A triple-band decoupling method for MIMO antennas without connection

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Abstract: In recent years, MIMO technology is used in many mobile terminals to increase channel capacity. MIMO uses multiple antennas, however, if MIMO antennas are put closely such as a small terminal, a strong mutual coupling occurred. Then it causes decreasing radiation efficiency and channel capacity.

Besides, CA technology which uses multiple frequencies is also utilized. Therefore, reducing the mutual coupling at multiple frequencies is required corresponding to CA. In the previous study, a method of adding a branch element connecting by inductor L and capacitor C has been proposed. In this paper, focusing on the relationship between the number of decoupling frequencies and current paths, we propose a novel triple-band decoupling method without connecting and confirm that the proposed model performed decoupling and increased radiation efficiency.

Keywords: MIMO, CA, decoupling, short stub

Classification: Wireless Communication Technologies

References

1 Introduction

MIMO (Multiple-Input Multiple-Output) technology which uses plural antennas and CA (Carrier Aggregation) which operates multiple frequencies are introduced in many mobile terminals to increase channel capacity. If MIMO antennas are inserted to small terminals, plural antennas are needed to put closely from the viewpoint of an installing space and designability. However, a strong mutual coupling by putting plural antennas closely causes deteriorating radiation efficiency, and channel capacity decreases [1]. Therefore, to reduce mutual coupling at multiple frequencies is required corresponding to CA. In the previous study, a method of making antennas branch structure and connecting antennas by inductor L and capacitor C is proposed [2]. However, this method needs to connect antennas, hence, wiring routing is troublesome, and power loss by L and C is occurred. In this paper, focusing on the relationship between the number of decoupling frequencies \( N_{fd} \) and current paths, we propose a non-connected triple-band decoupling method.

2 Antenna models and decoupling method

We use simulator CST MW-Studio 2018 [3]. In this paper, 2 elements monopole antennas are a base model assuming \( 2 \times 2 \) MIMO shown in Fig. 1(a). This antenna array is implemented on a \( 140 \times 50 \times 0.8 \) mm one-side \( 35 \mu \)m copper plate FR4 substrate whose relative permittivity is 4.3, a ground plate is \( 100 \times 50 \) mm. If admittance between antennas \( Y_{21} \) set to 0 at desired frequencies, decoupling can be obtained [4]. Fig. 2(a), (b) show \( S_{11} \) and \( Y_{21} \) respectively of Fig. 1(a). From Fig. 2(a), the downtrend of \( S_{11} \) is obtained at around 1.9 GHz, the resonance of \( Y_{21} \) also generated at around the downtrend of \( S_{11} \) (1.9 GHz). Here, the frequency at which the real and imaginary part of \( Y_{21} \) change is defined as “resonance”. The downtrend of \( S_{11} \) and the resonance correspond to each other, if the downturn of \( S_{11} \) moves higher frequency, the resonance also moves higher. Hence, the frequency of the resonance can be adjusted because of altering monopole element length.

Fig. 1(b) shows the proposed antenna model to decouple at 3 frequencies: 800 MHz, 1.7 GHz and 2.1 GHz. This model is constructed by attaching the long branch element, the short branch element and the short stub to the monopole of Fig. 1(a). The long branch is a meander structure because the antenna volume to z-direction is reduced [5]. Fig. 2(c) shows \( Y_{21} \) of eliminated the short branch and the short stub of the proposed model. From this figure, one more resonance is generated at 900 MHz in addition to the resonance of monopole. Then, \( Y_{21} = 0 \) is obtained 1.3 GHz between two resonances. Therefore, to get \( Y_{21} = 0 \), engendering two resonances is required. Fig. 2(d) shows \( Y_{21} \) of eliminated only the short stub of the proposed model. One more resonance is generated at 2.1 GHz. \( Y_{21} = 0 \) is obtained at two frequencies 1.3 GHz between resonances of meander (900 MHz) and monopole (1.7 GHz), 1.9 GHz between resonances of the monopole (1.7 GHz) and the short branch (2.1 GHz). Fig. 2(e) shows \( Y_{21} \) of the proposed model. The resonance of the short stub added at DC (0 Hz) [6], a total of four resonances appear. At 900 MHz, 1.7 GHz and 2.1 GHz, decoupling condition \( Y_{21} = 0 \) is achieved.
As a result, to decouple at three frequencies, four resonances should be generated. In the proposed model, current paths are assumed four: the monopole, the short branch, the meander, the short stub. Thus, by preparing one more current path than $N_{fd}$, decoupling at multiple frequencies can be realized. Moreover, to decouple at three frequencies, we propose a trifurcation structure with the short stub. In fact, four branch elements without the short stub are also realized. However, the number of branches can be reduced by using the short stub, we adopt the short stub. In summary, to perform decoupling at multiple frequencies, preparing branch elements same at $N_{fd}$, the short stub is added. The branch element and the short stub is not needed to connect antennas, hence, decoupling without connection is performed.

3 S-parameters and radiation efficiency

Fig. 3 shows S-parameter of each model with matching circuits. $S_{11}$ shown in blue is less than $-10$ dB at the desired frequencies in both models. However, in only monopoles, $S_{21}$ shown in red is $-2.0$ dB at 800 MHz, $-3.2$ dB at 1.7 GHz, $-5.7$ dB at 2.1 GHz. On the other hand, $S_{21}$ of the proposed model is $-6.3$ dB at 800 MHz, $-10.3$ dB at 1.7 GHz, $-15.7$ dB at 2.1 GHz. Therefore, $S_{21}$ decreases 4.3 dB, 7.1 dB and 10.0 dB respectively.

In addition, radiation efficiency of only monopoles is $-8.6$ dB at 800 MHz, $-3.9$ dB at 1.7 GHz, $-2.0$ dB at 2.1 GHz. By contrast, in the proposed model, radiation efficiency is $-3.0$ dB at 800 MHz, $-3.3$ dB at 1.7 GHz, $-1.5$ dB at

![Fig. 1. Base and proposed antenna models (Unit: mm)](image)

(a) 2 elements monopole antennas  (b) Proposed antenna

![Fig. 3. Base and proposed antenna models (Unit: mm)](image)
Fig. 2. Relationship between resonances and decoupling frequencies
2.1 GHz. As a result, radiation efficiency increased 5.6 dB, 0.6 dB and 0.5 dB respectively.

4 Conclusion

In this paper, we proposed the multiband decoupling method focused on the number of resonances of $Y_{21}$ and $N_{fd}$. In an arbitrary number of decoupling frequencies, if one more current path than $N_{fd}$ is prepared, decoupling can be realized ($Y_{21} = 0$ is obtained).

Based on this theory, we make the triple-band decoupling model by using the trifurcation element and the short stub. As a result, resonances of $Y_{21}$ corresponding to each current path are generated by the proposed model, then, $Y_{21} = 0$ can get at desired frequencies.

Compared with only monopole antennas model, mutual coupling $S_{21}$ can be reduced 4.3 dB, 7.1 dB and 10.0 dB respectively and radiation efficiency improves 5.6 dB, 0.6 dB and 0.5 dB respectively. Hence, it is confirmed that decoupling can perform at triple-band frequencies.
TDOA/FDOA geolocation in space radio monitoring using RLMS and gating

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Abstract: In this paper, we consider the problem of improving the accuracy of time difference of arrival (TDOA) and frequency difference of arrival (FDOA)-based geolocation for unknown emitters. Our approach integrates multiple geolocation results by using a recursive least mean square (RLMS) algorithm and removing outliers. Simulation results show that the proposed method improves geolocation accuracy and that gating effectively removes the outliers. For instance, if two out of 20 measurements are outliers, then the root mean square error (RMSE) of the proposed method has been reduced by 74.31% (12.84 km) compared with conventional methods.

Keywords: TDOA/FDOA, geolocation, RLMS, gating

Classification: Space Utilization Systems for Communications

References


1 Introduction

In satellite communication, uplink interference from unknown emitters has posed a severe problem. With regard to radio monitoring, a geolocation algorithm (shown in Fig. 1) using time difference of arrival (TDOA) and frequency difference of arrival (FDOA) between the main and adjacent satellites has been developed
However, when the accuracy of the TDOA and FDOA measurements is insufficient, geolocation accuracy degrades. In the worst cases, (especially outliers) these results are completely unusable.

In the real time monitoring, measurement data sets are obtained sequentially over time. In these cases, it is conventional to update the estimation on the basis of newly collected data. This is called the recursive least mean square (RLMS) method [4]. Furthermore, in cases where coarse data sets are obtained, gating methods can be applied to exclude and abandon them [5]. In this paper, we apply RLMS with gating to TDOA/FDOA-based geolocation. We further show, by numerical simulation, the benefits of our proposed method.

2 Conventional TDOA/FDOA geolocation

2.1 Coordinate definition

We first employ the definition of earth centered earth fixed (ECEF) and polar coordinates [1, 2, 3]. Next, we define the earth surface position vectors of two coordinates by

\[ \mathbf{p}_{\text{ecef}} = \begin{pmatrix} x_{\text{ecef}} \\ y_{\text{ecef}} \\ z_{\text{ecef}} \end{pmatrix} \] and \[ \mathbf{p}_{\text{polar}} = \begin{pmatrix} \text{Lon} \\ \text{Lat} \end{pmatrix} \].

The coordinate transformation between the two coordinates is then defined as:

\[ \mathbf{p}_{\text{ecef}} = \mathbf{f}(\mathbf{p}_{\text{polar}}) = \begin{pmatrix} R_E \cos(\text{Lon}) \cos(\text{Lat}) \\ R_E \sin(\text{Lon}) \cos(\text{Lat}) \\ R_E \sin(\text{Lat}) \end{pmatrix} \] (1)

\[ \mathbf{p}_{\text{polar}} = \mathbf{g}(\mathbf{p}_{\text{ecef}}) = \begin{pmatrix} \tan^{-1} \frac{y_{\text{ecef}}}{x_{\text{ecef}}} \\ \tan^{-1} \frac{z_{\text{ecef}}}{\sqrt{x_{\text{ecef}}^2 + y_{\text{ecef}}^2}} \end{pmatrix} \] (2)

where \( R_E \) is the radius of the earth.

2.2 TDOA/FDOA measurement model

As shown in [1], measurement models of TDOA and FDOA between two satellites with the help of known reference stations are described as follows:

\[ \mathbf{z} = \mathbf{h}(\mathbf{p}, \mathbf{p}_{\text{ref}}, \mathbf{v}) + \mathbf{v} \] (3)
\[
\begin{align*}
\mathbf{h}(\mathbf{p}_t, \mathbf{p}_{si}, \mathbf{v}_{si}) & = \left( \begin{array}{c} h_1(\mathbf{p}_t, \mathbf{p}_{si}) \\
 h_2(\mathbf{p}_t, \mathbf{p}_{si}, \mathbf{v}_{si}) 
\end{array} \right) = \left( \begin{array}{c}
\frac{1}{c} (\|\mathbf{p}_t - \mathbf{p}_{si1}\| - \|\mathbf{p}_t - \mathbf{p}_{si2}\|) \\
\frac{1}{\lambda} \left( \frac{\mathbf{v}_{si1}^T (\mathbf{p}_t - \mathbf{p}_{si1})}{\|\mathbf{p}_t - \mathbf{p}_{si1}\|} - \frac{\mathbf{v}_{si2}^T (\mathbf{p}_t - \mathbf{p}_{si2})}{\|\mathbf{p}_t - \mathbf{p}_{si2}\|} \right)
\end{array} \right) \\
\|\cdot\| \text{ indicates the Euclidean norm, } c \text{ is a speed of light, and } \lambda \text{ is the wave length.}
\end{align*}
\]

Furthermore, we assumed that the unknown emitter was located on the surface of the earth. Hence:

\[
\mathbf{R} = \mathbb{E} \{ \mathbf{v} \mathbf{v}^T \} = \left( \begin{array}{cc} \sigma_1^2 & 0 \\
 0 & \sigma_2^2 \end{array} \right)
\]

2.3 Conventional TDOA/FDOA geolocation

Using equations (4) and (6), the estimated emitter location was obtained by solving the following least square problem. We describe the coordinates using subscripts ecef and polar for clarity. In the polar coordinates, the geolocation problem can be recast as follows:

\[
\hat{\mathbf{p}}_{t,polar} = \arg \min_{\mathbf{p}_{t,polar}} (\mathbf{z} - \mathbf{h}(\mathbf{p}_{t,polar}, \mathbf{p}_{si}, \mathbf{v}_{si})) \mathbf{R}^{-1} (\mathbf{z} - \mathbf{h}(\mathbf{p}_{t,polar}, \mathbf{p}_{si}, \mathbf{v}_{si}))^T
\]

subject to \( \mathbf{p}_{t,ecef} = \mathbf{f}(\mathbf{p}_{t,polar}) \).

The constraint of the unknown emitter being located on the earth’s surface is incorporated in (8). Thus, the above problem can be solved using a conventional iteration procedure, such as the Gauss-Newton method [4].

2.4 Error covariance matrix of the conventional method

The error covariance matrix of \( \hat{\mathbf{p}}_{t,polar} \) is obtained by the following equation:

\[
\begin{align*}
\mathbf{Q}(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si}) & = (\mathbf{H}^T(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si}) \mathbf{R}^{-1} \mathbf{H}(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si}))^{-1} \\
\mathbf{H}(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si}) & = \left( \begin{array}{c}
\mathbf{H}_1(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}) \\
\mathbf{H}_2(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si})
\end{array} \right) = \left( \begin{array}{c}
(\mathbf{v}_{p_{t,polar}} h_1(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}))^T \\
(\mathbf{v}_{p_{t,polar}} h_2(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si}))^T
\end{array} \right)
\end{align*}
\]

Each element in (10) is derived as follows:

\[
(\mathbf{v}_{p_{t,polar}} h_1(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}))^T = (\mathbf{v}_{p_{t,ecef}} h_1(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}))^T \left( \frac{\partial \mathbf{p}_{t,ecef}}{\partial \text{Lon}} \frac{\partial \mathbf{p}_{t,ecef}}{\partial \text{Lat}} \right)
\]

\[
(\mathbf{v}_{p_{t,polar}} h_2(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si}))^T = (\mathbf{v}_{p_{t,ecef}} h_2(\mathbf{p}_{t,ecef}, \mathbf{p}_{si}, \mathbf{v}_{si}))^T \left( \frac{\partial \mathbf{p}_{t,ecef}}{\partial \text{Lon}} \frac{\partial \mathbf{p}_{t,ecef}}{\partial \text{Lat}} \right)
\]

\[
\left( \frac{\partial \mathbf{p}_{t,ecef}}{\partial \text{Lon}} \frac{\partial \mathbf{p}_{t,ecef}}{\partial \text{Lat}} \right) = \begin{pmatrix}
-R_E \sin(\text{Lon}) \cos(\text{Lat}) & -R_E \cos(\text{Lon}) \sin(\text{Lat}) \\
R_E \cos(\text{Lon}) \cos(\text{Lat}) & -R_E \sin(\text{Lon}) \sin(\text{Lat}) \\
0 & R_E \cos(\text{Lat})
\end{pmatrix}
\]
The first terms of the right hand side of (11) and (12), are obtained by using (4):

\[
\nabla_{\mathbf{p}_{\text{t,ceef}}} h_1(\mathbf{p}_{\text{t,ceef}}, \mathbf{p}_s) = \frac{1}{c} \left( \frac{\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_s}{\|\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_s\|} - \frac{\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_z}{\|\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_z\|} \right)
\]

(14)

\[
\nabla_{\mathbf{p}_{\text{t,ceef}}} h_2(\mathbf{p}_{\text{t,ceef}}, \mathbf{p}_s, \mathbf{v}_s) = \frac{1}{\lambda} \left( \frac{\mathbf{v}_s}{\|\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_s\|} - \frac{\mathbf{v}_s^T (\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_s)}{\|\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_s\|^2} (\mathbf{p}_{\text{t,ceef}} - \mathbf{p}_s) \right)
\]

(15)

\[
\text{err} = \sqrt{\sum \text{diag}(\mathbf{Q}(\mathbf{p}_{\text{t,ceef}}, \mathbf{p}_s, \mathbf{v}_s))}
\]

(16)

3 Proposed TDOA/FDOA geolocation by RLMS with gating

Hereinafter, we will call a single TDOA/FDOA-based geolocation result the estimated location (EL), and a recursively updated cumulative geolocation result the cumulative location (CL). A block diagram of the proposed method is shown in Fig. 2. Define \( k \) as a time index of time; \( t_k, \hat{\mathbf{p}}_{t,polar,k} \) is the EL obtained in (7) and (8); \( \mathbf{Q}_k \) is the error covariance matrix obtained in (9); \( \mathbf{\hat{x}}_k \) and \( \mathbf{P}_k \) are the CL and the corresponding error covariance matrix. The proposed RLMS equation with gating is given by the following equations:

**Initialization** \( k = 1, \mathbf{P}_1 = \mathbf{Q}_1, \mathbf{\hat{x}}_1 = \hat{\mathbf{p}}_{t,polar,1} \)

- **TDOA/FDOA localization**

  Solve the optimization problem for (7) and (8), and obtain \( \hat{\mathbf{p}}_{t,polar,k} \).

- **Gating**

  \( \mathbf{S}_k = \mathbf{P}_{k-1} + \mathbf{Q}_k \)
  \( (\mathbf{\hat{x}}_{k-1} - \hat{\mathbf{p}}_{t,polar,k})\mathbf{S}_k^{-1}(\mathbf{\hat{x}}_{k-1} - \hat{\mathbf{p}}_{t,polar,k}) < \gamma \)  \( (17) \) and (18)

- **If inside the gate:** Update the cumulative location by RLMS

  \( \mathbf{P}_k = [\mathbf{P}_{k-1}^{-1} + \mathbf{Q}_k^{-1}]^{-1} \)
  \( \mathbf{\hat{x}}_k = \mathbf{\hat{x}}_{k-1} + \mathbf{P}_k \mathbf{Q}_k^{-1} (\hat{\mathbf{p}}_{t,polar,k} - \mathbf{\hat{x}}_{k-1}) \)

- **If outside of the gate:** Stay (memory track)

  \( \mathbf{P}_k = \mathbf{P}_{k-1} \)
  \( \mathbf{\hat{x}}_k = \mathbf{\hat{x}}_{k-1} \)

- **Update the time index**

  \( k = k + 1 \)

Equations (17) and (18) denote gating and \( \gamma \) is a setting parameter that follows Chi-square of freedom two. Finally, the theoretical CL error can be evaluated by the following equation:

\[
\text{err}_k = \sqrt{\sum \text{diag}(\mathbf{P}_k)}
\]

(24)
4 Numerical simulation

4.1 Simulation setting

Fig. 3(a) shows the geometry of the unknown emitter, reference, and two satellites. We assumed that two satellites were located at 150°E and 154°E. The orbital elements were obtained from NORAD element sets [6]. The frequency was 14 GHz (Ku band). The unknown emitter was located at Kyoto, and the reference was located at Tokyo. The accuracy of TDOA and FDOA were 5 µs and 5 mHz, respectively. The number of EL geolocation results was 20 and were obtained sequentially. Following this, we evaluated the RMS of the geolocation error of the CL by running a Monte Carlo simulation 1000 times. Next, we set the gate parameter $\gamma$ to 18.42068074 (0.9999%). Finally, the outliers were added to the TDOA and FDOA measurements at random timing with $3\sigma$ error. First, we evaluated the relationship between RMSE of the CL and the number of ELs for two outliers with random timing. Second, we evaluated the relationship between the RMSE of the CL at $k = 20$ and the number of outliers.

4.2 Simulation results

Fig. 3(b) shows an example of the CL, EL, and gating of the proposed method, Fig. 3(c) shows the RMSE of the CL and EL versus the number of ELs when there are two outliers, and Fig. 3(d) shows the RMSE of CL and EL at $k = 20$ versus the number of outliers. In (b), the blue-squared plots indicate 20 of the ELs obtained sequentially over time. The black lines indicate the ellipsoidal gate for each gating process. The red-starred line shows how the CL is converging at each process. In (c) and (d), the proposed method, the proposed method without gating, and theoretical error bounds of the ELs and CL derived in (16) and (24) are also plotted. In (b), we observed that the two outliers were outside of the gate, and the CL (red plot) converged to the true location (Kyoto). In (c), we observed that the RMSE of CL of the proposed method decreased as the number of ELs increased; however, the theoretical EL remained unchanged. For example, the RMSE of the CL of the proposed method decreased by 74.31% (12.84 km) after 20 ELs. In theory, if the satellite movement is small enough during the measurement, the improvement should be $1/\sqrt{20}$ or 77.63%. On the other hand, two among 20 ELs were removed by gate in this case. Therefore, the improvement should be $1/\sqrt{18}$ or 76.43%. Thus, the RMSE value of the CL for the proposed method is slightly larger than the value of theoretical CL. On the other hand, the RMSE of CL without gating did not decrease as quickly as that of the proposed method, as the outliers were not properly removed by gating. For example, when $k = 20$, the RMS of the CL without gating increased by 39.82% (2.92 km) compared with that of the proposed method.
From (d), we confirmed that as the number of outliers increases, the RMSE of CL for the proposed method increased; the theoretical CL remained unchanged. Thus, the improvement should theoretically be $1/\sqrt{15}$ or 74.18%. It is for this reason that the RMSE of the CL for the proposed method was slightly larger than the value of theoretical CL. In addition, the RMSE of the CL without gating increased more rapidly than that of the proposed method. This was also because the outliers are not being properly removed by gating. For example, when the number of outliers was five, the RMSE of the CL without gating increased by 102% (5.23 km) compared with that of the proposed method.

5 Conclusion

In this paper, we proposed a TDOA/FDOA-based geolocation method using an RLMS algorithm with gating. Simulation results showed that the accuracy of the CL improved as the number of EL increases, owing to the RLMS algorithm. Furthermore, outliers were effectively removed using gating. For instance, when two out of 20 measurements were outliers, the RMSE of the CL for the proposed method was reduced by 74.31% (12.84 km) compared with the theoretical EL value.
Dynamically controlled transmission standby in WLAN systems

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Abstract: With the spread of the WLAN, WLAN devices densely exist, and radio interferences between devices which degrade performance of WLAN systems have been increasing. In this study, we propose the WLAN system which has the transmission standby in which devices with poor channel condition wait for transmissions, and other devices can transmit frames without radio interferences from the devices which are waiting for transmissions. Simulations to evaluate transmission performance of WLAN systems show the transmission standby technique reduces radio interferences and effectively utilizes radio resources.

Keywords: wireless LAN, transmission standby

Classification: Wireless Communication Technologies

References


1 Introduction

With the spread of the WLAN (Wireless Local Area Network), WLAN devices densely exist, and radio wave interferences between devices [1] which degrade performance of WLAN systems have been increasing. The SINR (Signal to Interference plus Noise power Ratio) which indicates the condition of a received signal is expressed as

$$\gamma_{\text{SINR}} = \frac{S}{\sum_{n} I_n + N},$$

where $S$ represents the received signal power, $I_n$ represents the interference power from the device with number $n$, and $N$ represents the noise power. As the sum of interference power increases, SINR decreases.

In a WLAN system, one AP (Access Point) and STAs (Stations) belonging to BSS (Basic Service Set) deployed by the AP perform frame transmissions and receptions. Channel assignment schemes [2] reduces interferences by setting the channel of each BSS to a different channel from channels used by BSSs which cause strong interferences to the BSS. In this study, we propose the transmission standby technique to reduce interferences. The WLAN system which has the transmission standby in which devices whose SINRs are lower than the threshold wait for transmissions, and other devices can transmit frames without radio interferences from the devices which are waiting for transmissions. Because the transmission standby technique decreases the number of devices which compete with one another to obtain access opportunity, interferences from adjacent devices are less, and devices with better channel condition can transmit frames with less transmission failure and higher transmission rate.

2 Related works

The conventional WLAN system based on DCF (Distributed Coordination Function) which is a specific CSMA/CA (Carrier Sense Multiple Access/Collision Avoidance) mechanism defined in IEEE 802.11 standard [3] provides an equal access opportunity to WLAN devices, and Tuning the Carrier Sensing Range [4] can reduce harm of interferences by optimization of carrier sensing range.

A WLAN system with Opportunistic CSMA/CA [5] provides efficient use of radio resources by giving transmission opportunity to WLAN devices with better channel condition. A WLAN system with RATOP (Resource Allocation based on the area Throughput Optimization Policy) [6] effectively utilizes radio resources by setting the bandwidth and the channel of each AP based on channel state information which is collected from APs in an area.
We propose the transmission standby technique to use radio resources more efficiently by reducing interferences. A WLAN system with the transmission standby technique has two parameters TSR (Transmission Standby Rate) and TSL (Transmission Standby Length) which decide the rule to wait for transmissions. In the proposed WLAN system, at first, the AP measures the distribution of the SINR for $i$-th STA $\gamma_{\text{SINR},i}$ and determines the threshold for $i$-th STA $v_{\text{th},i}$ to satisfy the following equation.

$$
\int_{\gamma_{\text{SINR},\text{low}}}^{v_{\text{th},i}} p(\gamma_{\text{SINR},i})d\gamma_{\text{SINR},i} = \text{TSR}.
$$

In the above equation, $\gamma_{\text{SINR},\text{low}}$ is the lowest SINR to receive a frame with no bit error, $p(\gamma_{\text{SINR},i})$ is the probability density function (pdf) of $\gamma_{\text{SINR},i}$, and TSR ($0 \leq \text{TSR} < 1$) is the parameter to control the rate of the transmission standby possibility for $i$-th STA. The AP collects data of $\gamma_{\text{SINR},i}$ only when $\gamma_{\text{SINR},i}$ is higher than $\gamma_{\text{SINR},\text{low}}$, in other words, when frames are received with no bit error. If the set of samples of $\gamma_{\text{SINR},i}$ which are collected by the AP is $\{X_1, X_2, \ldots, X_m, \ldots, X_{M-1}, X_M\}$ in ascending order, $v_{\text{th},i}$ will be $X_m$ when TSR is $\frac{m}{M}$. TSL determines the duration to wait for transmissions. If TSR and TSL are too large, since all devices in the proposed WLAN system will concurrently wait for transmissions and not able to utilize radio resource efficiently, TSR and TSL need to be optimized.

In the proposed WLAN system, by using TSR, the fairness in transmission opportunity will be kept as the conventional DCF-based WLAN system since devices which have higher average of SINR are set the threshold to higher value and devices which have lower average of SINR are set the threshold to lower value. The proposed WLAN system has the advantage to improve the received SINR and efficiently utilize the radio resource because the devices with lower SINR which can not utilize the radio resource efficiently wait to transmit frames and devices with better channel condition can transmit frames with less interferences.

The uplink transmission sequence of the proposed WLAN system which has the transmission standby is shown in Fig. 1. The proposed WLAN system is based
on the DCF protocol with the medium reservation scheme using an RTS/CTS (Request to Send/Clear to Send) frame. In proposed WLAN system, the AP assesses SINR of the STA by the received RTS frame from the STA, and devices perform two types of transmission as shown in Fig. 1.

1. SINR of the STA ≥ the threshold
   In case 1), devices transmit frames same as the conventional WLAN system. The STA transmits an RTS frame to the AP, the AP transmits a CTS frame to the STA, the STA transmits a data frame to the AP, and the AP transmits an ACK (ACKnowledge) frame to the STA.

2. SINR of the STA < the threshold
   In case 2), a TSC (Transmission Standby Command) frame is transmitted to the STA by the AP instead of a CTS frame. If the STA receives a TSC frame, the STA suspends the transmission of data frame and sets the waiting time of which length is TSL.

Since channel condition changes with time, and a BSS can move around with a mobile AP, the mechanism for dynamic control of TSR and TSL in the transmission standby technique is necessary to obtain maximum benefit of waiting for transmissions. We propose the dynamic control mechanism for the transmission standby technique in which a controller for optimization of TSR and TSL collects throughput data in each BSS from APs in an area via the network, and sets TSR and TSL by using collected data. In the proposed WLAN system, the mechanism for setting parameters TSR and TSL has only two patterns of process which are a process to increase a parameter and a process to decrease a parameter. Since the optimum values of TSR and TSL change with situation of transmissions which changes with time, TSR and TSL are not fixed to a specific value in the dynamic control mechanism.

The mechanism for setting TSR in the proposed WLAN system will simply perform the same process as the previous process when the total throughput is improved by performing the previous process, and the mechanism will simply perform the opposite process to the previous process when the total throughput is reduced by performing the previous process. The mechanism for setting TSL is similar to the mechanism for setting TSR.

Since the proposed WLAN system has a mechanism to keep equal access opportunity to devices, the proposed WLAN system considers only the total throughput to set parameters. When devices in the proposed WLAN system share a same band with other wireless devices, equal access opportunity between devices in the proposed WLAN system and other devices will not be kept. However, at least, devices in the proposed WLAN system do not give harm to other devices because devices in the proposed WLAN system only wait to transmit frames according to TSR and TSL.

### 4 Performance evaluation

We carried out two computer simulations to examine the performance of the proposed WLAN system, which are a simulation performed by two BSSs and a simulation performed by three BSSs. Table I shows the simulation conditions. In
the simulations, if there are premises that there are no radio interferences and $\gamma_{\text{SINR}_i}$ continues to increase, it is assumed that the transition from the minimum value to the maximum value of $\gamma_{\text{SINR}_i}$ takes $0.1$ s on an average. In the proposed WLAN system with the mechanism of dynamically setting parameters, as the time for collecting throughput data sufficiently to set TSR and TSL, the periods for setting TSR and TSL are set to $1$ s and $5$ s respectively in the simulations. In the proposed WLAN system with fixed parameters, TSR and TSL is set to the best value in each arrangement of devices to obtain maximum benefit of waiting for transmissions.

Fig. 2(a) shows relationship between total throughput of each WLAN system and distance between APs of each BSSs, and transmissions are performed by two BSSs for $4,000$ s at each distance between APs in this simulation. Throughput in the WLAN system with the proposed technique of which TSR and TSL are set dynamically is close to the throughput in the WLAN system with the proposed technique of which TSR and TSL are fixed to the best values. At the distances between APs which are around $100$ m, effect of interferences becomes higher, and throughput in WLAN systems with the proposed technique do not become as low as throughput in the conventional DCF-based WLAN system. This is because effect of interferences is reduced by waiting for transmissions in WLAN systems with the proposed technique.

In the simulation to output numerical data shown in Fig. 2(b), transmissions are performed for $6,000$ s at each distance by three BSSs which are set on an equilateral triangle. The more BSSs are, the higher effect of interferences is. Fig. 2(b) shows that, effect to improve the throughput by the proposed technique will become higher when effect of interferences is higher.

From these results, we can conclude that, the proposed WLAN system reduces radio interferences and effectively utilizes radio resources.

Table I. Simulation conditions.

<table>
<thead>
<tr>
<th>Maximum transmission opportunity length</th>
<th>4 ms</th>
</tr>
</thead>
<tbody>
<tr>
<td>MCS (Modulation and Coding Scheme) of data frame (r is a coding rate)</td>
<td>256QAM ($r = 5/6$), 256QAM ($r = 3/4$)</td>
</tr>
<tr>
<td>Channel frequency</td>
<td>2.4 GHz</td>
</tr>
<tr>
<td>Path loss model</td>
<td>$30 \times \log_{10}x$ (dB)</td>
</tr>
<tr>
<td>(x (m) is the distance between transmitter and receiver.)</td>
<td></td>
</tr>
<tr>
<td>Traffic model</td>
<td>Full buffer</td>
</tr>
<tr>
<td>Fading model</td>
<td>Flat Rayleigh fading</td>
</tr>
<tr>
<td>Number of STAs in each BSS</td>
<td>2</td>
</tr>
<tr>
<td>Distance between the AP and a STAs in each BSS</td>
<td>5 m</td>
</tr>
</tbody>
</table>
Conclusion

In densely deployed WLAN systems, the interference from adjacent WLAN device is one of the major causes of performance degradation of WLAN system. In this study, we proposed the transmission standby technique to improve the performance of WLAN systems by reducing interferences from other WLAN devices in any environments where are radio interferences from adjacent WLAN devices. In a WLAN system with the transmission standby technique, since WLAN devices with poor channel condition wait for transmissions, other WLAN devices can transmit and receive frames with higher SINR. From the numerical results, we confirmed that, the proposed WLAN system works better in environments where are higher effect of interferences.

Fig. 2. Relationships between throughput and distance between APs, simulations were performed by (a) two BSSs, and (b) three BSSs.

5 Conclusion

In densely deployed WLAN systems, the interference from adjacent WLAN device is one of the major causes of performance degradation of WLAN system. In this study, we proposed the transmission standby technique to improve the performance of WLAN systems by reducing interferences from other WLAN devices in any environments where are radio interferences from adjacent WLAN devices. In a WLAN system with the transmission standby technique, since WLAN devices with poor channel condition wait for transmissions, other WLAN devices can transmit and receive frames with higher SINR. From the numerical results, we confirmed that, the proposed WLAN system works better in environments where are higher effect of interferences.
Semi-blind channel estimation using knowledge of a pulse shape for faster-than-Nyquist signaling

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Abstract: In this paper, we propose a semi-blind channel estimation method for faster-than-Nyquist (FTN) signaling. The proposed method combines the least-squares (LS) method using training symbols with a blind estimation method using knowledge of the pulse shape. It is shown that the proposed semi-blind method requires fewer training symbols than the LS method, and it is superior to the blind method regardless of the packing ratio of FTN signaling.

Keywords: faster-than-Nyquist signaling, channel estimation, semi-blind estimation

Classification: Wireless Communication Technologies

References


1 Introduction

Faster-than-Nyquist (FTN) signaling is a non-orthogonal transmission scheme that sends pulses at a rate greater than the Nyquist rate, and it can increase the data rate without expanding bandwidth. However, due to the non-orthogonal nature, FTN signaling essentially suffers from inter-symbol interference (ISI). In frequency-selective channel scenarios, the effect of ISI is significant, so a powerful and robust equalizer is necessary. To date, several equalization methods for FTN signaling have been proposed [1, 2, 3]. Because the performance of these equalization methods depends on the accuracy of the estimated channel, channel estimation is a critical task for FTN signaling.

It is inefficient to estimate the total channel composed of a frequency-selective physical channel and a Nyquist pulse. Because the receiver knows the pulse shape used, it is sufficient to estimate only the physical channel [4, 5]. In [4], a frequency-domain channel estimation method for cyclic-prefixed (CP) FTN signaling was proposed. Training symbols embedded in the CP were used to estimate the channel based on the minimum mean square error criterion. Its disadvantage is the data rate loss caused by the insertion of CP. In [5], a time-domain channel estimation method using a message-passing algorithm was proposed. In this method, joint channel estimation and data decoding were performed in an iterative manner. To simplify iterative processing, a channel estimate initially obtained by the least-squares (LS) method using the training symbols was refined. Its disadvantage is the computational complexity increase due to the joint estimation/detection processing and the iterative processing.

For Nyquist signaling, there have been various blind channel estimation methods that require no training symbols; however, most of them attempt to estimate the total channel. In [6], a blind estimation method that estimated only the physical channel by using knowledge of the pulse shape was proposed, and its superiority to the corresponding method that ignores the known pulse shape was reported. Although this approach can be applied to FTN signaling in principle, such studies have not yet been done.

In this paper, we propose a semi-blind channel estimation method for FTN signaling, which is a combination of the LS estimation method using training symbols and the blind estimation method in [6]. The proposed method can improve the performance compared to the blind method with the help of training symbols, and it can reduce the number of training symbols compared to the LS method.

2 System model

Fig. 1 shows the system model of FTN signaling. At the transmitter, data symbol $s[k]$ is transmitted after passing through a transmit filter $g_t(t)$ every $T = \gamma T_0$ seconds, where $0 < \gamma \leq 1$ is the packing ratio and $T_0$ is the symbol period of Nyquist signaling. The transmitted signal goes through an unknown frequency-selective physical channel $c(t)$, which has finite support $[0, L T_0)$. At the receiver, the received signal passed through a receive filter $g_r(t)$ is given by

$$r(t) = \sum_k s[k] h(t - kT) + \eta(t)$$

(1)
where \( h(t) = \int c(\tau)g(t - \tau)d\tau \) is the “total” channel impulse response (IR) that includes the physical channel \( c(t) \) and the combined transmit/receive filter \( g(t) = \int g_1(\tau)g_2(t - \tau)d\tau \), which is a Nyquist pulse truncated to \([-NT_0, NT_0]\). In this case, \( n(t) = \int n(\tau)g(t - \tau)d\tau \) is a colored noise process with the autocorrelation function \( E[n(t)n^*(t + \tau)] = N_0g(\tau) \), where \( n(\tau) \) is a complex-valued white Gaussian random process of PSD \( \frac{N_0}{2} \).

The received signal is oversampled with an interval of \( \frac{T}{\delta p} \), where \( p \) is an integer oversampling factor. By defining \( r_j[i] = r\left((i + \frac{j}{p})T\right), \ h_j[i] = h\left((i + \frac{j}{p})T\right) \) and \( \eta_j[i] = \eta\left((i + \frac{j}{p})T\right) \), we obtain the \((ip + j)\)th received sample as

\[
 r_j[i] = \sum_{l=-\tilde{N}}^{\tilde{N} + \tilde{L}} h_j[l]s[i-l] + \eta_j[i], \quad j = 0, \ldots, p-1 \tag{2}
\]

where \( \tilde{N} = \left\lfloor \frac{N}{p} \right\rfloor \) if \( \frac{N}{p} - \frac{\tilde{N}}{p} < \frac{p-1}{p} \); otherwise, \( \tilde{N} = \left\lfloor \frac{N}{p} \right\rfloor \), and \( \tilde{L} = \left\lfloor \frac{L-1}{p} \right\rfloor \) if \( \frac{L-1}{p} < \frac{p-1}{p} \); otherwise, \( \tilde{L} = \frac{L-1}{p} \). We define the total channel vector as \( \mathbf{h} = [\mathbf{h}[0] \cdots \mathbf{h}[L_h - \tilde{N} - 1]]^T \in \mathbb{C}^{L_h p x 1} \), where \( \mathbf{h}[i] = [h_0[i] \cdots h_{p-1}[i]]^T \) and \( L_h = 2\tilde{N} + \tilde{L} + 1 \). We can write the \( i \)th received sample vector \( \mathbf{r}[i] = [r_0[i] \cdots r_{p-1}[i]]^T \) as

\[
 \mathbf{r}[i] = \mathbf{S}[i]\mathbf{h} + \eta[i] \tag{3}
\]

where \( \mathbf{S}[i] = [\tilde{S}[i + \tilde{N}] \cdots \tilde{S}[i - \tilde{N} - \tilde{L}]] \in \mathbb{C}^{p x L_h} \) is the transmit symbol matrix consisting of the diagonal matrices \( \tilde{S}[d] \in \mathbb{C}^{p x p} \) whose diagonal elements are \( s[d] \) and \( \eta[i] = [\eta_0[i] \cdots \eta_{p-1}[i]]^T \). Stacking \( \mathbf{r}[i] \) over \( M \) symbols, we have

\[
 \mathbf{r}_M = [\mathbf{r}[i] \cdots \mathbf{r}[i-M+1]]^T = \mathbf{S}_M\mathbf{h} + \eta_M \in \mathbb{C}^{Mp x 1} \tag{4}
\]

where \( \mathbf{S}_M = [\mathbf{S}[0] \cdots \mathbf{S}[i-M+1]]^T \) and \( \eta_M = [\eta[0] \cdots \eta[i-M+1]]^T \).

We define that \( c_j[i] = c((i + \frac{j}{p})T) \). The physical channel vector is defined as \( \mathbf{c} = [\mathbf{c}[0] \cdots \mathbf{c}[\tilde{L}]]^T \in \mathbb{C}^{(L+1)p x 1} \), where \( \mathbf{c}[i] = [c_0[i] \cdots c_{p-1}[i]]^T \). The total channel can be decomposed as \( \mathbf{h} = \mathbf{G}\mathbf{c} \), where the Nyquist pulse matrix \( \mathbf{G} \in \mathbb{R}^{L_h p x (L+1)p} \) is a Toeplitz matrix whose first row is \( [g(-\tilde{N}T) \cdots 0] \in \mathbb{R}^{1 x (L+1)p} \) and first column is \( [g(-\tilde{N}T) \cdots g(\tilde{N}T) 0 \cdots 0] \in \mathbb{R}^{L_h p x 1} \). Then, we can rewrite (4) as \( \mathbf{r}_M = \mathbf{S}_M\mathbf{G}\mathbf{c} + \eta_M \). Our goal is to estimate the unknown physical channel \( \mathbf{c} \) from \( \mathbf{r}_M \) rather than the total channel \( \mathbf{h} \) using knowledge of the pulse shape \( \mathbf{G} \) and a few training symbols \( \mathbf{S}_M \).

## 3 Semi-blind channel estimation method

First, we consider the LS estimation of the physical channel. The LS estimation \( \hat{\mathbf{c}}_{\text{LS}} \) is obtained by minimizing the squared error \( \| \mathbf{r}_M - \mathbf{S}_M\mathbf{G}\hat{\mathbf{c}} \|^2 \). The estimation \( \hat{\mathbf{c}}_{\text{LS}} \) satisfies the following equation:

![System model](image-url)
Note that $S_M G$ has full column rank only if $M \geq L + 1$, and the matrix $S_M$ consists of $L_h + M - 1 = \tilde{N} + \tilde{L} + M$ training symbols. Thus, the minimum number of training symbols required for (6) is $N_{LS} = 2(\tilde{N} + \tilde{L}) + 1$, which increases as the channel IR length $L$ increases or the packing ratio $\gamma$ decreases.

Next, we consider a blind estimation method called subchannel matching [6]. Subchannel matching determines the subchannels $\hat{h}_n[k]$ that satisfy the relationship $\hat{h}_n[k] * r_m[k] = \hat{h}_m[k] * r_m[k]$ in noise-free environments, where $*$ represents convolution. This leads to the problem $\hat{h} = \arg\min_{\|h\|_2 = 1} h^H \Psi h$, where $\Psi = E G^H E^H$. Here, $\Phi$ is an $L_h p \times L_h p$ block matrix whose $(i, j)$th block is $\sum_{l \neq i} R_l$ for $i = j$ and $-R_{i,j}$ for $i \neq j$, where $R_{i,j} = E[\tilde{r}_i[k]\tilde{r}_j^H[k]]$ and $\tilde{r}_j[i] = [r_j[i] \ r_j[i - 1] \cdots r_j[i - L + 1]]^T$; and $E = [E_1 \cdots E_p]$, where $E_j$ is an $L_h p \times L_h$ matrix whose $j$th column is $[0_{i \times (j-1)p} \ e_j \ 0_{i \times (L_h-j)p}]^T$, and $e_j$ is a $1 \times p$ unit vector whose $i$th entry is $1$. By using the decomposition $h = Gc$, this problem can be modified to estimate the physical channel as [6]

$$
\hat{c}_{\text{blind}} = \arg\min_{\|c\|_2 = 1} c^H G^H \Psi Gc.
$$

Applying the eigenvector decomposition to $G^H \Psi G$, $\hat{c}_{\text{blind}}$ can be found from the eigenvector corresponding to the minimum eigenvalue. We will show in our simulation that the performance of the blind method is unsatisfactory when channel IR $L$ is long.

Now, we propose a semi-blind method that combines the LS method in (5) with the blind method in (7). We expect that the proposed method can improve the performance of the blind method by using fewer training symbols than the LS method. It is known that if the subchannels share no common zeros, the minimum of $c^H G^H \Psi Gc$ in (7) is zero in noise-free environments. Thus, we rewrite the blind estimation as $\sqrt{\Lambda} V^H Gc = 0$, where $\Lambda$ is a diagonal matrix whose diagonal entries are the eigenvalues of $\Psi$, and the columns of $V$ are the corresponding eigenvectors.

Then, we obtain the following semi-blind estimation:

$$
S_M G \hat{c}_{\text{semi}} = \begin{bmatrix} r_M \\ \beta \sqrt{\Lambda} V^H \end{bmatrix}
$$

(8)

where $\beta \geq 0$ is the weighting factor. Solving (8) by a numerical method such as Gaussian elimination, we obtain the semi-blind estimate $\hat{c}_{\text{semi}}$. In (8), because $M \geq 1$, the minimum number of the training symbols is $N_{\text{semi}} = 2\tilde{N} + \tilde{L} + 1$, which is less than $N_{LS}$. Finally, we appropriately determine $\beta$ by proposing the following simple method:

$$
\beta = \frac{||S_M||_F}{\sqrt{\Lambda} V^H ||_F}
$$

(9)

where $\| \cdot \|_F$ represents the Frobenius norm of a matrix. The choice of (9) attempts to make the contribution of the blind estimation equal to that of LS.
The computational complexity of the proposed method is dominated by the computation of the eigenvalue decomposition of $\mathbf{P}$ and solving (8). The complexity of these computations is proportional to $(L+1)^3p^3$, which is almost the same as that of (6) and (7).

4 Simulation

We evaluate the performance of the proposed semi-blind method in (8) by computer simulation. The estimation performance is measured by the normalized mean square error (NMSE) averaged over $I$ trials

$$\text{NMSE} = \frac{\sum_{i=1}^{I} \| \mathbf{Gc}_i - \mathbf{h} \|^2}{\sum_{i=1}^{I} \| \mathbf{h} \|^2}$$

(10)

where the subscript $i$ indicates the $i$th trial. Unless otherwise stated, parameters used in the simulation are as follows: modulation scheme QPSK, length of physical channel IR $L = 10$, roll-off factor $\alpha = 0.7$, $E_b/N_0 = 30$ dB, pulse truncation length $N = 3$, and number of trials $I = 10^5$. The correlation matrices $R_{ij}$ are obtained by averaging 200 received samples.

First, we compare the proposed semi-blind method with the LS method in (6). Fig. 2(a) shows the NMSE performances versus $E_b/N_0$ for various values of the packing ratio $\gamma$ and the roll-off factor $\alpha$, where both methods use $N_{\text{LS}} = 2(\hat{N} + \hat{L}) + 1$ training symbols. It can be observed that the proposed semi-blind method is superior to the LS method in all cases. In Fig. 2(b), the effect of the number of training symbols is shown, where the minimum required numbers of training symbols are $N_{\text{LS}} = 31$, $N_{\text{semi}} = 20$ for $\gamma = 0.8$ and $N_{\text{LS}} = 41$, $N_{\text{semi}} = 26$ for $\gamma = 0.6$. For reference, we also plotted the NMSE performances obtained by the optimum $\beta$, which is determined by an exhaustive search over a range of values $\beta \in [0, 100]$. The semi-blind method can achieve a lower NMSE using a fewer number of training symbols compared to the LS method. Although the choice of $\beta$ in (9) is useful, there is little room for improvement.

Next, we compare the proposed semi-blind method, which uses the minimum number of training symbols $N_{\text{semi}} = 2\hat{N} + \hat{L} + 1$, with the blind method in (7). In Fig. 3(a), the effect of the packing ratio $\gamma$ is illustrated. The semi-blind method is
significantly superior to the blind method. As for the semi-blind method, a lower $r$ tends to exhibit a better NMSE performance. This might be because the choice of $\beta$ in (9) tends to be closer to the optimum $\beta$ as $r$ decreases. Fig. 3(b) shows the effect of the IR length of the physical channel $L$. The performance of the blind method degrades significantly as $L$ increases, while that of the semi-blind method is almost independent of $L$.

5 Conclusion

In this paper, we proposed a semi-blind channel estimation method for FTN signaling, which is a combination of a subchannel matching based blind method and the LS method using training symbols. Our simulation results show that the proposed method requires fewer training symbols than LS, and its performance is not influenced significantly by the packing ratio and the length of the physical channel impulse response, unlike the blind method. It would be interesting to use the channel estimate obtained by the semi-blind method as an initial estimate for the iterative estimation methods in [4, 5] to achieve further performance improvement.