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A Bayesian Approach to Adaptive RAKE Receiver

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ABSTRACT The RAKE receivers are widely used in code division multiple access communication systems to achieve anti-multipath fading. However, a traditional RAKE receiver requires pilot data stream inserted into the sequence, which occupies channel resources and limits its applications. In this paper, a new adaptive RAKE receiver based on Bayesian theory is reported that only uses received signals to estimate its channel parameters. Observed data are used to obtain the information of the channel impulse response. Next, the prior information is used. In the iterative process, *a priori* information is accumulated to improve the receiver performance. Thus, the mean and covariance of the channel impulse response that is modeled as a complex and uncertain Gaussian random vector are recursively estimated using Bayesian theory. Finally, the RAKE weights are obtained using the mean and covariance. As shown in the simulation results, the bit error rate (BER) decreases as the number of fingers increases. The performance of the new RAKE receiver has been greatly improved compared with the all-RAKE receiver with maximal ratio combining, RAKE receiver with singular value decomposition, and RAKE receiver with fast approximated power iteration. Under medium to high SNR conditions (i.e., ≥ -5 dB), the BER performance of the new RAKE receiver provides at least 3×10^{-4} less than that of the other receiver tested.

INDEX TERMS Anti-multipath fading, Bayesian, CDMA, RAKE receiver.

I. INTRODUCTION

RAKE receivers were first proposed by Price and Green in 1958 as a key technology of spread spectrum communication systems [1]. This type of receiver collects signals from multiple paths and functions similarly to agricultural polygonal RAKE, which explains its name. RAKE receivers do not weaken or cut multipath signals but rather take full advantage of the multipath signal energy. The receivers use several correlators to individually process multipath signal components [2], and the output of each correlator is weighted and combined to improve the receiver signal's signal-to-noise ratio (SNR) and decrease the probability of fading [3]. Although usually viewed as a deteriorating factor, multipath fading can also be exploited to improve performance using RAKE receivers [4]. Due to its unique advantages, the RAKE receiver has many applications [5], [6]. It has been designed for multiuser underwater communications [7]–[9], visible light communications [10], and efficient optical code (OC) [11]. The combined performance of a turbo decoder and RAKE receiver was investigated in [12]. To minimize BER, a maximum likelihood (ML) optimal combiner using an optimal linear RAKE receiver was developed to detect signals in alpha-stable noise [13]. In [14], a receiver based on ML estimation is proposed to compare conventional RAKE reception, as well as approximate ML-based approaches, the signal model of which is similar to that used in this paper. The optimal receiver for RAKE diversity combining on channels with a sparse impulse response was reported in [15], was based on Bayesian philosophy and was shown to outperform a classical training-based MRC detector in the simulations.

Researchers have studied several aspects of RAKE receiver, such as multipath collection and multipath merging strategy. In terms of multipath collection strategy, a standard "ideal" RAKE receiver that combines the complete resolvable multipath component is called All-RAKE (ARAKE) [16], which has the best bit error rate (BER) performance and the highest complexity [17]. As a tradeoff between complexity and performance, selective RAKE (SRAKE) and partial RAKE (PRAKE) are more practical RAKE receivers. SRAKE selects the L best resolvable paths, and PRAKE combines the first L arriving paths [18]. PRAKE is less complex and provides worse performance than SRAKE because it combines the first arriving paths and not the strongest ones, as SRAKE does [19]. For the multipath merging strategy, RAKE receivers use different combining methods. The most classical methods are maximum-ratio-combining (MRC), equal gain combining (EGC) and selective combining (SC), which are all based on correlation detection and thus, become more complex as the number of fingers increases. In third generation mobile communication, RAKE receivers with MRC are one of the most commonly used receiver. MRC is an optimal linear combining technique that combines all available fingers with different weights that are in proportional to the SNR (or amplitude) of the corresponding branch.

In this paper, an adaptive RAKE receiver based on the Bayesian approach is proposed. There are three primary contributions of this paper. First, according to Bayesian theory and the minimum mean square error (MMSE), this adaptive RAKE receiver does not require a pilot data stream inserted into the sequence and only uses received signals to estimate its channel parameters. The mean and covariance of the channel impulse response based on Bayesian model is modeled as a complex and uncertain Gaussian random vector. The character of the Rayleigh or Ricing fading channel is described by a tapped delay line (TDL) channel model. The second contribution of this paper is to propose a recursive RAKE weights calculation algorithm, which increases the use of prior information. To obtain the RAKE weights, the mean and covariance of the channel impulse response are recursively estimated by using Bayesian theory. In the recursive iteration, a priori information is accumulated to improve the receiver performance. The third contribution of this paper is to do several simulations to verify the improvement of the Bayesian RAKE receiver performance compared to that of other channel estimation algorithms, such as singular value decomposition (SVD) algorithm and fast approximated power iteration (FAPI) algorithm. Theoretically, the SVD algorithm based on the batched and sampling process can be used to compute the dominant eigenvector, which increases system processing delay and the amount of computation and processing time. The FAPI algorithm is similar to the Bayesian algorithm in that both use the concept of iteration. However, the Bayesian algorithm is characterized by a lower BER. In section IV.B, a detailed comparison is presented.

The rest of this paper is organized as follows. In section II, we describe a multipath channel model and a RAKE receiver. In section III, we present a Bayesian RAKE receiver. In section IV, several simulations are reported. Finally, section V presents the paper's conclusion.

II. MULTIPATH CHANNEL MODEL AND RAKE RECEIVER

Suppose the coded sequence of user q is $\{b_q(i) = \pm 1\}$, where $q = 1, 2, \cdots, Q$, and Q is the number of users. The sequence from the user qth's Pseudo Noise (PN) generator is $\left\{C_q(i) = \pm 1\right\}$, where i is the chip index. The elements of the coded sequence are mapped into a binary PSK signal according to the following relation:

$$b_q(t, i) = b_q(i)\, g(t - iT_c), \tag{1}$$

where $g(t)$ represents a pulse of duration T_c seconds and arbitrary shape, and T_c is chip interval. Similarly, we define a waveform $p_q(t, i)$ as:

$$p_q(t, i) = C_q(i) \prod (t - iT_c), \tag{2}$$

where $\prod(t)$ is a rectangular pulse of duration T_c. Thus, the equivalent low-pass transmitted signal corresponding to the ith coded bit is:

$$x_q(t, i) = b_q(t, i)\, p_q(t, i) = b_q(i)\, C_q(i)\, g(t - iT_c), \tag{3}$$

and the i th coded bit of all users is:

$$x(t, i) = \sum_{q=1}^{Q} x_q(t, i) = \left[\sum_{q=1}^{Q} b_q(i)\, C_q(i)\right] g(t - iT_c). \tag{4}$$

The TDL channel model is described as:

$$\begin{aligned} u(t, i) &= \sum_{n=1}^{N} a(t, n) x(t - \tau(t, n), i) + n_o(t) \\ &= \sum_{n=1}^{N} a(t, n) \left[\sum_{q=1}^{Q} b_q(i)\, C_q(i)\right] g(t - iT_C - \tau(t, n)) + n_o(t), \end{aligned} \tag{5}$$

where $u(t, i)$ is the received equivalent low-pass signal for the i th code element, $a(t, n)$ is the tap weight parameter of the TDL model, $n_o(t)$ is the noise in the model, N is the length of the TDL model, and $\tau(t, n)$ is the delay of the nth finger that changes more slowly than $a(t, n)$. Thus, $\tau(t, n)$ can be written as $\tau(n)$, and $\tau(n) = \frac{n-1}{W}$, $n = 1, 2, \cdots, N$, where W is the bandwidth of transmitted signals. Then, using cross-correlation with $g^*(t)$, the received equivalent low-pass signal through cross-correlating can be written as:

$$\begin{aligned} y(t, i) &= u(t, i) g^*(t) \\ &= \sum_{n=1}^{N} a(t, n) \left[\sum_{q=1}^{Q} b_q(i)\, C_q(i)\right] + n_c(t), \end{aligned} \tag{6}$$

where $n_c(t) = n_o(t) g^*(t)$.

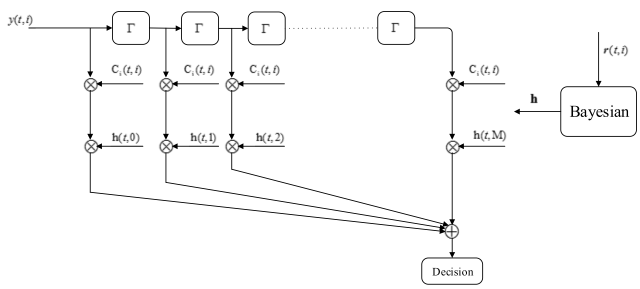

FIGURE 1. **Structure of a RAKE receiver.**

The structure of a RAKE receiver is shown in Fig. 1. The basic version of the RAKE receiver consists of multiple correlators (i.e., fingers) where each finger can detect/extract the signal from one of the multipath [16]. In Fig. 1, $M + 1$ is the number of RAKE fingers and the outputs of the finger are appropriately weighted and combined to reap the benefits of multipath diversity [16]. $\boldsymbol{h} = (h(t, 0), h(t, 1), \cdots, h(t, M))$ is a row vector with length $M + 1$, and $h(t, m)$ is the weight of each finger. Γ is the delay of each finger, and $M + 1 = N$ and $\Gamma = \frac{1}{W}$ in this paper.

For a chip interval, the channel parameters do no change. Thus, after the received signal is despread by each finger's despreader, that is:

$$\boldsymbol{r}(t,i)=\begin{bmatrix} a(0) \\ \vdots \\ a(m) \\ \vdots \\ a(M) \end{bmatrix} b_q(i)+\boldsymbol{n}_a(t)=\boldsymbol{a}b_q(i)+\boldsymbol{n}_a(t), \quad (7)$$

where $\boldsymbol{a}$ is the weight of the channel impulse response combined with the spread spectrum, channel processing, matched filtering, and dispreading; $b_q(i)$ is the desired coded bit with known power $E\{b_q(i)b_q(i)^*\} = \sigma_b^2$; and $\boldsymbol{n}_a(t) = \boldsymbol{a}n_c(t)$ is the noise that components with unknown covariance matrix $R_n = E\left\{\boldsymbol{n}_a\boldsymbol{n}_a^H\right\}$.

The output of the RAKE receiver is:

$$z(t,i)=\boldsymbol{hr}(t,i)=\boldsymbol{ha}b_q(i)+n_h(t), \quad (8)$$

where $n_h(t) = \boldsymbol{hn}_a(t)$. To creat a simple and accurate calculation, let $\boldsymbol{ha} = 1$; thus, $\boldsymbol{h} = \boldsymbol{a}^H$, which requires precise channel parameter estimation. From (8), the weight of the RAKE receiver can be obtained by estimating $\boldsymbol{a}$ using the method of the maximum posterior probability. For simplicity, $\boldsymbol{r}(t,i)$ is written as $\boldsymbol{r}$, $\boldsymbol{n}_a(t)$ is written as $\boldsymbol{n}$, and $b_q(i)$ is written as b:

$$\boldsymbol{r}=\boldsymbol{a}b+\boldsymbol{n}. \quad (9)$$

To precisely estimate the channel response $\boldsymbol{a}$ in a manner similar to those used in [20] and [21], we assume that the channel parameters $\boldsymbol{a}$ has a complex Gaussian priori probability density function (PDF) with mean $\boldsymbol{a}_0$ and covariance matrix $\boldsymbol{C}_0$:

$$p_0(\boldsymbol{a})=\frac{1}{\pi^N\left|\boldsymbol{C}_0\right|}\exp\left\{-(\boldsymbol{a}-\boldsymbol{a}_0)^H\boldsymbol{C}_0^{-1}(\boldsymbol{a}-\boldsymbol{a}_0)\right\}. \quad (10)$$

The output signal is processed in short-term integration (STI) windows with K time samples. For arbitrary $jK \le k < (j+1)K$, in each STI, the channel parameter $\boldsymbol{a}$ is assumed to be time-invariant, and the received samples after despreading are $\boldsymbol{r}_j = (\boldsymbol{r}_{jK}, \ldots, \boldsymbol{r}_{(j+1)K-1})$, where j is the index of STI. The goal is to design a RAKE receiver to estimate the bit of interest $\boldsymbol{b}_j = (b_{jK}, \ldots, b_{(j+1)K-1})$, which is a row vector with length of K.

III. BAYESIAN RAKE RECEIVER

A. RECURSIVE ESTIMATION FOR RAKE RECEIVER WEIGHTS

The finger weights of the Bayesian RAKE receiver are now computed. According to the Bayesian principle, the posteriori PDF $p\left(\boldsymbol{a}\left|\boldsymbol{r}_{0:j}\right.\right)$ can be shown as:

$$\begin{aligned} p(\boldsymbol{a}\left|\boldsymbol{r}_{0:j}\right.) &= \frac{p(\boldsymbol{a},\boldsymbol{r}_{0:j})}{p(\boldsymbol{r}_{0:j})}=\frac{p(\boldsymbol{r}_{0:j-1})p(\boldsymbol{a}\left|\boldsymbol{r}_{0:j-1}\right.)p(\boldsymbol{r}_j\left|\boldsymbol{a}\right.,\boldsymbol{r}_{0:j-1})}{p(\boldsymbol{r}_{0:j-1})p(\boldsymbol{r}_j\left|\boldsymbol{r}_{0:j-1}\right.)} \\ &= \frac{p(\boldsymbol{a}\left|\boldsymbol{r}_{0:j-1}\right.)p(\boldsymbol{r}_j\left|\boldsymbol{a}\right.,\boldsymbol{r}_{0:j-1})}{p(\boldsymbol{r}_j\left|\boldsymbol{r}_{0:j-1}\right.)}, \end{aligned} \quad (11)$$

where $\boldsymbol{r}_{0:j} = (\boldsymbol{r}_0, \ldots, \boldsymbol{r}_j)$ is the received samples after despreading. Because successive snapshots of b_k and $\boldsymbol{n}_a$ are all statistically independent, it can be obtained from (7) that $\boldsymbol{r}_k$ is sample independent at different snapshots when $\boldsymbol{a}$ is given. Next, $\boldsymbol{r}_j$ and $\boldsymbol{r}_{0:j-1}$ are independent given $\boldsymbol{a}$, since they are in the different STI windows.

Thus, we have $p\left(\boldsymbol{r}_j\left|\boldsymbol{a}\right.,\boldsymbol{r}_{0:j-1}\right) = p\left(\boldsymbol{r}_j\left|\boldsymbol{a}\right.\right)$ and

$$p\left(\boldsymbol{a}\left|\boldsymbol{r}_{0:j}\right.\right)=\frac{p\left(\boldsymbol{a}\left|\boldsymbol{r}_{0:j-1}\right.\right)p\left(\boldsymbol{r}_j\left|\boldsymbol{a}\right.\right)}{p\left(\boldsymbol{r}_j\left|\boldsymbol{r}_{0:j-1}\right.\right)}, \quad (12)$$

where $p\left(\boldsymbol{r}_j\left|\boldsymbol{r}_{0:j-1}\right.\right) = \int p\left(\boldsymbol{a}\left|\boldsymbol{r}_{0:j-1}\right.\right)p\left(\boldsymbol{r}_j\left|\boldsymbol{a}\right.\right)d\boldsymbol{a}$ is the regularization probability. Suppose that the posteriori PDF $p\left(\boldsymbol{a}\left|\boldsymbol{r}_{0:j-1}\right.\right)$ follows a complex Gaussian distribution with mean $\boldsymbol{a}_{j-1}$ and covariance matrix $\boldsymbol{C}_{j-1}$:

$$p(\boldsymbol{a}\left|\boldsymbol{r}_{0:j-1}\right.)=\frac{1}{\pi^N\left|\boldsymbol{C}_{j-1}\right|}\exp\left\{-(\boldsymbol{a}-\boldsymbol{a}_{j-1})^H\boldsymbol{C}_{j-1}^{-1}(\boldsymbol{a}-\boldsymbol{a}_{j-1})\right\}. \quad (13)$$

The recursive expressions for $\boldsymbol{a}_{j-1}$ and $\boldsymbol{C}_{j-1}$ can be obtained in the following discussions. $p\left(\boldsymbol{r}_j\left|\boldsymbol{a}\right.\right)$ can be given by [22]:

$$\begin{aligned} p\left(\boldsymbol{r}_j\left|\boldsymbol{a}\right.\right) &= \prod_{k=jK}^{(j+1)K-1}\frac{1}{\pi^N\left|\boldsymbol{R}_r(\boldsymbol{a})\right|}\exp\left\{-\boldsymbol{r}_k^H\boldsymbol{R}_r^{-1}(\boldsymbol{a})\boldsymbol{r}_k\right\} \\ &= \pi^{-NK}\left|\boldsymbol{R}_r(\boldsymbol{a})\right|^{-K}\exp\left\{-\sum_{k=jK}^{(j+1)K-1}\boldsymbol{r}_k^H\boldsymbol{R}_r^{-1}(\boldsymbol{a})\boldsymbol{r}_k\right\}, \end{aligned} \quad (14)$$

As we know, $\boldsymbol{R}_r(\boldsymbol{a})$ is the data covariance matrix given $\boldsymbol{a}$ and $\boldsymbol{R}_r(\boldsymbol{a})$ is:

$$\boldsymbol{R}_r(\boldsymbol{a})=\sigma_b^2E(\boldsymbol{aa}^H)+\boldsymbol{R}_n, \quad (15)$$

where $\boldsymbol{R}_a = E(\boldsymbol{aa}^H)$, σ_b^2 is the energy of the information bits b_q. The output signal is processed in STI windows with K time samples. Thus, $\sigma_b^2 = K$.

The above equation can be converted into:

$$\boldsymbol{R}_r(a)=K\boldsymbol{R}_a+\boldsymbol{R}_n, \quad (16)$$

where $\boldsymbol{R}_n$ can be simplified with the following formulas:

$$\boldsymbol{C}_{j-1}=E\left[(\boldsymbol{a}-\boldsymbol{a}_{j-1})(\boldsymbol{a}-\boldsymbol{a}_{j-1})^H\right]. \quad (17)$$

From the above formula, $\boldsymbol{R}_a = \boldsymbol{C}_{j-1} + \boldsymbol{a}_{j-1}\boldsymbol{a}_{j-1}^{\mathrm{H}}$, and (15) can be rewritten as:

$$\boldsymbol{R}_{\mathrm{n}}=\boldsymbol{R}_r(\boldsymbol{a})-K(\boldsymbol{C}_{j-1}+\boldsymbol{a}_{j-1}\boldsymbol{a}_{j-1}^H). \quad (18)$$

The determinant $|\boldsymbol{R}_r(\boldsymbol{a})|$ has the form given by [23]

$$\left|\boldsymbol{R}_r(\boldsymbol{a})\right|=\left|\boldsymbol{R}_n\right|\left(1+\sigma_b^2\boldsymbol{a}^H\boldsymbol{R}_n^{-1}\boldsymbol{a}\right). \quad (19)$$

Expanding $\boldsymbol{R}_r^{-1}(\boldsymbol{a})$ using the matrix inversion lemma yields:

$$\boldsymbol{R}_r^{-1}(\boldsymbol{a})=\boldsymbol{R}_n^{-1}-\frac{\sigma_b^2\boldsymbol{R}_n^{-1}\boldsymbol{aa}^H\boldsymbol{R}_n^{-1}}{1+\sigma_b^2\boldsymbol{a}^H\boldsymbol{R}_n^{-1}\boldsymbol{a}}. \quad (20)$$

The sample autocorrelation matrix is:

$$\hat{\boldsymbol{R}}_{r,j}=\frac{1}{K}\sum_{k=jK}^{(j+1)K-1}\boldsymbol{r}_k\boldsymbol{r}_k^H, \quad (21)$$

and thus, the likelihood function is given by:

$$p(r_j|\boldsymbol{a}) = \alpha(1+\sigma_b^2\beta(\boldsymbol{a}))^{-K} exp\left\{\frac{K\sigma_b^2\boldsymbol{a}^H\boldsymbol{R}_n^{-1}\hat{\boldsymbol{R}}_{r,j}\boldsymbol{R}_n^{-1}\boldsymbol{a}}{1+\sigma_b^2\beta(\boldsymbol{a})}\right\}, \tag{22}$$

where $\alpha = \pi^{-NK}|\boldsymbol{R}_n|^{-K} exp\left\{-\sum_{k=jK}^{(j+1)K-1}\boldsymbol{r}_k^H\boldsymbol{R}_n^{-1}\boldsymbol{r}_k\right\}$, and $\beta(\boldsymbol{a}) = \boldsymbol{a}^H\boldsymbol{R}_n^{-1}\boldsymbol{a}$.

According to the derivation in [24], (22) can be rewritten as:

$$\begin{aligned} &\boldsymbol{p}(r_j|\boldsymbol{a}) \\ &= \alpha(1+\sigma_b^2\beta(a))^{-K}\exp \\ &\times\left\{K\sigma_b^2\left(\frac{2+\sigma_b^2\beta(\boldsymbol{a}_d)}{1+\sigma_b^2\beta(\boldsymbol{a})}\beta(\boldsymbol{a}) - \frac{1+\sigma_b^2\beta(\boldsymbol{a}_d)}{1+\sigma_b^2\beta(\boldsymbol{a})}\boldsymbol{a}^H\hat{\boldsymbol{R}}_{r,j}^{-1}\boldsymbol{a}\right)\right\} \end{aligned} \tag{23}$$

where $\boldsymbol{a}_d$ is the ideal channel impulse response that can be approximated by $\boldsymbol{a}_{j-1}$. Computing this possibility PDF presents more difficult. As in [21], [22], and [24], the quadratic functional $\beta(\boldsymbol{a})$ can be approximately equal to the constant $\beta(\boldsymbol{a}_{j-1})$, which is defined by:

$$\beta(\boldsymbol{a}_{j-1}) = \boldsymbol{a}_{\mathrm{j-1}}^{\mathrm{H}}\boldsymbol{R}_{\mathrm{n}}^{-1}\boldsymbol{a}_{\mathrm{j-1}}. \tag{24}$$

The likelihood function can be alternatively approximated by

$$\begin{aligned} &\boldsymbol{p}(r_j|\boldsymbol{a}) \\ &\approx \alpha(1+\sigma_b^2\beta(\boldsymbol{a}_{j-1}))^{-K}\exp\left\{K\sigma_b^2\left(\mu(\boldsymbol{a}_{j-1})\beta(\boldsymbol{a}) - \boldsymbol{a}^H\hat{\boldsymbol{R}}_{r,j}^{-1}\boldsymbol{a}\right)\right\} \\ &= \gamma\exp\left\{-K\sigma_b^2\boldsymbol{a}^H\left(\hat{\boldsymbol{R}}_{r,j}^{-1} - \mu(\boldsymbol{a}_{j-1})\boldsymbol{R}_n^{-1}\right)\boldsymbol{a}\right\} \end{aligned} \tag{25}$$

where $\mu(\boldsymbol{a}_{j-1}) = \frac{2+\sigma_b^2\beta(\boldsymbol{a}_{j-1})}{1+\sigma_b^2\beta(\boldsymbol{a}_{j-1})}$. And $\gamma = \alpha(1+\sigma_b^2\beta(\boldsymbol{a}_{j-1}))^{-K}$ is a normalization factor that ensures the likelihood function integrates to one. Substituting (13) and (25) into (12), the posterior PDF $p\left(\boldsymbol{a}\,|\boldsymbol{r}_{0:j}\right)$ can be shown as:

$$\begin{aligned} p(\boldsymbol{a}\,|\boldsymbol{r}_{0:j}) &\approx \eta\exp\left\{-(\boldsymbol{a}-\boldsymbol{a}_{j-1})^H\boldsymbol{C}_{j-1}^{-1}(\boldsymbol{a}-\boldsymbol{a}_{j-1})\right\} \\ &\quad\times\exp\left\{K\sigma_b^2\boldsymbol{a}^H\left(\hat{\boldsymbol{R}}_{r,j}^{-1} - \mu(\boldsymbol{a}_{j-1})\hat{\boldsymbol{R}}_n^{-1}\right)\boldsymbol{a}\right\} \\ &= \xi\exp\left\{-(\boldsymbol{a}-\Sigma\boldsymbol{C}_{j-1}^{-1}\boldsymbol{a}_{j-1})^H\Sigma^{-1}(\boldsymbol{a}-\Sigma\boldsymbol{C}_{j-1}^{-1}\boldsymbol{a}_{j-1})\right\} \end{aligned} \tag{26}$$

where

$$\Sigma = \left(K\sigma_b^2\hat{\boldsymbol{R}}_{r,j}^{-1} - \mu(\boldsymbol{a}_{j-1})K\sigma_b^2\boldsymbol{R}_n^{-1} + \boldsymbol{C}_{j-1}^{-1}\right)^{-1}, \tag{27}$$

and $\eta = \frac{\gamma}{\pi^N|\boldsymbol{C}_{j-1}|p(\boldsymbol{r}_j|\boldsymbol{r}_{0:j-1})}$, $\xi = \eta\exp\{-\boldsymbol{a}_{j-1}^H(\boldsymbol{C}_{j-1}^{-1} - \boldsymbol{C}_{j-1}^{-1}\Sigma\boldsymbol{C}_{j-1}^{-1})\boldsymbol{a}_{j-1}\}$.

The posterior PDF $p\left(\boldsymbol{a}\,|\boldsymbol{r}_{0:j}\right)$ is a complex Gaussian with mean $\boldsymbol{a}_j$ and covariance matrix $\boldsymbol{C}_j$, where

$$\begin{aligned} \boldsymbol{a}_j &= \Sigma\boldsymbol{C}_{j-1}^{-1}\boldsymbol{a}_{j-1} \\ \boldsymbol{C}_j &= \Sigma. \end{aligned} \tag{28}$$

Because $\beta(\boldsymbol{a})$ can be approximately equal to $\beta(\boldsymbol{a}_{j-1})$, we multiply (20) with the channel impulse response $\boldsymbol{a}$ to obtain:

$$\begin{aligned} \boldsymbol{R}_r^{-1}(\boldsymbol{a})\boldsymbol{a} &= \frac{1}{1+\sigma_b^2\boldsymbol{a}^H\boldsymbol{R}_n^{-1}\boldsymbol{a}}\boldsymbol{R}_n^{-1}\boldsymbol{a} \\ &= \frac{1}{1+\sigma_b^2\beta(\boldsymbol{a})}\boldsymbol{R}_n^{-1}\boldsymbol{a} \\ &\approx \frac{1}{1+\sigma_b^2\beta(\boldsymbol{a}_{j-1})}\boldsymbol{R}_n^{-1}\boldsymbol{a}. \end{aligned} \tag{29}$$

From [23], we can obtain the similar form of $\boldsymbol{h}_j^{\mathrm{MMSE}}$:

$$\begin{aligned} \boldsymbol{h}_j^{MMSE} &= \left(\int p(\boldsymbol{a}\,|\boldsymbol{r}_{0:j})\sigma_b^2\boldsymbol{a}^H\boldsymbol{R}_r^{-1}(\boldsymbol{a})d\boldsymbol{a}\right)^H \\ &= \int\sigma_b^2\boldsymbol{R}_r^{-1}(\boldsymbol{a})\boldsymbol{a}p(\boldsymbol{a}\,|\boldsymbol{r}_{0:j})d\boldsymbol{a}, \end{aligned} \tag{30}$$

so the weights of Bayesian RAKE receiver can be written as:

$$\begin{aligned} \boldsymbol{h}_j^{MMSE} &\approx \frac{\sigma_b^2}{1+\sigma_b^2\beta(\boldsymbol{a}_{j-1})}\boldsymbol{R}_n^{-1}\int\boldsymbol{a}p(\boldsymbol{a}\,|\boldsymbol{r}_{0:j})d\boldsymbol{a} \\ &= \frac{\sigma_b^2}{1+\sigma_b^2\beta(\boldsymbol{a}_{j-1})}\boldsymbol{R}_n^{-1}\boldsymbol{a}_j, \end{aligned} \tag{31}$$

where $\boldsymbol{a}_j = \int\boldsymbol{a}p(\boldsymbol{a}\,|\boldsymbol{r}_{0:j})d\boldsymbol{a}$.

B. CONSTELLATION ROTATION AND NORMALIZATION

Due to phase ambiguity in the estimated bit $\hat{\boldsymbol{b}}_j$, the constellation is in the wrong position, but its shape is correct. To solve this problem, we need to rotate the constellation and normalize it. Therefore, any one bit of b_{bit}, the norm of which is $|b_{bit}|$, is selected, and the phase is set equal to θ_{bit} randomly. Next, one constellation center is chosen with a norm $|b_{cen}|$ and a phase θ_{cen}. Assuming that b_{bit} is adjusted to the center that we choose, the rotation phase θ_{Rot} and normalization factor $|b_{Nor}|$ can be obtained as:

$$\begin{aligned} \theta_{Rot} &= \theta_{Cen} - \theta_{bit} \\ |b_{Nor}| &= \frac{|b_{Cen}|}{|b_{bit}|}. \end{aligned} \tag{32}$$

Thus, we can use (32) to rotate and normalize all estimated bits.

Although the estimated bits are processed through rotation and normalization, they still have phase ambiguities. In this paper, differential detection is used to solve this problem.

C. ALGORITHM SUMMARY AND COMPUTATIONAL COMPLEXITY

In summary, we assume that $p(\boldsymbol{a}\,|\boldsymbol{r}_{0:j-1})$ is a complex Gaussian PDF with mean $\boldsymbol{a}_{j-1}$ and covariance matrix $\boldsymbol{C}_{j-1}$. The proposed Bayesian RAKE receiver in STI j can be described as follows:

1) Compute $\hat{R}_{r,j}$ using (21);
2) Compute Σ using (27) and update $\boldsymbol{a}_j$ and $\boldsymbol{C}_j$ using (28);
3) Compute $\boldsymbol{h}_j^{\mathrm{MMSE}}$ using (31).

The computation complexity can be analyzed as follows: the complexity of $\hat{R}_{r,j}$ is $O(KN^2)$ according to (21); the complexity of Σ is $O(4N^3)$; the complexity of $\boldsymbol{a}_j$ and $\boldsymbol{C}_j$ is $O(N^3 + 2N^2)$; the complexity of $\boldsymbol{h}_j^{\text{MMSE}}$ based on (31) is about $O(N^3 + N^2)$. Thus, the overall complexity of weights $\boldsymbol{h}$ is about $O(6N^3 + KN^2)$. However, in practice, because the value of K (1000 in this paper) is much greater than that of N (6 in this paper), the complexity of weights $\boldsymbol{h}$ is approximately $O(KN^2)$.

IV. NUMERICAL SIMULATION

The simulation parameters are shown in Table 1.

TABLE 1. Simulation parameters.

Parameters	Value
Raised cosine roll-off factor	50%
Symbols rate	2.54 MHz
Sampling rate	5.08 MHz
Information rate	20 kHz
Spreading gain	17 dB
Information amount of each frame	1000
Number of test samples	10^8
Number of multi-paths	6
Encoding polarization	Differential encoding
Channel statistical model	SCM
modulation	QPSK
SNR range	-10dB to 0dB
Spreading code	m sequence

A. ROBUST PERFORMANCE EVALUATION

In this section, several simulations are conducted to evaluate the performance of the proposed Bayesian RAKE receiver. The performance of the Bayesian RAKE receiver with different fingers is shown in Fig. 2.

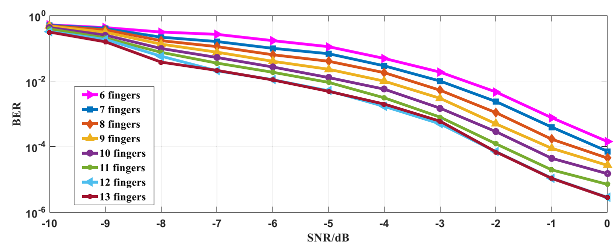

FIGURE 2. Bayesian RAKE receiver with different fingers.

The finger is the most important factor in improving system performance and plays a significant role in reducing error rates [25]–[27]: more receiver fingers tends to improve the performance. Given the certainty of the BER, this simulation shows that the SNR is increased by approximately 0.4 dB accordingly for every additional finger. However, when the equalizer length is more than twice as much as the channel length, the BER shows no changes. For example, when the BER is 1×10^{-3}, the performance of the 12 fingers is approximately 0.5 dB better than that of 10 fingers, 0.2 dB better than that of 11 fingers, and 0.05 dB better than that of 13 fingers. As the BER is decreased, the SNR advantage of 12 fingers increases. In this paper, the channel length is set equal to 6. To balance complexity and performance, it is more appropriate to choose 12 as the equalizer length. In other cases, the BER is 0 when the SNR is above 2 dB. When the SNR is not more than -10 dB, the BER of different fingers is nearly equal.

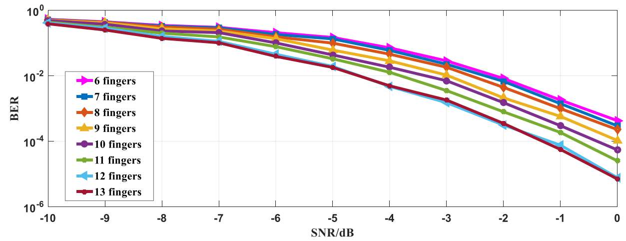

FIGURE 3. FAPI RAKE receiver with different numbers of fingers.

Moreover, Fig. 3 illustrates the BER performance with different numbers of fingers for the FAPI RAKE receiver. The conditions are the same as those in the simulations of the Bayesian RAKE receiver. As in Fig. 2, the MRC [28] and SVD algorithms [29] of the RAKE receiver show similar characteristics, namely the more receiver fingers used, the better performance can be achieved.

B. COMPARISON WITH OTHER RAKE RECEIVER ALGORITHMS

In this section, a comparative simulation is conducted to highlight the superior performance of the Bayesian RAKE receiver compared to the All-RAKE receiver using the MRC algorithm, a RAKE receiver using the SVD algorithm, and a RAKE receiver using the FAPI algorithm. The results of this simulation are shown in Fig. 4.

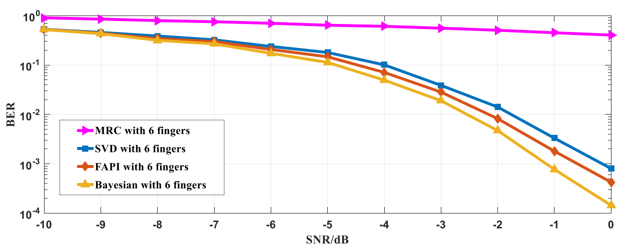

FIGURE 4. Bayesian RAKE receiver compared with the All-RAKE receiver using the MRC algorithm, a RAKE receiver using the SVD algorithm, and a RAKE receiver using the FAPI algorithm.

The All-RAKE receiver with the MRC algorithm is based on linear process and the RAKE receiver with the SVD algorithm is based on a batched process. The RAKE receiver with the FAPI algorithm is similar to the Bayesian RAKE receiver because both use the concept of iteration. However, Bayesian RAKE receivers increase the use of prior information. In the iterative process, priori information is accumulated and thus, improves the receiver performance. It is shown that the performance of the Bayesian RAKE receiver is similar to those of the other algorithms for low SNR values (i.e., <-10 dB). As SNR increases, the advantage of the Bayesian RAKE receiver becomes more apparent. Under medium to high SNR conditions (i.e., ≥ -5 dB), the Bayesian RAKE receiver provides the best BER performance among the receiver tested.

For complementary, the complexities of the different algorithms are listed in Table 2. As mentioned above, the value of

TABLE 2. Computational complexity of four algorithms investigated.

Algorithm	Bayesian	MRC	SVD	FAPI
Complexity	$O(KN^2)$	$O(N^2)$	$O(K^2)$	$O(KN)$

TABLE 3. Comparison of non-similar power users in four algorithms investigated.

Algorithm	non-similar power users	BER ($SNR_1 = -10$ dB)	BER ($SNR_1 = -5$ dB)	BER ($SNR_1 = 0$ dB)
BAYESIAN	user 1	0.4147	0.0306	5.08×10^{-5}
FAPI		0.4539	0.0472	6.79×10^{-5}
SVD		0.5592	0.0871	7.79×10^{-5}
MRC		0.7459	0.6201	0.5212
BAYESIAN	user 2	0.3904	0.0156	1.50×10^{-5}
FAPI		0.4224	0.0386	2.53×10^{-5}
SVD		0.5021	0.0742	3.26×10^{-5}
MRC		0.7238	0.6078	0.5018

K is much larger than N. From Table 2, the Bayesian method shows a slightly higher complexity compared with MRC and FAPI. Considering the lowest BER, as shown in Fig. 4, we can conclude that the Bayesian algorithm is quite competitive.

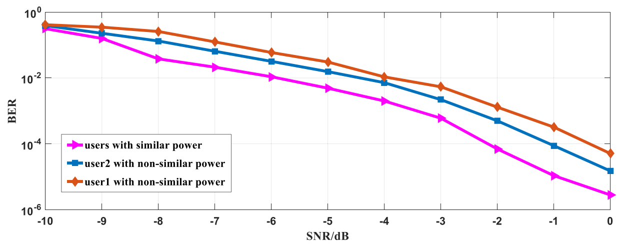

FIGURE 5. Bayesian RAKE receiver with non-similar power users and similar power users.

C. COMPARISON OF MULTIPLE USERS WITH DIFFERENT POWERS

Another simulation is used to examine the performance of multiple users with different powers. The number of RAKE fingers is 12. The results of this simulation are shown in Fig. 5 and Table 3. The curves in Fig. 5 can be categorized into two groups. The first group is the curve with similar power users, and the other group is the curve with non-similar power users. It has been experimentally observed that the performance of similar power users is more robust. In terms of non-similar power users, the signal power of the second user is twice that of the first user (3 dB). Thus, the performance of the second user shows higher than that of the first. To further investigate

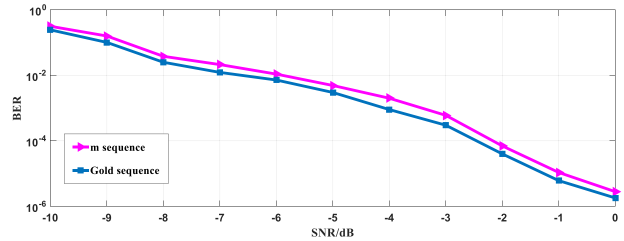

FIGURE 6. Bayesian RAKE receiver with m sequence and Gold sequence.

TABLE 4. Comparison of coherency and non-coherency in four algorithms investigated.

Algorithm	Spreading code	BER (SNR= -10 dB)	BER (SNR= -5 dB)	BER (SNR= 0 dB)
BAYESIAN	coherency (m sequence)	0.3148	0.0049	2.80×10^{-6}
FAPI		0.3848	0.0179	3.69×10^{-6}
SVD		0.4009	0.0346	5.43×10^{-6}
MRC		0.7039	0.5830	0.4849
BAYESIAN	non-coherency (Gold sequence)	0.2449	0.0030	1.08×10^{-6}
FAPI		0.2586	0.0119	3.02×10^{-6}
SVD		0.2596	0.0219	4.86×10^{-6}
MRC		0.6854	0.5698	0.4683

the superiority of Bayesian algorithm, Table 3 shows the BER comparisons of non-similar power users in four algorithms when the SNR_1 (the SNR of first user) is -10 dB, -5 dB and 0 dB. We can see the Bayesian RAKE receiver shows the best BER performance compared to other receivers tested.

D. COMPARISON OF COHERENCY AND NON-COHERENCY

The comparison of coherency and non-coherency is discussed in this section. The number of RAKE fingers is 12. The results of this simulation are shown in Fig. 6 and Table 4. In terms of coherency, the orthogonality of the m sequence is slightly worse than that of the Gold sequence. Thus, the m sequence is used as the coherent spreading code, and the Gold sequence is used as the non-coherent spreading code. Fig. 6 shows that the BER performance of Gold sequence is slightly better than that of the m sequence. Thus, the stronger non-coherency of the spreading code tends to produce the improved performance. Table 4 shows the detailed BER comparisons of coherency and non-coherency in four algorithms when the SNR is -10 dB, -5 dB and 0 dB. By comparison, Bayesian RAKE receiver shows the superior BER performance compared to the receivers tested.

V. CONCLUSION

In this paper, a new RAKE receiver, known as the "Bayesian RAKE receiver", which only uses received signals to estimate its channel parameters, is proposed. The mean and covariance of the channel impulse response are recursively estimated via Bayesian theory based on the MMSE. Next, the combined weight can be obtained. From the simulation results, the performance of the proposed receiver is shown to be considerably improved compared to other types of RAKE receivers. Under medium to high SNR conditions (i.e., ≥ -5 dB), the BER performance of the new RAKE receiver provides at least 3×10^{-4} less than that of the other receiver tested. Thus, the proposed Bayesian RAKE receiver is a reliable structure and quite competitive.

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