer 8 cells, \( p_{ri} = 0 \) \((i = 1, \cdots, 8)\), \( P_{b0} = 1 \) or 0, \( \alpha_{rb} = 0.22 \)

\[
\begin{align*}
\{p_{ri} = 1 \text{ or } 0, w_{r0i} = 1, w_{r0i} = 0.22 \} & \quad \{p_{ri} = 1 \text{ or } 0, p_{ri} = 0 \text{ (i = 1, \cdots, 8)}, w_{r0i} = 1, \\
\{i = 1, \cdots, 8\}, P_{b0} = 1 \text{ or } 0, \alpha_{rb} = 0.22 \} & \quad \{p_{ri} = 1 \text{ or } 0, r_{ri} = 0 \text{ (i = 1, \cdots, 8)}, P_{b0} = 1 \text{ or } 0, \alpha_{rb} = 0.22 \}
\end{align*}
\]

Fig. 2. Calculated red pixel value distributions, \( P_{r0} \).
4 Experimental results

To verify the validity of 2-wavelength adaptive thresholding, symbol error rate (SER) of WDM/SDM transmission was measured. Figure 3(a) shows the measurement specifications. Uplink distance is 3.5 meters. SER was measured indoors under fluorescent light conditions. Pseudo-random binary sequence 20 (PRBS20) was transmitted as symbols.

Figure 3(b) shows SER versus symbol rate, where R and B pixel values on the screen are reduced to 95. Two-wavelength thresholding corresponds to Eqs. (7) and (8), while the single-wavelength thresholding only corresponds to the first term of Eqs. (7) and (8). Two-wavelength thresholding categorizes both inter-wavelength and spatial ISIs, while the single-wavelength thresholding categorizes only spatial ISIs. Two-wavelength thresholding significantly reduces SER more than the single-wavelength thresholding. The WDM/SDM with 200 × 120 cells in size transmits 720 kbit/s in total with bit error rates of less than 1.7 × 10⁻⁵.

Figure 3(c) shows the procedure for the thresholding, where P₀ needs to be categorized by Eq. (7). First, to remove the blue inter-wavelength ISI from the red wavelength, unknown cells are categorized as “B on” and “B off” by the threshold for P₁₀. Second, the “B on” and “B off” cells are adaptively categorized by the outer 8-cell red symbol pattern in Eq. (7) as “R on” and “R off.” The outer 8-cell pattern is estimated by the fixed threshold that is determined by the known symbols in the preamble [3]. The individually categorized “R on” and “R off” cells are recategorized as “R on” and “R off.” Third, the “R on” and “R off” cells are categorized by the outer 8-cell blue symbol pattern in Eq. (8) as “B on” and “B off.” The individually categorized “B on” and “B off” cells are recategorized as “B on” and “B off”. Furthermore, categorizations by Eqs. (7) and (8) are iterated.

To verify the effectiveness of the thresholding further, Fig. 3(d) shows red and blue pixel value distributions of WDM/SDM with 200 × 120 cells in size. Since the distributions overlap each other, it is difficult to distinguish between “R on” and “R off” cells. First, in Fig. 3(d) right, the blue pixel value distributions are categorized by the threshold for P₁₀ that is determined at 63 by the known symbols in the preamble. Figure 3(e) shows red pixel value distributions, “B on” and “B off,” categorized by the threshold for P₁₀. Most of the “B on” and “B off” distributions are categorized. Second, in Fig. 3(e), the red pixel value threshold for “B on” and “B off” is adaptively determined by the outer 8-cell red symbol pattern. Figure 3(f) shows examples of the red pixel value distributions categorized by the outer 8-cell red symbol pattern, where the outer 8 cells are black. The outer 8-cell pattern categorization eliminates overlap between “R on” and “R off” distributions. The threshold for “B on” and “B off” is determined at 36 and 28, respectively by the known symbols in the preamble. The SER performance is obtained in each outer 8-cell pattern categorization.

5 Conclusion

Two-wavelength adaptive thresholding was numerically analyzed and experimentally verified for uplink SCC from smartphone’s low-luminance WDM/SDM screen to camera. The thresholding categorizes both the inter-wavelength and spatial ISIs due to the defocus blur at a distance of 3.5 m. The low-luminance WDM/SDM with the
Fig. 3. Measured SER versus symbol rate and pixel value distributions.
adaptive thresholding achieved 720 kbit/s transmission in total with bit error rates of less than $1.7 \times 10^{-5}$.

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Propagation of photoluminescence photons in fluorescent optical fibers

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Abstract: In this paper, we present a simple numerical model to describe the propagation characteristics of PL photons in fluorescent optical fibers. Furthermore, we clarify that the photoluminescent intensity distribution is expressed by a simple approximate solution, and we demonstrate its validity through numerical calculations. The experimental results show that the calculated photoluminescent spectra agree well with the measured spectra for fluorescent fiber fabricated by a heat-shrinkable tube, an ultraviolet curable resin, and Lumogen F Red 305 of fluorescent material.

Keywords: fluorescent optical fibers, photoluminescent spectra

Classification: Sensing

References

1 Introduction

Recently, the applications of fluorescent fiber have been actively studied because of its attractive features, such as wavelength conversion, change toward light, and low transmission loss. For example, fluorescent fiber has been applied to antennas for visible light communication to expand the light receiving range [1]. Also, it has been studied as luminescent solar concentrators for photovoltaics [2]. Scintillating fiber, a type of fluorescent fiber, has been used as a radiation detector because it emits scintillation when exposed to radiation [3]. Scintillation fibers have been studied for applications in in vivo dosimetry during radiotherapy and as several radiation dose monitors because of their low transmission loss, lightweight, and small diameter. Recently, we proposed a position-sensitive detector based on redshifts in PL spectra that use the wavelength dependence of the transmission loss of fluorescent fibers [4]. However, it is difficult to measure the optical spectra because the intensity of the scintillating light due to the radiation is small. Therefore, we proposed a position detector using a dichroic mirror and a silicon photomultiplier [5]. In these applications, the relationship between the propagation distance and the intensity of PL light in fluorescent fibers is important. The propagation characteristics of fluorescent waveguides, such as fluorescent fibers, are often calculated using numerical methods based on the Monte Carlo method. The calculations are complicated [6].

In this study, we first present a simple numerical model to describe the propagation characteristics of PL photons in a fluorescent fiber. By neglecting the reemission caused by the self-absorption during the propagation in the fluorescent fiber, we show that the PL intensity can be expressed by a simple approximate solution. Furthermore, we calculate the propagation characteristics of PL photons in fluorescent fibers under various conditions and clarify the errors of the approximate solution. A fluorescent fiber is fabricated using a heat-shrinkable tube, ultraviolet (UV) curable resin, and fluorescent material. The emission spectra of the fabricated fluorescent fiber are measured and compared with those calculated by the presented model.

2 Theory

Figure 1 shows the measurement system. An excitation laser beam is injected from above into a point of an optical fiber containing a fluorescent material. A proportion of the PL photons generated by the laser beam propagates through the fiber. In
addition to the light coupled to the core mode of the fiber, the light coupled to
the cladding modes of the fiber would propagate over short distances. However, for
simplicity, only the core mode of the fiber is considered in this analysis. The intensity
of the fluorescent light propagating through the fiber \( I_S(\lambda, 0) \) can be expressed by
the following equation:

\[
I_S(\lambda, 0) = \eta \beta(\lambda) S_{em}(\lambda) \alpha_{ab}(\lambda) I_P(\lambda_P),
\]

where \( \beta, S_{em}, \eta, \alpha_{ab}, I_P, \) and \( \lambda_P \) are the capture ratio of the fiber, emission
spectrum, quantum efficiency of the fluorescent material, absorption spectrum of
the fluorescent material, intensity of the excitation light, and excitation wavelength,
respectively.

The intensity of the PL photons at a distance \( z \) from the incident position of the
excitation light \( I_S(\lambda, z) \) can be obtained by solving the following differential equation
with the initial value \( I_S(\lambda, 0) \).

\[
\frac{dI_S(\lambda, z)}{dz} = -(\alpha_F(\lambda) + \alpha_a(\lambda)) I_S(\lambda, z) + \eta \beta(\lambda) S_{em}(\lambda) \int_0^\infty \alpha_{ab}(\lambda) I_S(\lambda, z) d\lambda,
\]

where \( \alpha_F \) and \( \alpha_a \) are the attenuation coefficient of the fiber and the absorption
coefficient of the fluorescent material, respectively. In Eq. (2), the first term on
the right-hand side represents the transmission loss in the fiber. The integral in
the second term on the right-hand side represents the spectral overlap between the
propagating light and the absorption of the fluorescent material. As the PL photon
propagates through the fiber, it is absorbed by the fluorescent material in the fiber and
reemission occurs. The second term on the right-hand side represents the intensity
of the reemission during propagation through the fiber, which is coupled to the core
mode of the fiber.

The capture ratio of a multimode fiber with a step-index profile can be expressed
by the following equations [7, 8]:

\[
\beta(\lambda) = C \left( \frac{NA(\lambda)}{n_{core}(\lambda)} \right)^2,
\]

\[
NA(\lambda) = \sqrt{n_{core}^2(\lambda) - n_{clad}^2(\lambda)},
\]

where \( NA, n_{core}, \) and \( n_{clad} \) are the numerical aperture, core refractive index, and
cladding refractive index of the fiber, respectively. \( C \) is a constant determined by
the refractive index profile. The typical value of \( C \) for a multimode fiber is 0.38 [8].
In the case of a scintillating fiber (Kuraray Co., Ltd., Japan, Model SCSF-78), the
capture ratio $c$ is 0.031 [9]. In the case of the fiber fabricated with UV curing resin and heat-shrinkable tubing [5], $NA = 1.20$, $n_{core} = 1.56$, $n_{clad} = 1.00$, and the capture ratio calculated from these parameters is as small as 0.224. By ignoring the second term on the right-hand side of Eq. (2), Eq. (2) can be solved as follows:

$$I_S(\lambda, z) = I_S(\lambda, 0) \exp \left(- \int_0^z (\alpha_F(\lambda) + \alpha_a(\lambda))dz \right).$$  \hfill (5)

If $\alpha_F$ and $\alpha_a$ are assumed to be constant regardless of the distance, the following analytical approximate solution is obtained:

$$I_S(\lambda, z) = I_S(\lambda, 0) \exp(- (\alpha_F(\lambda) + \alpha_a(\lambda))z).$$  \hfill (6)

3 Simulation results

Equations (1) and (2) were used to calculate the propagation characteristics of the PL photons in fibers containing the fluorescent material Lumogen F Red 305 [10]. For simplicity, we set $\eta = 1$, $\alpha_F = 0$, and $\beta = 0.224$. Figure 2 shows the simulation conditions and results. Figure 2(a) shows the emission and absorption coefficient spectra of Lumogen F Red 305 used in the simulation [10]. The solid and broken lines show the emission and absorption coefficient, respectively. Both spectra are normalized by the peaks.

Figure 2(b) shows the PL spectra as a function of the propagation distance $z$ in the fiber. The attenuation coefficient at the wavelength of 400 nm was set at 20 dB/m. The solid and broken lines represent the true PL spectrum calculated by Eq. (2) and the approximate one calculated from Eq. (6), respectively. As the distance $z$ increases, the light with a shorter wavelength is absorbed by the fluorescent material and the light intensity decreases, while the light intensity with a longer wavelength hardly decreases due to the reemission of the fluorescence. It can be seen that as the distance $z$ increases, the approximation error increases. Here, we defined the approximation error as the relative error between the true intensity calculated by Eq. (2) and calculated by approximate solution of Eq. (6).

Figure 2(c) shows the approximation error. The inset shows a magnified view of the wavelength range from 640 to 700 nm. The attenuation coefficient at the wavelength of 400 nm was set at 20 dB/m. The error is approximately 100% at short wavelengths, whereas the error is small and constant at long wavelengths. This phenomenon can be explained as follows. The absorption by fluorescent material is large at short wavelengths, but it is small at long wavelengths [10]. Therefore, the attenuation of PL intensity with distance $z$ is larger at short wavelengths but smaller at long wavelengths. In the approximate calculation, the increase in fluorescence intensity due to reemission is neglected. Therefore, the approximate value approaches 0 before the true value at short wavelengths, resulting in the error of approximately 100%. Focusing on the error above the wavelength of 640 nm at which sufficient PL intensity is obtained, we observed that the error is independent of the wavelength.

Figure 2(d) shows the approximation error as a function of the attenuation coefficient. As the attenuation coefficient increases, the error increases, but it can be seen that the increase in the error gradually becomes more gradual. It can also be seen that as the propagation distance $z$ increases, the error increases, but the
increase in the error gradually becomes more gradual. This phenomenon can be explained as follows. In the approximate calculation, the increase in optical power due to the reemission of fluorescence is neglected. When the distance $z$ is short, the propagating light contains enough short wavelength components that are well absorbed by the fluorescent material; therefore, the intensity of reemission and the increase in the error are large. However, as the distance $z$ increases, both the intensity of the propagating light in a short wavelength and the intensity of the reemission decreases, resulting in a smaller increase in error. Under the calculation conditions, the error was found to be less than a few percentage in the wavelength range of 640–700 nm, where sufficient emission intensity is obtained.

Figure 2(e) shows the normalized intensity of the PL spectra as a function of the distance $z$. The attenuation coefficient at the wavelength of 400 nm was set at 20 dB/m. It can be seen that as the propagation distance $z$ increases, the intensity at short wavelengths decreases and the intensity at long wavelengths increases relatively. Hence, the peak wavelength moves to longer wavelengths with respect to the
increase in propagation distance $z$.

4 Experimental results

The PL spectra of a fluorescent fiber were measured using the measurement configuration shown in Fig. 1. At the end of the fluorescent fiber, the position of the excitation laser beam into the fluorescent fiber was varied from 0.02 to 0.27 m. The light emitted from the laser was attenuated through a neutral density filter and then focused onto the fiber by a plano-convex lens. The excitation power into the fiber was 348 $\mu$W. The integration time of the spectrometer was 11 ms, and the number of averaging times was one. Note that as the propagation distance increases, the intensity at shorter wavelengths becomes lower than that at longer wavelengths, therefore the setting of the integration time of the spectrometer is important for accurate measurements.

The fluorescent fiber was fabricated using a mixed solution of UV curing resin NOA81 (Norland Products Inc.) and fluorescent materials Lumogen F Red 305 (BASF Japan Ltd.) at 0.02 wt% and heat-shrinkable tube NF040 (HAGITEC CO. LTD.) [5]. The length was 0.4 m and the diameter of the fiber was 3.3 mm.

Figure 3 shows the measured PL spectra normalized at peak intensities. The solid and broken lines represent the measured and fitted spectra in Eq. (6), respectively. It is seen that the fitted spectra agreed well with the measured spectra. Similar to the simulation results shown in Fig. 2(e), the peak wavelength shifts to the longer wavelength as the propagation distance $z$ increases, indicating the occurrence of redshift. The difference between the simulated and measured results is considered to be mainly because the simulation neglects losses other than absorption by the fluorescent materials.

![Fig. 3. Experimental results](image_url)

5 Conclusion

In this study, we presented a simple numerical model to describe the propagation characteristics of PL photons in fluorescent fibers. Furthermore, we clarified that the PL intensity could be expressed by a simple approximate expression, and its validity was demonstrated by numerical calculations. Under the calculation conditions, the error of the approximate solution was found to be less than a few percentage. A fluorescent fiber was fabricated using a heat-shrinkable tube, UV-curable resin, and Lumogen F Red 305. The measured PL spectra of the fabricated fiber were compared...
with those calculated using the presented model. As a result, the calculated results agreed well with the measured results.

Acknowledgments

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Indirect diagnosis methods of energy storage capability for mobile devices with USB power delivery

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Abstract: Autonomous distributed power grids have attracted attention as a way to utilize renewable energy to achieve a carbon-neutral society. In order to properly operate these grids, it is necessary to obtain sufficient information on the supply and demand power capabilities and battery health of connected devices in a short time. In addition, methods based on direct current are essential to maximizing the use of renewable energy. This study proposes a method for acquiring information about the energy storage of devices connected to the grid via USB power delivery using deep learning techniques. Furthermore, we propose a method to diagnose the embedded battery health of the device based on short-time monitoring.

Keywords: virtual grid system, USB PD, mobile device, deep learning, battery, degradation

Classification: Energy in Electronics Communications

References

1 Introduction

Renewable energy is being used extensively to realize a decarbonized society. Due to stabilizing the power supply, autonomous distributed power grids that can be operated efficiently through mutual assistance are attracting extensive attention. In these power grids, a cooperative power supply based on the device information, such as the amount of available power supply (State of Charge, SoC) and the embedded battery health (State of Health, SoH), is performed. However, the method to obtain this information in a short time is a big concern, as it should be automatic and not require additional dedicated equipment on the device side, as well as securely and indirectly. Although methods to estimate the product type have already been proposed [1], obtaining information on SoC and SoH based on direct current supply is essential to maximize the use of renewable energy.

This study proposes a method for diagnosing connected devices via USB-PD interface [2] in an autonomous distributed power grid by investigating how to indirectly obtain SoC and SoH by conducting charging experiments and accelerated degradation tests using the power grid for mobile terminals.

2 Proposed diagnosing methods for embedded batteries

Several proposals and reports have already been on SoC and SoH diagnostics; a systematic review on SoC diagnostics [3] reported a dichotomy between model-based and data-driven methods. Model-based diagnostics are not suitable for embedded battery diagnostics because they require in-depth knowledge of the battery’s structure and physicochemical reactions. On the other hand, data-driven SOC estimation is a relatively new approach made possible by the advent of large amounts of data and powerful computers. It can be constructed based on minimal knowledge and empirical observations and does not require information about the battery’s internal chemistry. Therefore, it is suitable for performing short-term diagnostics in the dynamically operating power grid, where various devices are repeatedly connected and disconnected. Diagnostic methods such as LSTM (Long Short-Term Memory) have been studied and reported and have been found to provide superior results compared to UKF (Unscented Kalman Filter) [4]. In this study, we apply this method to the voltage-current fluctuation of a USB-PD when it is connected and confirm the effect. However, since these methods represent autoregressive estimation for batteries that can be continuously observed for electric vehicles (EVs), their
applicability to embedded devices whose observations are interrupted by connection and disconnection is unknown. In this study, the LSTM-based method will be applied to voltage-current variations in devices connected to the grid using USB-PD.

Data-driven SoH diagnostics have also been studied to ensure battery reliability and safety, and their performance has been evaluated in actual electric vehicle operating environments [5]. These diagnostics are also based on data from continuous measurements during operation in EVs. Because of its autoregressive approach, it may not be suitable for the dynamic diagnosis of devices with embedded batteries when connected to the grid, which is the subject of this paper. Therefore, this paper presents a simple method for estimating SoH from the accumulated charge and power data obtained when a USB-PD is connected and verifies its effectiveness from accelerated test results.

3 Results and discussion

3.1 SoC diagnostics on embedded batteries

Current and voltage values were measured for several types of mobile devices, repeatedly charging and pausing every 15 minutes. In all devices, the internal circuitry began to control the device so that it did not exceed its allowable storage capacity as it approached full charge. As the charge level increased, the device was charged using less power, as shown in Fig. 1(a).

This characteristic is particularly noticeable in personal computers and smartphones that USB-PD can power. This is because they are equipped with active functional blocks that require a stable operation, such as CPUs and displays, instead of devices such as mobile batteries that only have an energy storage function. Since the type of functional blocks, a control algorithm, and the capacity and health of the battery differ from device to device, the observed characteristics also differ. Furthermore, observed time-dependent variation of current-voltage characteristics will reflect the control by the device itself and the internal state of the battery. Therefore, this study examined a method to use this difference in power charging and consump-

![Fig. 1. Results of charge level measurement experiment. (a) An example of the charging waveform of Google Pixel 3a. (b) Classification accuracy of the charge level by the proposed LSTM discriminator.](image-url)
tion to estimate the SoC of devices connected to the power grid via USB-PD. We developed a discriminator that determines the approximate charge level by learning the current-voltage characteristics of USB-PD connected devices during charging using LSTM.

The estimation is based on the classification of SoCs into gradual classes, as defined below:

- Class 1: State in which charging is urgently required (SoC = 0~49%).
- Class 2: State in which recharging is necessary but less urgent than in Class 1 (SoC = 50~79%).
- Class 3: Near full charge or full charge state (SoC = 80~100%).

The results of the SoC estimation based on the defined classes show an average performance of 86% correct for various types of devices (Fig. 1(b)). In an autonomous decentralized power grid, knowing the rough SoC of connected devices is essential to prioritize the power supply. LSTM with the three-class classification model showed high classification performance for the purpose and will be able to contribute to charging management of the power grid.

In particular, USB PD has a roll-swap function, which allows devices that are close to being fully charged to be transferred from the receiving side to the supplying side. In other words, it can be expected to realize a cooperative power supply among devices in the power grid and contribute to improving the grid’s resilience.

### 3.2 SoH diagnostics on embedded batteries

The charge behavior of smartphones was investigated by an accelerated degradation test for seven months. Three smartphones were stressed under different operating load conditions in a thermostatic oven and periodically measured the charge waveforms outside the oven from SoH = 0% to SoH = 100%. The observed SoH tended to be smallest for the most heavily loaded iPhone8_1, highest for the lightly loaded iPhone8_3, and between for iPhone8_2. As shown in Fig. 2(a), it was found that
differences in the charge waveforms occurred due to differences in the degradation state of the batteries because of usage loads of individual devices, although they were the same product.

Focusing on the area of this Wattage–cumulative charge curve, the area decreases as degradation progresses, indicating that battery degradation affects the behavior of the charge waveform. The comparison results show a strong correlation between the variable’s difference in SoH and the ratio in the charging waveform area, as shown in Fig. 2(b). By estimating this relationship using a simple linear model, the amount of degradation could be predicted with an accuracy of \( \text{RMSE} = 3.97\% \).

The ratio of the charging waveform area does not need to be observed over the entire range from SoC = 0% to SoC = 100%; it can also be estimated with a ratio based on observations over some coverage from the start of charging. Verification results show that the degradation state can be roughly estimated by measuring the charging waveform for approximately one hour.

The current verification was conducted using the charging waveform from SoC = 0%. In the future, a modified method of estimation using charge waveforms from intermediate SoC states will be required to improve practicality.

3.3 Verification of the proposed method
We implemented the proposed model in an electric power hub developed in [6] and empirically verified the diagnosis of connected devices in an autonomous distributed power grid. We estimated the rough classification of the charge state with 71% accuracy in approximately 30 seconds. An accuracy of \( \text{RMSE} = 9.32\% \) was obtained in about one hour of conducting the measurement to estimate the degradation state. The lower accuracies compared to the above results are caused by the difference in accuracies of voltage and current measuring instrument mounted in the electric power hub and can be improved by a circuit design. Consequently, these results indicate the possibility of practical use for the proposed methods.

4 Conclusion
This study investigated a method to indirectly obtain information on the SoC and SoH of embedded batteries connected via the USB PD using the LSTM discriminator and charge waveform degradation model.

We investigated LSTM discriminator to automatically classify the charging level of the connected devices based on the characteristics of the charging waveform. We also proposed a method to predict the relative amount of degradation considering the charging behavior changes depending on the degradation state.

The indirect acquisition of device SoC and SoH information would enable efficient power supply and reception in the autonomous distributed power grid using renewable energy without an additional unit and a security concern. It will contribute to the stability and resilience of the power grid.

Shortening SoH estimation times and establishing SoH estimation using data in intermediate SoC states will be required in future works.
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