Segment Training Based Individual Channel Estimation for Multi-pair Two-Way Relay Network with Power Allocation

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Abstract

In this paper, we design a segment training based individual channel estimation (STICE) scheme for the classical two-way relay network (TWRN) with multi-pair sources (MPS) and amplify-and-forward (AF). We adopt the linear minimum mean square error (LMMSE) channel estimator to minimize the mean square error (MSE) without channel estimation error, where the optimal power allocation strategy from the relay for different sources is obtained. Then the MSE gains are given with different source pairs among the proposed power allocation scheme and the existing power allocation schemes. Numerical results show that the proposed method outperforms the existing ones.

Keywords: Channel estimation, LMMSE, power allocation, two-way relay networks, amplify-and-forward

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1. Introduction

The two-way relay network (TWRN) has been popular studied due to its capability of improving the spectral efficiency compared to the one-way relay network (OWRN) [1-4]. Several simple but effective relay protocols, such as LMMSE transceiver [5][6], beamforming [7][8], distributed space-time coding (DSTC) [9][10], linear precoding [11], etc., have been proposed to capture the advantages for the relay networks.

Following the same guideline, the training design and power allocation for amplify-and-forward (AF) based TWRN have been studied in [12-16]. In [12], the author considered a two-hop non-regenerative multiple-input multiple-output (MIMO) relay system and computed the optimal source and relay pilot matrixes by using LMMSE which allows to use the prior knowledge of channel correlations. To make the method more practical, the optimal training and optimal relay's power allocation were given resorting to LMMSE estimators in our previous work [4] and [6]. A new channel estimation prototype was proposed in [14] to allow the relay firstly estimate the channel parameter and then allocate the powers based on these parameters. Both [15] and [16] studied in two-way MIMO relay networks, where they derived the optimal training structure and the optimal power allocation to minimize MSE. [17] extended the channel estimation to frequency selective channels by applying the orthogonal frequency division multiplex (OFDM) modulation.

All researchs above, including our previous work, are mainly focused on the classical three-node relay network where two sources exchange their information via a single relay node. However, in real systems, one relay may work for multi-pair sources, which has been examined in [18, 19]. The authors in [18, 19] focused on the estimation of the convolution channels (called co-channels here) between the source-to-relay links and relay-to-source ones. However, purely knowing the co-channels is insufficient to support the optimal system design in certain scenarios. For example, in the relay beamforming scheme, the individual channels (called in-channels here) between the sources and the relays are required to design the relay's operation and to let the source predict the relay's operation[7, 8].

In this paper, we propose a practical segment training based in-channel estimation(STICE) algorithm under the multi-pair sources(MPS) TWRN scenario. Furthermore, to avoid the interference, we adopt orthogonal frequency division multiple access(OFDMA) and schedule source paris into different subcarriers. Then, we derive the MSEs of the in-channel estimations, and derive the optimal power allocation for different sources.

The paper is organized as follows. Section 2 presents the system model. In Section 3, we derive the expressions of the power allocation factors for different sources. Simulation results are provided in Section 4. Finally, Conclusions are made in Section 5.

2. System Model

A typical $2n+1$ -node TWRN with n pairs of sources $\mathbf{s}_a=[s_{a1},s_{a2},\cdots,s_{an}]^T$, $\mathbf{s}_b=[s_{b1},s_{b2},\cdots,s_{bn}]^T$ and one relay node R is shown in **Fig. 1**. Each node works in half-duplex mode, and FDD is applied for different source pairs. We assume that there is no direct link between $\mathbf{s}_a$ and $\mathbf{s}_b$. The in-channels from sources to relay and that from relay to sources are reciprocal, and assumed to be block fading. The in-channels between s_{ai} and R, R

and s_{bi} are denoted by h_i and g_i, $i=1,2,\ldots,n$, respectively. We assume that all h_i and g_i are zero mean circularly symmetric complex Gaussian (CSCG) random variables, i.e., $h_i \sim CN(0,\sigma_{h_i}^2)$ and $g_i \sim CN(0,\sigma_{g_i}^2)$. Furthermore, h_i and g_i are assumed to be independent, and perfect synchronization are among all these nodes.

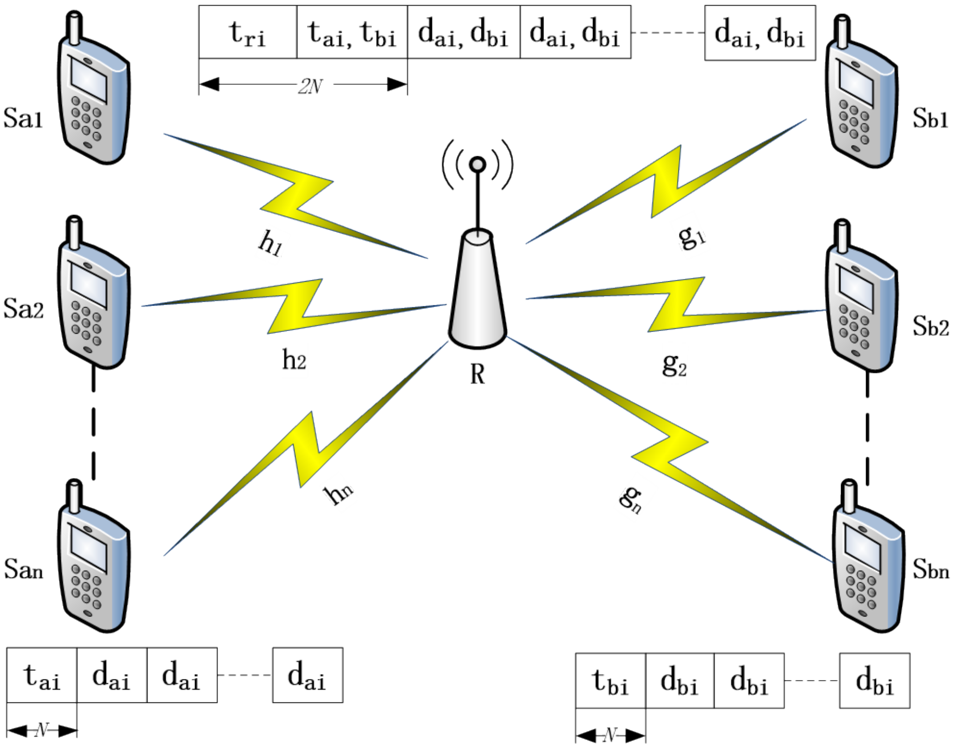

Fig. 1. The STICE scheme for the classical 2n+1-node TWRN

As shown in **Fig. 1**, during the STICE, one round of the signal exchange between $\mathbf{s}_a$ and $\mathbf{s}_b$ can be divided into two phases. Phase I, s_{ai} and s_{bi} concurrently send one signal frame, including one source-training block and several data blocks, to R, and the source-training block and data blocks from s_{ji}, $j=a$, b, are denoted by the column vectors $\mathbf{t}_{ji}$ and $\mathbf{d}_{ji}$, respectively; Phase II, R imposes one relay-training block $\mathbf{t}_{ri}$ in front of the received signal frame, and broadcasts the coded frame to s_{ai} and s_{bi}.

Without loss of generality, all the training blocks, i.e., $\mathbf{t}_{ai}$, $\mathbf{t}_{bi}$ and $\mathbf{t}_{ri}$, are assumed to have the same length N. The received training block at R in phase I can be expressed as

$$\mathbf{X}_r = \mathbf{T}_a\mathbf{h} + \mathbf{T}_b\mathbf{g} + \mathbf{N}_r, \tag{1}$$

in which $\mathbf{T}_a = [\mathbf{t}_{a1},\mathbf{t}_{a2},\ldots\mathbf{t}_{an}]$, $\mathbf{T}_b = [\mathbf{t}_{b1},\mathbf{t}_{b2},\ldots\mathbf{t}_{bn}]$, $\mathbf{h} = diag\{h_i\}$, $\mathbf{g} = diag\{g_i\}$, and

$\mathbf{N}_r = [\mathbf{n}_{r1}, \mathbf{n}_{r2}, \ldots \mathbf{n}_{rn}]$ represents the additive-white Gaussian noise (AWGN) vector where each element is an $N\times 1$ noise vector with variance $N\sigma_n^2$. The power of $\mathbf{T}_j$ is denoted by $\mathbf{P}_j = \mathbf{T}_j^H \mathbf{T}_j = diag\{P_{ji}\}$, $j=a, b, i=1,2,\ldots,n$.

In the phase II, the relay-training $\mathbf{t}_{ri}$ is imposed in front of the received source-training at R, and the overall training broadcasted by R can be written as the $2N\times n$ vector

$$\mathbf{R}_t = [\mathbf{T}_r^T, (\mathbf{A}\mathbf{X}_r)^T]^T, \tag{2}$$

where $\mathbf{T}_r = \left[\mathbf{t}_{r1}, \mathbf{t}_{r2}, \ldots \mathbf{t}_{rn}\right]$, the factor $\mathbf{A} = diag\{\alpha_i\}$ controls the power allocated to the forwarded relay-training part.

The powers of $\mathbf{T}_r$ and $\mathbf{R}_t$ are defined as $\mathbf{P}_r = \mathbf{T}_r^H \mathbf{T}_r$ and $\mathbf{P}_t = \mathbf{R}_t^H \mathbf{R}_t = diag\{P_{ti}\}$, respectively. The total relay power can be given by $P_t = \sum_{\mathrm{i}=1}^{\mathrm{n}} P_{ti} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \beta_i P_t$, where β_i controls the relay power allocated to the i^{th} sources. Thus, from (2), we can obtain

$$\mathbf{P}_r = \mathbf{P}_t - \mathbf{A}^2(\mathbf{C}_\mathbf{h}\mathbf{P}_a + \mathbf{C}_\mathbf{g}\mathbf{P}_b + N\sigma_n^2\mathbf{I}), \tag{3}$$

where $\mathbf{C}_\mathbf{h} = E\left\{\mathbf{h}\mathbf{h}^H\right\}$, $\mathbf{C}_\mathbf{g} = E\left\{\mathbf{g}\mathbf{g}^H\right\}$, $\alpha_i \in [0, \sqrt{\frac{\beta_i P_t}{\sigma_{hi}^2 P_{ai} + \sigma_{gi}^2 P_{bi} + N\sigma_n^2}}]$ to make P_{ri} a non-negative value. The received training at $\mathbf{s}_a$ can be divided into two parts, i.e.,

$$\mathbf{Z}_a^r = \mathbf{T}_r\mathbf{h} + \mathbf{N}_a^r, \tag{4}$$

$$\mathbf{Z}_a^s = \mathbf{T}_a\mathbf{A}\mathbf{h}^2 + \mathbf{T}_b\mathbf{A}\mathbf{h}\mathbf{g} + \mathbf{N}_r\mathbf{A}\mathbf{h} + \mathbf{N}_a^s , \tag{5}$$

where $\mathbf{N}_a^r = \left[\mathbf{n}_{a1}^r, \mathbf{n}_{a2}^r, \ldots, \mathbf{n}_{an}^r\right]$ and $\mathbf{N}_a^s = \left[\mathbf{n}_{a1}^s, \mathbf{n}_{a2}^s, \ldots, \mathbf{n}_{an}^s\right]$ are $N\times n$ AWGN matrixes at $\mathbf{s}_a$, each element is an $N\times 1$ noise vector with variance $N\sigma_n^2$.

3. Segment Training Based In-channel Estimation

When the number of source pair is 1, which is n=1, the model reduces to the classical three-node TWRN where two sources exchange their information via a single relay node. This model has been carefully examined in our previous work [6], where we have derived and given the optimal power allocation factor α_1 by Eqn. (22). When n>1, the power allocation process can be divided into two steps: the allocation among different source pairs and that between source and relay. With respect to the former step, the power allocation is characterized by the parameter β_i , while the latter one is described by the parameter α_i . If the factor β_i is determined, according to the Eqn. (22) in [6], the optimal power allocation factor α_i can be given by

$$\alpha_{opt\_i}^2 = \frac{F_c}{F_b}\left(1 - \sqrt{1 - \frac{F_b \beta_i P_t}{F_a F_c}}\right), \tag{6}$$

where $F_a = \sigma_h^2 P_a + \sigma_g^2 P_b + N\sigma_n^2$, $F_b = (N-1)\sigma_h^2\sigma_n^2 + \sigma_h^4 P_a$, $F_c = \sigma_h^2 \beta_i P_t + \sigma_n^2$.

From (4), we can formulate the standard LMMSE estimator of $\mathbf{h}$ as

$$\hat{\mathbf{h}} = \mathbf{C_h}\mathbf{T}_r^H(\sigma_n^2\mathbf{I} + \mathbf{T}_r\mathbf{C_h}\mathbf{T}_r^H)^{-1}\mathbf{Z}_a^r. \tag{7}$$

The variances of both the error $\mathbf{e_h} = \mathbf{h} - \hat{\mathbf{h}}$ and the estimated result $\hat{\mathbf{h}}$ are computed by

$$\mathbf{C}_{\mathbf{e_h}} = (\mathbf{C_h}^{-1} + \mathbf{P_r}\sigma_n^{-2})^{-1}, \tag{8}$$

$$\mathbf{C}_{\hat{\mathbf{h}}} = \mathbf{C_h} - \mathbf{C}_{\mathbf{e_h}} = (\sigma_n^2\mathbf{I} + \mathbf{P}_r\mathbf{C_h})^{-1}\mathbf{P}_r\mathbf{C_h}^2, \tag{9}$$

then $\mathbf{Z}_a^s$ in (5), can be rewritten as

$$\mathbf{Z}_a^s - \mathbf{T}_a\mathbf{A}\hat{\mathbf{h}}^2 = \mathbf{T}_b\mathbf{A}\hat{\mathbf{h}}\mathbf{g} + \mathbf{N}_t, \tag{10}$$

where $\mathbf{N}_t = 2\mathbf{T}_a\mathbf{A}\hat{\mathbf{h}}\mathbf{e_h} + \mathbf{T}_a\mathbf{A}\mathbf{e_h}^2 + \mathbf{T}_b\mathbf{A}\mathbf{e_h}\mathbf{g} + \mathbf{N}_r\mathbf{A}(\hat{\mathbf{h}} + \mathbf{e_h}) + \mathbf{N}_a^s$ is the equivalent noise at $\mathbf{s}_a$. Since the terms $\mathbf{e_h}$, $\mathbf{g}$, $\mathbf{N}_r$, $\mathbf{N}_a^s$ are uncorrelated, the covariance matrix of $\mathbf{N}_t$ conditioned on $\hat{\mathbf{h}}$ can be derived as

$$\mathbf{C}_{\mathbf{N}_t|\hat{\mathbf{h}}} = E\left\{\mathbf{N}_t\mathbf{N}_t^H\right\} = \mathbf{T}_a\boldsymbol{\Psi}_a\mathbf{T}_a^H + \mathbf{T}_b\boldsymbol{\Psi}_b\mathbf{T}_b^H + \lambda\mathbf{I}, \tag{11}$$

where $\boldsymbol{\Psi}_a = 2\mathbf{A}^2\mathbf{C}_{\mathbf{e_h}} + 4\mathbf{A}^2\hat{\mathbf{h}}^2\mathbf{C}_{\mathbf{e_h}}$, $\boldsymbol{\Psi}_b = \mathbf{A}^2\mathbf{C_g}\mathbf{C}_{\mathbf{e_h}}$, $\lambda = n\sigma_n^2\left(\sum_{i=1}^{n}\alpha_i^2\sigma_{hi}^2 + N\right)$.

From the equation (10), $\mathbf{s}_a$ can be used to compute the LMMSE estimator of $\mathbf{g}$ as

$$\hat{\mathbf{g}} = \mathbf{C_g}(\mathbf{T}_b\mathbf{A}\hat{\mathbf{h}})^H[(\mathbf{T}_b\mathbf{A}\hat{\mathbf{h}})\mathbf{C_g}(\mathbf{T}_b\mathbf{A}\hat{\mathbf{h}})^H + \mathbf{C}_{\mathbf{N}_t|\hat{\mathbf{h}}}]^{-1}(\mathbf{Y}_a^s - \mathbf{T}_a\mathbf{A}\hat{\mathbf{h}}^2). \tag{12}$$

The corresponding $\mathbf{g}$ estimation error variance conditioned on $\hat{\mathbf{h}}$ can be obtained as

$$\mathbf{C}_{\Delta\mathbf{g}|\hat{\mathbf{h}}} = \left(\mathbf{C}_{\mathbf{g}}^{-1} + (\mathbf{T}_b\mathbf{A}\hat{\mathbf{h}})^H \mathbf{C}_{\mathbf{N}_t|\hat{\mathbf{h}}}^{-1} \mathbf{T}_b\mathbf{A}\hat{\mathbf{h}}\right)^{-1} . \tag{13}$$

For the inverse matrix $\mathbf{\Theta} = \mathbf{I} + \mathbf{XBX^H}$, there is

$$\mathbf{\Theta}^{-1} = \mathbf{I} - \mathbf{X}\left(\mathbf{B}^{-1} + \mathbf{\Omega}\right)^{-1} \mathbf{X^H}, \tag{14}$$

where $\mathbf{\Omega} = \mathbf{X^H X}$.

The $\mathbf{C}_{\mathbf{N}_t|\hat{\mathbf{h}}}$ presented in (11) can be worked out by the similar derivation to the equation (14), where $\mathbf{X} = [\mathbf{T}_a, \mathbf{T}_b]$, $\mathbf{B} = \frac{1}{\lambda}\begin{bmatrix} \mathbf{\Psi}_a & \\ & \mathbf{\Psi}_b \end{bmatrix}$, $\mathbf{C}_{\mathbf{N}_t|\hat{\mathbf{h}}} = \lambda\left(\mathbf{I} + \mathbf{XBX^H}\right)$. Then we can obtain

$$\mathbf{C}_{\mathbf{N}_t|\hat{\mathbf{h}}}^{-1} = \frac{1}{\lambda}\left(\mathbf{I} - \mathbf{X}\left(\mathbf{B}^{-1} + \mathbf{\Omega}\right)^{-1} \mathbf{X^H}\right). \tag{15}$$

So (13) can be rewritten as

$$\mathbf{C}_{\Delta\mathbf{g}|\hat{\mathbf{h}}} = \left(\mathbf{C}_{\mathbf{g}}^{-1} + (\mathbf{T}_b\mathbf{A}\hat{\mathbf{h}})^H \frac{1}{\lambda}\left(\mathbf{I} - \mathbf{X}\left(\mathbf{B}^{-1} + \mathbf{\Omega}\right)^{-1} \mathbf{X^H}\right)\mathbf{T}_b\mathbf{A}\hat{\mathbf{h}}\right)^{-1} . \tag{16}$$

And the MSE of $\mathbf{g}$ is

$$\begin{aligned} MSE &= E\left\{tr(\mathbf{C}_{\Delta\mathbf{g}|\hat{\mathbf{h}}})\right\} \\ &= \sum_{i=1}^{n} \sigma_{gi}^2 \underbrace{E\left\{\frac{\Gamma_{ai} + \Gamma_{bi}\left|\overline{h}_i\right|^2}{\Gamma_{ai} + \left|\overline{h}_i\right|^2}\right\}}_{\Sigma_i} , \end{aligned} \tag{17}$$

where $\Gamma_{ai} = \frac{\sigma_n^2}{\sigma_{hi}^2 P_{ri}} + \frac{\sigma_n^2(\sigma_n^2 + \sigma_{hi}^2 P_{ri})}{\alpha_i^2(\sigma_n^2 + \sigma_{gi}^2 P_{bi})\sigma_{hi}^4 P_{ri}}$, $\Gamma_{bi} = \frac{\sigma_n^2}{\sigma_n^2 + \sigma_{gi}^2 P_{bi}}$, $P_{ri} = \beta_i P_t - \alpha_{opt\_i}^2(\sigma_{hi}^2 P_{ai} + \sigma_{gi}^2 P_{bi} + N\sigma_n^2)$.

From (6), we know the MSE in (17) is an equation about β_i and $\left|\overline{h}_i\right|^2 = \hat{h}_i / \sigma_{\hat{h}_i} \sim CN(0,1)$. After some integral calculation, we can obtain the closed-form expression of Σ_i as

$$\Sigma_i = \Gamma_{bi} - \Gamma_{ai}(1 - \Gamma_{bi})\exp(\Gamma_{ai})Ei(-\Gamma_{ai}) , \tag{18}$$

where $Ei(\mathrm{x}) = \int_{-\infty}^{\mathrm{x}} \frac{e^t}{t} dt$. Applying (18) into (17), we obtain

$$MSE = \sum_{i=1}^{n} \{\sigma_{gi}^2 \Gamma_{bi} - \sigma_{gi}^2 \Gamma_{ai} (1-\Gamma_{bi}) \exp(\Gamma_{ai}) Ei(-\Gamma_{ai})\} . \tag{19}$$

Then, we can optimize the power allocation factor β_i through minimizing MSE.

$$\begin{aligned} &\min_{\beta_i} MSE \\ &\text{s.t.} \quad \sum_{i=1}^{n} \beta_i = 1, 0 \le \beta_i \le 1, i = 1, 2, ..., n \end{aligned} . \tag{20}$$

From (19), it is obvious that we can minimize the MSE by minimizing the Γ_{ai}. Through the derivation of Γ_{ai} and after some tedious mathematical operations, we could see that Γ_{ai} is a convex function. Overall, based on (20), we can obtain the optimal power allocation factor β_{opt_i} by calculating this optimization problem, which can be easily computed by using the "fmincon" in MATLAB.

4. Simulation

In this section, numerical simulations are provided to test the performance of optimal power allocation for MPS AF based TWRN. The parameters are set as following: $\sigma_{hi}^2 = \sigma_{gi}^2 = 1, \sigma_n^2 = 1$, N=8, and we assume that s_{ai} and s_{bi} are symmetrical, the SNR of s_{ai} and s_{bi} are defined as $SNR_i = \frac{P_{ai}}{\sigma_n^2} = \frac{P_{bi}}{\sigma_n^2}$, and the SNR of R is given as $SNR_t = \frac{P_t}{\sigma_n^2}$.

We compared three methods as shown in following figures, where the proposed method is denoted as OPA with $\alpha_i = \alpha_{opt\_i}$ and $\beta_i = \beta_{opt\_i}$, the conventional method, in which $\alpha_i = 0.5\sqrt{\frac{\beta_i P_t}{\sigma_{hi}^2 P_{ai} + \sigma_{gi}^2 P_{bi} + N\sigma_n^2}}$ and $\beta_i = \frac{1}{n}$, is marked by EPA, and the power allocation algorithm mentioned in [6], where $\alpha_i = \alpha_{opt\_i}$ and $\beta_i = \frac{1}{n}$, is marked by PA[6]. The reader is encouraged to find more performance comparisons with other training scheme in our previous work [4, 6]. We also assume that SNR_1=SNR_2=$0dB$ and SNR_3 varies from -10dB to 10dB.

Fig. 2 gives the simulation results when $SNR_t = 10dB$, which is defined as a low SNR scenario. It shows that the system MSE decreases when SNR_3 increases, and the OPA outperforms the others obviously. **Fig. 3** shows the optimal power allocation factors versus SNR_3 when $SNR_t = 10dB$. Since we set SNR_1=SNR_2=$0dB$, the factors β_1 is always equal to β_2 and $\beta_1 = \beta_2 = \beta_3 = 0.3333$ when SNR_3=0dB . From **Fig. 3**, we can see that $\beta_1 = \beta_2 > \beta_3$ when $SNR_3 < 0dB$, the lower SNR_3 the smaller β_3, and β_3 is near to zero when SNR_3 is lower than a threshold, such as -2dB.

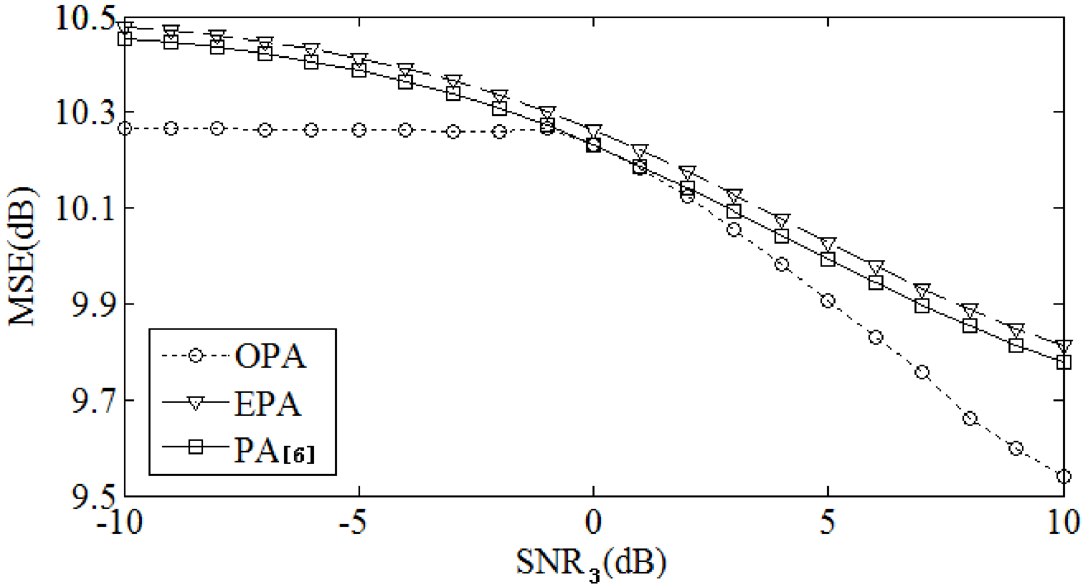

Fig. 2. MSE versus SNR_3 under OPA, EPA and PA[6] when $SNR_t = 10dB$ and $n = 3$

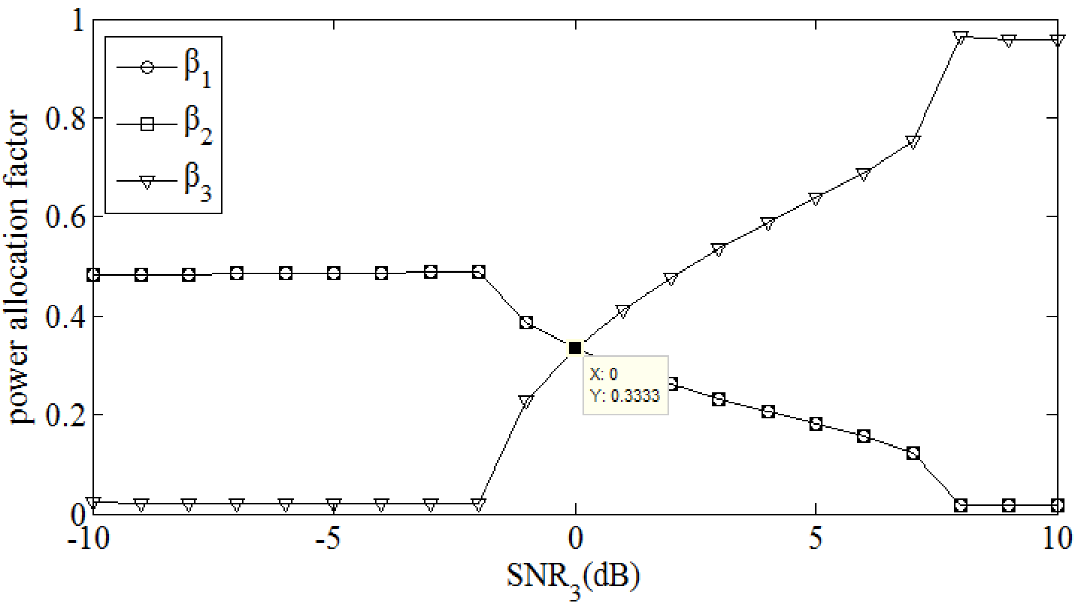

Fig. 3. Power allocation factor β_1, β_2 and β_3 versus SNR_3 when $SNR_t = 10dB$ and $n = 3$

Fig. 4 presents the simulation results when relay $SNR_t = 15dB$, which is defined as a middle SNR scenario. Similar to what are shown in **Fig. 2,** the system MSE decreases when SNR_3 increases. We can see the OPA outperforms EPA and PA[6] obviously when SNR_3 is low, which is explained in **Fig. 5**. **Fig. 5** shows the optimal power allocation factors versus SNR_3 when $SNR_t = 15dB$. Since $SNR_1 = SNR_2 = 0dB$, we get the factor $\beta_1 = \beta_2$, as well as $\beta_1 = \beta_2 = \beta_3 = 0.3333$ when $SNR_3 = 0dB$. From **Fig. 5**, we can see that $\beta_1 = \beta_2 > \beta_3$ when $SNR_3 < 0dB$, the lower SNR_3 the smaller β_3, and β_3 is near to zero when SNR_3 is lower than a threshold, such as -7dB.

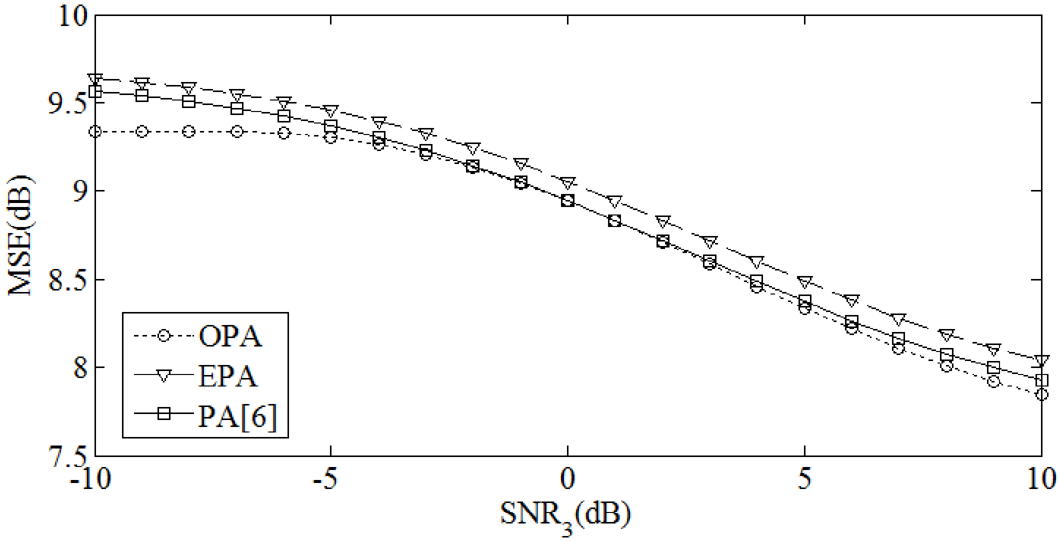

Fig. 4. MSE versus SNR_3 under OPA, EPA and PA$_{[6]}$ when $SNR_t = 15dB$ and $n = 3$

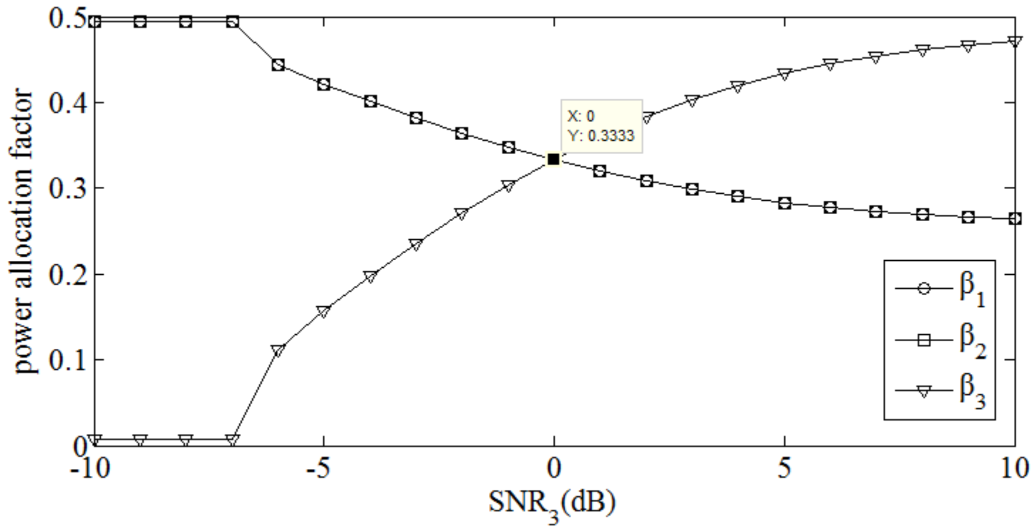

Fig. 5. Power allocation factor β_1, β_2 and β_3 versus SNR_3 when $SNR_t = 15dB$ and $n = 3$

Fig. 6 and **Fig. 7** give the performance when SNR_t is high. Here, the relay SNR is 20 dB. The performance is similar to the results in **Fig. 2** and **Fig. 3**, except for that the curves are more smooth in **Fig. 7**. This is because when the SNR of training data is above a level, the MSE changes little with the increasing of training data's power, which means more power needs to be allocated to the source pairs with small SNR.

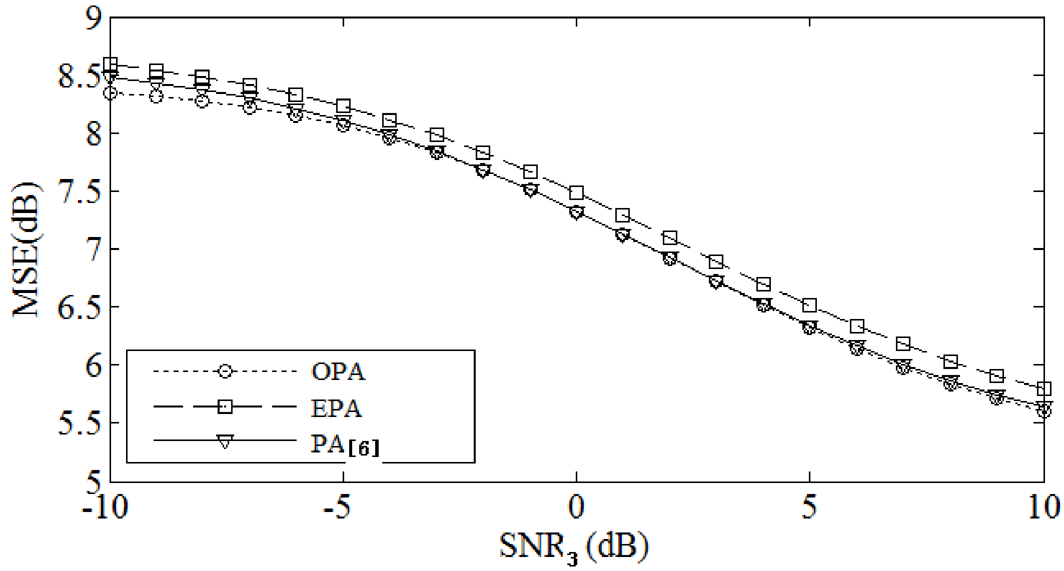

Fig. 6. MSE versus SNR_3 under OPA, EPA and PA[6] when $SNR_t = 20dB$ and $n = 3$

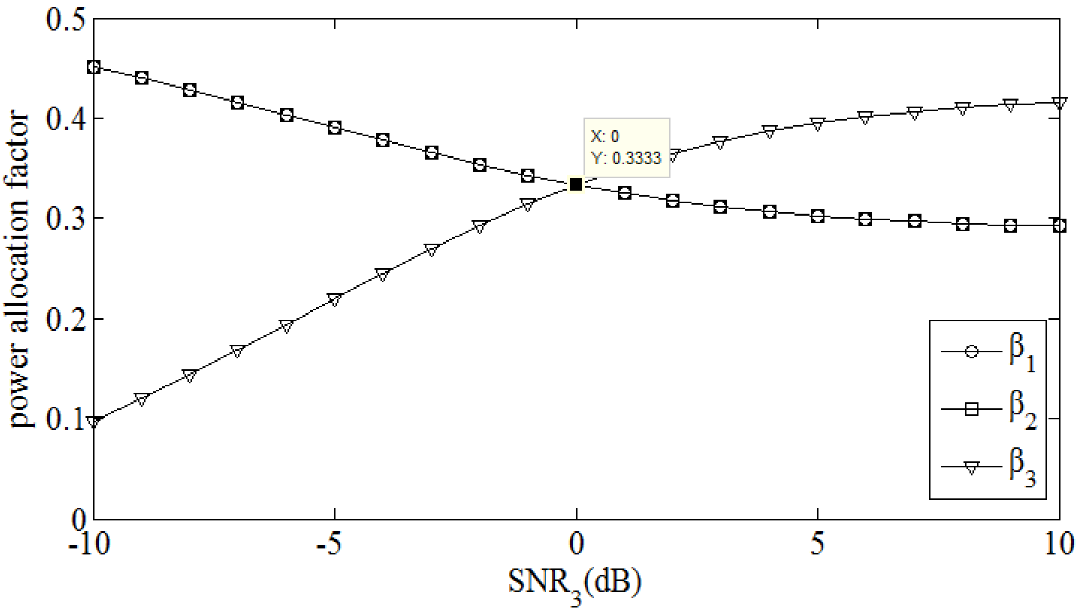

Fig. 7. Power allocation factor β_1, β_2 and β_3 versus SNR_3 when $SNR_t = 20dB$ and $n = 3$

In order to quantize the performance improvement between the OPA and the other existing algorithms, we define the gain of MSE_{equ} and $MSE_{[6]}$ as $MSE_{equ}gain = \frac{MSE_{equ}}{MSE_{opt}}$ and $MSE_{[6]}gain = \frac{MSE_{[6]}}{MSE_{opt}}$, respectively, which are shown in **Fig. 8** and **Fig. 9**. In these figures, we set the relay SNR as $SNR_t = 20dB$, SNR_i s are equal when i=1,3,4. **Fig. 8** shows the MSE gain versus SNR_2, where the source pair number n =3. In **Fig. 9**, three different source pair numbers n =2, 3 and 4 are adopted. Generally speaking, the larger differences between SNR_i and SNR_2, the higher gain we get. Furthermore, when SNR_2 is large, the MSE gain becomes bigger with the number of source pair increases, but the computation complexity increases dramatically. When SNR_2 is small, the MSE gain becomes smaller with the source number increases. These phenomena give a reference to choose the acceptable source-pair number when designing a real system.

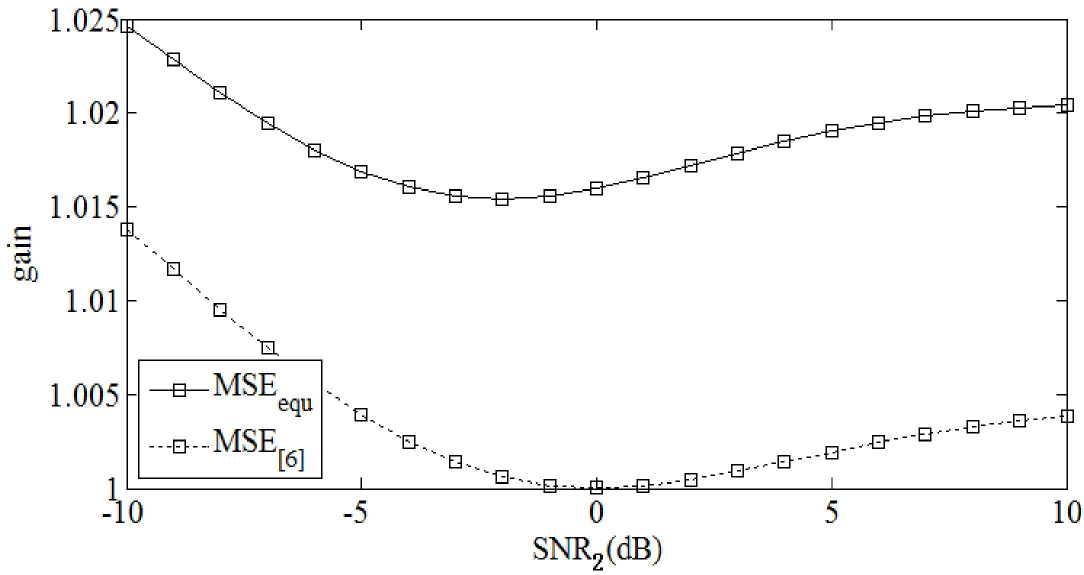

Fig. 8. MSE gain versus SNR_2 when $SNR_t = 20dB$

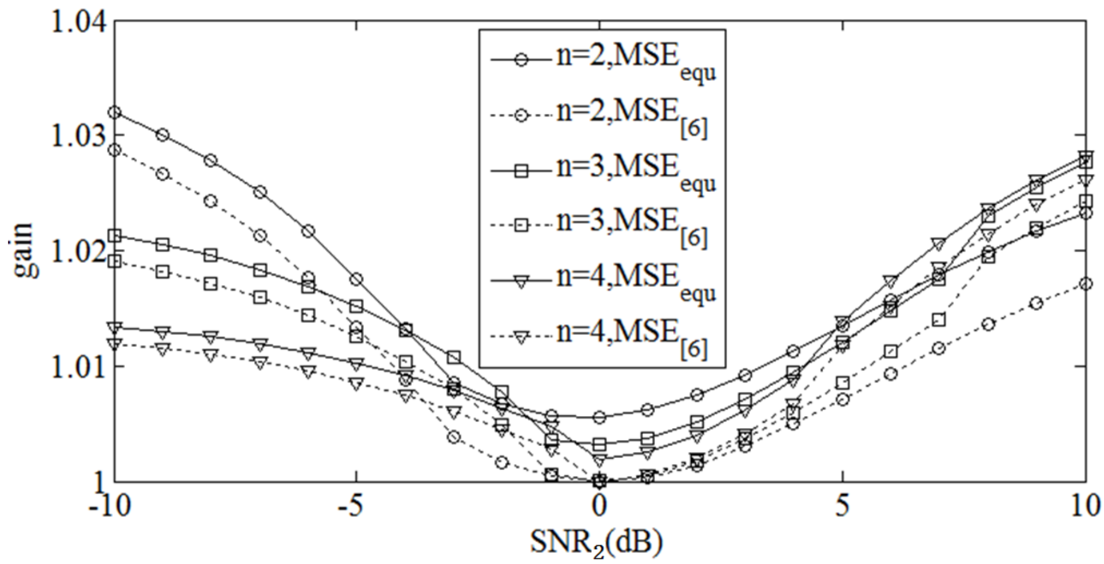

Fig. 9. MSE gain versus SNR_2 when $SNR_t = 20dB$

5. Conclusion

In this paper, we introduce a scheme to estimate channel state information for a typical $2n+1$-node TWRN, and propose a new algorithm to minimize the MSE by computing the optimal power allocation factors at relay node for different sources. The proposed method has gained better performance especially when the relay power is low. The numerical results give a reference to choose the acceptable source-pair number when designing a real system.

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