

Chapter 2

Space Domain Index Modulation

In this chapter, we discuss the realization of index modulation in the space domain. First, we take a brief review of the pioneering space domain index modulation technique, namely spatial modulation (SM). Then, we propose the generalized pre-coding aided quadrature spatial modulation (GPQSM) scheme, which extends SM to the receiver side, and the virtual spatial modulation (VSM) scheme, which can be used as either a transmitter-side SM or a receiver-side SM scheme depending on the configuration of transceiver antennas. Finally, we discuss the application of space domain index modulation techniques by taking SM as a representative to cooperative communications.

2.1 Spatial Modulation

In this section, we first present the principle of SM and then review some popular low-complexity detection methods. Finally, the performance of SM is evaluated via computer simulations.

2.1.1 System Model

In SM, the information bits are conveyed by not only the modulated symbol but also the index of the active antenna. Let us consider an $N_t \times N_r$ multiple-input multiple-output (MIMO) system with an M -ary constellation $\mathcal{X}$, where N_t , N_r , and M denote the number of transmit antennas, the number of receive antennas, and the cardinality of the constellation, respectively. The transceiver structure of SM is depicted in Fig. 2.1. At each time slot, the incoming $\log_2(N_t M)$ information bits are divided into two parts. The first part of $\log_2(M)$ bits draws a modulated symbol from $\mathcal{X}$. The second part of $\log_2(N_t)$ bits selects an antenna to transmit this symbol. Here, we simply assume that N_t equals a power of two. If this condition cannot be satisfied in practice, we may select partial antennas whose number equals a power of two to

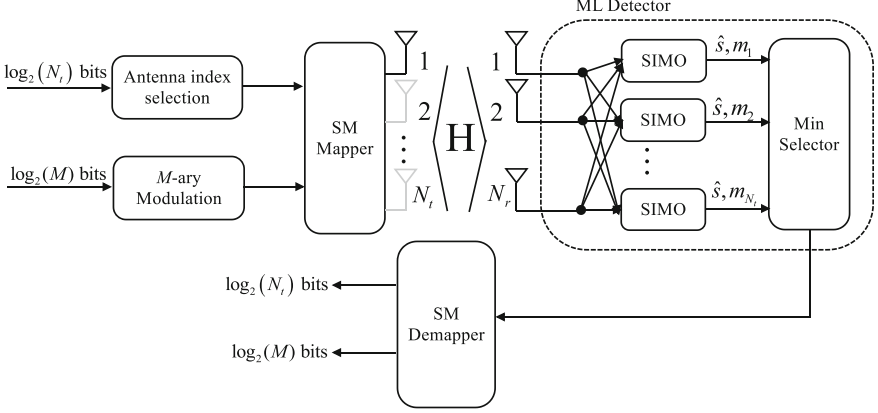


Fig. 2.1 Transceiver structure of SM

perform SM or employ the fractional bit encoding (FBE) to involve all antennas for index modulation [1]. Note that during each transmission only the chosen antenna is active while the other antennas remain idle.

Assume that at a given time slot, $s \in \mathcal{X}$ is selected and transmitted via the k -th antenna. Let $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ denote the MIMO channel matrix, whose (i, j) -th element $h_{i,j}$ represents the channel from the j -th transmit antenna to the i -th receive antenna. Then, the received signal vector can be expressed as

$$\mathbf{y} = \mathbf{h}_k s + \mathbf{w}, \quad (2.1)$$

where $\mathbf{h}_k$ denotes the k -th column of $\mathbf{H}$ and $\mathbf{w} \in \mathbb{C}^{N_r \times 1}$ is the additive white Gaussian noise (AWGN) vector.

From (2.1), the maximum-likelihood (ML) detection can be formulated as [2]

$$[\hat{k}, \hat{s}] = \arg \min_{k \in \{1, \dots, N_t\}, s \in \mathcal{X}} \|\mathbf{y} - \mathbf{h}_k s\|^2. \quad (2.2)$$

The ML detection in (2.2) is optimal at the expense of high search complexity, which is of order $\mathcal{O}(N_t M)$, since it invokes joint detection of the antenna index and modulated symbol.

2.1.2 Low-Complexity Detection

Attentive to the high computational complexity of the ML detection, many researchers have been focusing on the design of low-complexity detection methods for SM. In the following, we will introduce some popular ones.

The pioneering work is presented in [3], where the matched filtering (MF) detection is proposed. In this method, the detections for the antenna index and modulated symbol are decoupled. Specifically, first, the active antenna is estimated, which is realized by

$$\hat{k} = \arg \max_{k \in \{1, \dots, N_t\}} \hat{y}_k, \quad (2.3)$$

where $\hat{y}_k = |\mathbf{h}_k^H \mathbf{y}| / \|\mathbf{h}_k\|^2$. Then, the modulated symbol is estimated via

$$\hat{s} = \arg \min_{s \in \mathcal{X}} \|\mathbf{y} - \mathbf{h}_{\hat{k}} s\|^2. \quad (2.4)$$

The MF detection, however, comes at a cost of system performance, since it is required that $\|\mathbf{h}_j\|^2 < \|\mathbf{h}_k\|^2$ for all $j \neq k$ [2].

Another alternative is the signal vector based detection [4]. The main difference between this method and the MF detection lies in the estimation of the antenna index. In signal vector based detection, the active antenna is determined when the angle between its corresponding channel vector and the received signal vector is the minimum one, i.e.,

$$\begin{aligned} \theta(k) &= \arccos \frac{|\langle \mathbf{h}_k, \mathbf{y} \rangle|}{\|\mathbf{h}_k\| \cdot \|\mathbf{y}\|}, \\ \hat{k} &= \arg \min_{k \in \{1, \dots, N_t\}} \theta(k). \end{aligned} \quad (2.5)$$

However, the inaccuracy of the angle measurement due to the presence of the modulated symbol severely degrades the system performance.

To avoid angle ambiguity caused by the signal vector based detection, the signal vector based list (SVBL) detection is proposed [5]. In SVBL detection, the number of active antenna candidates is relaxed from 1 to L , whose indices, denoted by $\mathcal{L} = \{k_1, \dots, k_L\}$, are associated with the smallest L angles among $\{\theta(1), \dots, \theta(N_t)\}$. Then, the antenna index and the modulated symbol are jointly estimated as

$$[\hat{k}, \hat{s}] = \arg \min_{k \in \mathcal{L}, s \in \mathcal{X}} \|\mathbf{y} - \mathbf{h}_k s\|^2. \quad (2.6)$$

Explicitly, the improved performance is achieved at a price of increased complexity, whose amount depends on the value of L .

A similar idea is realized by the distance-based ordered detection [6]. In this method, first, by assuming the activation of the k -th transmit antenna, the modulated symbol carried on is estimated as

$$\hat{r}_k = \arg \min_{s \in \mathcal{X}} \|\mathbf{y} - \mathbf{h}_k s\|^2, \quad (2.7)$$

where $k \in \{1, \dots, N_t\}$. Note that $\{\hat{r}_1, \dots, \hat{r}_{N_t}\}$ are N_t symbol estimates, but only one of them is necessary. Let d_n denote the distance between r_k and $\hat{r}_k$, given by

$$d_k = \|\mathbf{h}_k\| |\hat{r}_k - r_k|. \quad (2.8)$$

Then, by sorting $\{d_1, \dots, d_{N_t}\}$ in ascending order and obtaining the indices $\mathcal{U} = \{u_1, \dots, u_p\}$ associated with the first p values, the antenna index and the modulated symbol are jointly estimated as

$$\hat{k} = \arg \min_{k \in \mathcal{U}} \|\mathbf{y} - \mathbf{h}_k \hat{r}_k\|^2, \quad (2.9)$$

$$\hat{s} = \hat{r}_{\hat{k}}, \quad (2.10)$$

where similar to the parameter L in the SVBL detection, the parameter p is used to reach a compromise between the system performance and the computational complexity. Explicitly, as p increases, the distance-based ordered detection approaches the optimal ML detection.

The above-mentioned four detection methods achieve sub-optimal performance. In the following, we introduce two low-complexity optimal detection methods, which reduce the search complexity to an order of $\mathcal{O}(N_t)$. The first one is the hard-limiter based ML detection [7], which applies to a square or rectangular QAM. The idea is motivated by the fact that the M -QAM constellation can be viewed as a product of M_1 -PAM and M_2 -PAM constellations, where $M = M_1 M_2$. Consequently, assuming the activation of the k -th transmit antenna, the real and the imaginary parts of the modulated symbol carried on can be directly estimated as

$$\Re\{\hat{r}_k\} = \min \left\{ \max \left\{ 2 \left\lfloor \frac{\Re(\hat{y}_k) + 1}{2} \right\rfloor, M_1 + 1 \right\}, M_1 - 1 \right\}, \quad (2.11)$$

and

$$\Im\{\hat{r}_k\} = \min \left\{ \max \left\{ 2 \left\lfloor \frac{\Im(\hat{y}_k) + 1}{2} \right\rfloor, M_2 + 1 \right\}, M_2 - 1 \right\}, \quad (2.12)$$

respectively, where $\lfloor \cdot \rfloor$ denotes the operation of rounding a real number to the nearest integer, $\hat{y}_k$ is given by (2.3), and $k \in \{1, \dots, N_t\}$. However, only one among $\{\hat{r}_1, \dots, \hat{r}_{N_t}\}$ is necessary. To determine the necessary one, one can resort to the ML criterion:

$$\begin{aligned} \hat{k} &= \arg \min_{k \in \{1, \dots, N_t\}} \|\mathbf{y} - \mathbf{h}_k \hat{r}_k\|^2, \\ \hat{s} &= \hat{r}_{\hat{k}}. \end{aligned} \quad (2.13)$$

The second one is the decision-zone based detection [8], which applies to an MPSK input. Assume that $\hat{y}_k = |\hat{y}_k| e^{j\vartheta_k}$ and $\hat{r}_k = e^{j\varphi_k}$, where ϑ_k and φ_k are the phases of

$\hat{y}_k$ and $\hat{r}_k$, respectively. According to the decision zones for the MPSK constellation, the phase of the modulated symbol can be directly estimated as

$$\hat{\varphi}_k = \frac{2\pi}{M} \left\lfloor \frac{\vartheta_k M}{2\pi} \right\rfloor >_M, \quad (2.14)$$

where $\langle \cdot \rangle_M$ denotes the module M operation. Then, having the phase, the symbol candidate can be directly obtained as $\hat{r}_k = e^{j\hat{\varphi}_k}$. Finally, the antenna index and modulated symbol can be estimated via (2.13).

It should be noted that besides all aforementioned methods, we may also apply the ideas of sphere decoding and compressed sensing for detection, which achieve different tradeoffs between the system performance and the computational complexity.

2.1.3 Performance Evaluation

The bit error rate (BER) performance of SM is shown in Fig. 2.2, where comparison is made with V-BLAST and their spectral efficiencies are equated to 8 bps/Hz. As can be seen, both V-BLAST and SM achieve the same diversity order of N_r , and SM can outperform V-BLAST by leveraging the numbers of space bits and modulation bits.

Taking the SVBL detector as a representative for all low-complexity SM detectors, we compare its performance with that of the optimal ML detector in Fig. 2.3. Two system configurations are considered, which are $\{N_t = 4, N_r = 2\}$ and $\{N_t = 8, N_r = 4\}$. Recall that for $L = 1$, the SVBL detector degenerates into the signal vector based detector and for $L = N_t$, the SVBL detector becomes the optimal ML detector. From the figure, we observe that the SVBL detector with $L = 1$ exhibits unsatisfactory performance, but the performance is improved significantly as L increases. Interestingly, for a value of L much smaller than N_t , near-optimal performance is already achieved by the SVBL detector.

2.2 Pre-coding Aided Spatial Modulation

In this section, we propose a novel scheme, called GPQSM, which extends SM to the receiver side. In GPQSM, index modulation works on both the in-phase and quadrature parts of the received signals. GPQSM is general and can degenerate into the conventional MIMO scheme. A closed-form upper bound on the average bit error probability (ABEP) of GPQSM is also derived.

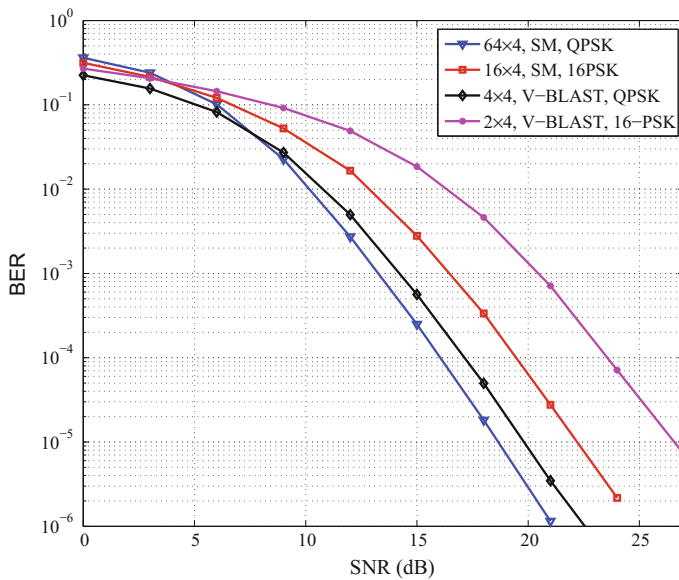


Fig. 2.2 Performance comparison between SM and V-BLAST in terms of BER under the spectral efficiency of 8 bps/Hz

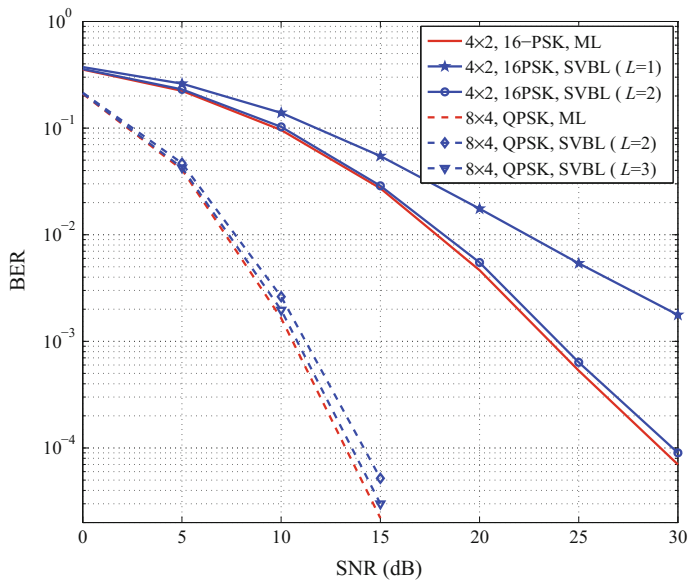


Fig. 2.3 Performance of the SVBL detector

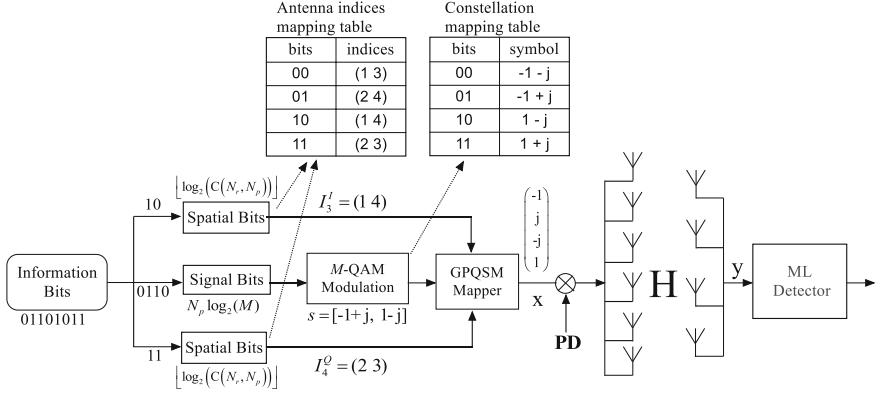


Fig. 2.4 Transceiver structure of GPQSM with $N_t = 6$, $N_r = 4$, and 4-QAM

2.2.1 System Model

The transceiver structure of GPQSM with $N_t = 6$, $N_r = 4$, and 4-QAM is depicted in Fig. 2.4. We always assume $N_t \geq N_r$ and perfect channel state information at the transmitter (CSIT) for ensuring the pre-coding design. In GPQSM, N_p ($1 \leq N_p \leq N_r$) receive antennas are activated to transmit the real (imaginary) parts of transmitted symbols. There are in total $C(N_r, N_p)$ possible antenna combinations. However, in order to modulate the space bits, only $N = 2^{\lfloor \log_2(C(N_r, N_p)) \rfloor}$ combinations will be used. Note that the conventional MIMO scheme is a special case of GPQSM with $N_p = N_r$.

At each time slot, $n = N_p \log_2(M) + 2 \lfloor \log_2(C(N_r, N_p)) \rfloor$ information bits are to be transmitted. First, the $N_p \log_2(M)$ bits are mapped into N_p modulated symbols $\mathbf{s} = \{s(1), \dots, s(N_p)\}$, of which each can be expressed by $s(\eta) = s^I(\eta) + js^Q(\eta)$, $s(\eta) \in \mathcal{X}$, where $s^I(\eta)$ and $s^Q(\eta)$ represent the in-phase and quadrature parts of $s(\eta)$, respectively. Note that $s^I(\eta) \in \mathcal{X}^I$ and $s^Q(\eta) \in \mathcal{X}^Q$, where $\mathcal{X}^I$ and $\mathcal{X}^Q$ denote the in-phase and quadrature sets of $\mathcal{X}$, respectively. Then, $\lfloor \log_2(C(N_r, N_p)) \rfloor$ bits are used to select an antenna combination for transmitting $\{s^I(1), \dots, s^I(N_p)\}$ and the other $\lfloor \log_2(C(N_r, N_p)) \rfloor$ bits are used to select another antenna combination for transmitting $\{s^Q(1), \dots, s^Q(N_p)\}$. Denote the ν -th legitimate active antenna combination for in-phase/quadrature parts as

$$\begin{aligned} I_\nu^I &= \{i_\nu^I(1), \dots, i_\nu^I(N_p)\}, \\ I_\nu^Q &= \{i_\nu^Q(1), \dots, i_\nu^Q(N_p)\}, \end{aligned} \quad (2.15)$$

where $i_\nu^I(a), i_\nu^Q(a) \in \{1, \dots, N_r\}$ with $\nu = 1, \dots, N$ and $a = 1, \dots, N_p$. If the u -th and o -th active antenna combinations are chosen by the incoming bits, respectively, then the signal vectors before pre-coding corresponding to the in-phase and quadrature parts can be written as $\mathbf{x}^I = [x^I(1), \dots, x^I(N_r)]^T$ and

$\mathbf{x}^Q = [x^Q(1), \dots, x^Q(N_r)]^T$, respectively, where

$$x^I(\eta) = \begin{cases} s^I(\eta), & \eta \in I_u^I \\ 0, & \text{otherwise} \end{cases}, x^Q(\eta) = \begin{cases} s^Q(\eta), & \eta \in I_o^Q \\ 0, & \text{otherwise} \end{cases}.$$

Finally, the transmitted signal vector is generated by combining the in-phase and quadrature parts with pre-coding:

$$\mathbf{X} = \mathbf{P}\mathbf{D}\mathbf{x} = \mathbf{P}\mathbf{D}(\mathbf{x}^I + j\mathbf{x}^Q), \quad (2.16)$$

where $\mathbf{P} \in \mathbb{C}^{N_r \times N_r}$ is the pre-coding matrix and $\mathbf{D}$ is an $N_r \times N_r$ diagonal matrix whose η -th diagonal element is $d(\eta) = \sqrt{1/||\mathbf{p}_\eta||^2}$ with $\mathbf{p}_\eta$ denoting the η -th column of $\mathbf{P}$.

Let $\mathbf{H}$ denote the MIMO channel, whose entries follow the Nakagami- m distribution with parameters $(1, m)$. The received signal vector $\mathbf{y} \in \mathbb{C}^{N_r \times 1}$ can be expressed by

$$\mathbf{y} = \mathbf{H}\mathbf{P}\mathbf{D}\mathbf{x} + \mathbf{w}, \quad (2.17)$$

where $\mathbf{w} \in \mathbb{C}^{N_r \times 1}$ is an AWGN vector with zero mean and covariance matrix $N_P \sigma^2 / N_r \mathbf{I}_{N_r}$. It should be noted that the imperfect channel estimation and pre-coding will break the orthogonality between the in-phase and quadrature components, which seriously deteriorates the performance of GPQSM. To ease the analysis, we simply assume perfect CSIT. The linear pre-coding schemes, such as zero-forcing (ZF) and minimum mean squared error (MMSE) pre-coding, can be applied to this system. Here, we only consider ZF pre-coding, which implies that the adopted pre-coder is $\mathbf{P} = \mathbf{H}^H (\mathbf{H}\mathbf{H}^H)^{-1}$. In this case, $d(\eta)$ can be expressed by

$$d(\eta) = \frac{1}{\sqrt{[(\mathbf{H}\mathbf{H}^H)^{-1}]_{\eta, \eta}}}. \quad (2.18)$$

Therefore, the received signal vector can be rewritten from (2.17) as

$$\mathbf{y} = \mathbf{D}\mathbf{x} + \mathbf{w} = \mathbf{D}\mathbf{x}^I + j\mathbf{D}\mathbf{x}^Q + \mathbf{w}. \quad (2.19)$$

The optimal ML detector is given by

$$\begin{aligned} \hat{\mathbf{x}} &= \arg \min_{\mathbf{x}} \|\mathbf{y} - \mathbf{D}\mathbf{x}\|^2 \\ &= \arg \min_{\mathbf{x}^I, \mathbf{x}^Q} \|\mathbf{y} - (\mathbf{D}\mathbf{x}^I + j\mathbf{D}\mathbf{x}^Q)\|^2. \end{aligned} \quad (2.20)$$

From (2.20), it can be seen that the optimal ML detector requires an exhausting search over all possible transmitted signal vectors. To reduce the search complexity,

we propose a low-complexity detection method as follows. Due to the independence between the in-phase and quadrature parts, (2.20) is equivalent to

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}^I} \|\mathbf{y}^I - \mathbf{D}\mathbf{x}^I\|^2 + j \arg \min_{\mathbf{x}^Q} \|\mathbf{y}^Q - \mathbf{D}\mathbf{x}^Q\|^2, \quad (2.21)$$

where $\mathbf{y}^I$ and $\mathbf{y}^Q$ represent the in-phase and quadrature parts of $\mathbf{y}$, respectively. Since the detection procedures for the in-phase and quadrature parts are the same, we now only consider the detection for the in-phase part, which can be expressed by

$$\begin{aligned} \hat{\mathbf{x}}^I &= \arg \min_{\mathbf{x}^I} \|\mathbf{y}^I - \mathbf{D}\mathbf{x}^I\|^2 \\ &= \arg \min_{\{x^I(\eta)\}_{\eta=1}^{N_r}} \sum_{\eta=1}^{N_r} |y^I(\eta) - d(\eta)x^I(\eta)|^2. \end{aligned} \quad (2.22)$$

From (2.22), it reveals that the search complexity is of order $(M^I)^{N_r} N$, where M^I denotes the cardinality of $\mathcal{X}^I$. A further reduction of search complexity is possible if we expand (2.22) as

$$\begin{aligned} &\arg \min_{\{x^I(\eta)\}_{\eta=1}^{N_r}} \sum_{\eta=1}^{N_r} |y^I(\eta) - d(\eta)x^I(\eta)|^2 \\ &= \arg \min_{\{x^I(\eta)\}_{\eta=1}^{N_r}} \sum_{\eta=1}^{N_r} \left[(y^I(\eta))^2 - 2d(\eta)x^I(\eta)y^I(\eta) + (d(\eta)x^I(\eta))^2 \right] \\ &= \arg \min_{I_\nu^I, \{s^I(\eta)\}_{\eta \in I_\nu^I}} \left[\sum_{\eta \in I_\nu^I} \left[(d(\eta)s^I(\eta))^2 - 2d(\eta)s^I(\eta)y^I(\eta) \right] + \sum_{\eta=1}^{N_r} (y^I(\eta))^2 \right] \\ &= \arg \min_{I_\nu^I} \left[\sum_{\eta \in I_\nu^I} \min_{s^I(\eta)} \left[(d(\eta)s^I(\eta))^2 - 2d(\eta)s^I(\eta)y^I(\eta) \right] \right]. \end{aligned} \quad (2.23)$$

Define $D(\eta) = (d(\eta)\hat{s}^I(\eta))^2 - 2d(\eta)\hat{s}^I(\eta)y^I(\eta)$, where

$$\hat{s}^I(\eta) = \arg \min_{s \in \mathcal{X}^I} |y^I(\eta) - d(\eta)s|^2. \quad (2.24)$$

Therefore, the detection for the active antenna combination in (2.23) is equivalent to

$$\hat{I}_\nu^I = \arg \min_{I_\nu^I} \sum_{\eta \in I_\nu^I} D(\eta). \quad (2.25)$$

It is clear that the order of the search complexity in (2.25) is reduced to $N_r M^I + N$. However, the search complexity is still high especially when N_r or N_p is large. For practical use, it is advisable to first obtain $[z_1, \dots, z_{N_r}] = \text{sort}(\{D(\eta)\}_{\eta=1}^{N_r})$, where $\text{sort}(\cdot)$ defines an ordering function that reorders the elements of the input vector in ascending order, and z_1, z_{N_r} are the indices of the maximum and minimum values in $\{D(\eta)\}_{\eta=1}^{N_r}$, respectively. Then, we simply obtain the active antenna indices by $\hat{I}_\nu^I = \{z_1, \dots, z_{N_p}\}$. Based on this manner, we may obtain an illegitimate antenna combination, which does not exist in the mapping table. To relieve this adverse effect, when this event occurs, we select $\hat{I}_\nu^I = \{z_1, \dots, z_{N_p-1}, z_{N_p+1}\}$ instead. After getting $\hat{I}_\nu^I$, the estimation of $\mathbf{x}^I$ is directly obtained by

$$\hat{x}^I(\eta) = \begin{cases} \hat{s}^I(\eta), & \eta \in \hat{I}_\nu^I \\ 0, & \text{otherwise} \end{cases}. \quad (2.26)$$

From the proposed detector, it follows that the equivalent detection only leads to a search complexity of order $N_r M^I$. Compared with the ML detector in (2.22), the search complexity is largely reduced.

2.2.2 Average Bit Error Probability Analysis

According to (2.16), it indicates that the n information bits can be treated as two independent bits $n_1 = \log_2(M) + \lfloor \log_2(C(N_r, N_p)) \rfloor$ and $n_2 = \log_2(M) + \lfloor \log_2(C(N_r, N_p)) \rfloor$ corresponding to in-phase and quadrature parts, respectively. Without loss of generality, we only analyze the average bit error probability (ABEP) for the n_1 bits.

An upper bound on ABEP for the n_1 bits can be derived according to the union bounding technique as [9]

$$P_E^I \leq \frac{1}{n_1 2^{n_1}} \sum_{\mathbf{x}^I} \sum_{\hat{\mathbf{x}}^I \neq \mathbf{x}^I} N(\mathbf{x}^I, \hat{\mathbf{x}}^I) \Pr(\mathbf{x}^I \rightarrow \hat{\mathbf{x}}^I), \quad (2.27)$$

where $\Pr(\mathbf{x}^I \rightarrow \hat{\mathbf{x}}^I)$ denotes the pairwise error probability (PEP) of detecting $\hat{\mathbf{x}}^I$ when $\mathbf{x}^I$ is transmitted and $N(\mathbf{x}^I, \hat{\mathbf{x}}^I)$ measures the number of bits in difference between $\mathbf{x}^I$ and $\hat{\mathbf{x}}^I$.

The PEP conditioned on $\mathbf{D}$ is given by

$$\Pr(\mathbf{x}^I \rightarrow \hat{\mathbf{x}}^I | \mathbf{D}) = Q\left(\sqrt{\frac{\lambda_I}{2}} \gamma\right), \quad (2.28)$$

where $\lambda_I = \mathbf{c}^H \mathbf{D}^2 \mathbf{c}$ with $\mathbf{c} = \mathbf{x}^I - \hat{\mathbf{x}}^I$ and $\gamma = 1/\sigma^2$ is the given signal-to-noise ratio (SNR). Let us expand λ_I as $\lambda_I = \sum_{\eta=1}^{N_r} c^2(\eta) d^2(\eta)$, where $c(\eta) = x^I(\eta) - \hat{x}^I(\eta)$. Since the zero elements normally exist in $\mathbf{c}$, we can rewrite λ_I as

$$\lambda_I = \sum_{o=1}^{N_F} c^2(\tau(o)) d^2(\tau(o)), \quad (2.29)$$

where N_F denotes the number of non-zero elements of $\mathbf{c}$ and $\{\tau(o)\}_{o=1}^{N_F}$ indicate the indices of non-zero elements in $\mathbf{c}$.

Careful inspection of (2.29) reveals that the phase distribution of the Nakagami- m channel has little impact on the distribution of $d^2(\tau(o))$, which implies that nearly the same system performance will be resulted over Nakagami- m channels with either uniform or non-uniform phases. Moreover, it also reveals that the derivation of PEP in (2.28) requires the probability density function (PDF) of the sum of $d^2(\tau(o))$. However, to the best of our knowledge, this PDF is not available for $m \neq 1$. Hence, for the ease of analysis, we only discuss the case with $m = 1$, in which $d^2(\tau(o)) \sim \text{Gamma}(L, 1)$ with $L = N_t - N_r + 1$ [10]. In [11], this PDF is given by

$$f_{\lambda_I}(y) = \prod_{j=1}^{N_F} \left(\frac{\beta_1}{\beta_j} \right)^L \left[\sum_{k=0}^{+\infty} \frac{\delta_k y^{N_F L + k - 1} e^{-y/\beta_1}}{\beta_1^{N_F L + k} \Gamma(N_F L + k)} \right] H_0(x), \quad (2.30)$$

where $H_0(x)$ and $\Gamma(\cdot)$ denote the Heaviside step function and gamma function, respectively, and $\{\beta_j\}_{j=1}^{N_F}$ are the eigenvalues of $\mathbf{A} = \mathbf{B}\mathbf{C}$ with $\beta_1 = \min\{\beta_j\}_{j=1}^{N_F}$. Here, $\mathbf{B}$ is an $N_F \times N_F$ diagonal matrix with the diagonal elements $\{c^2(\tau(o))\}_{o=1}^{N_F}$ and $\mathbf{C}$ is an $N_F \times N_F$ matrix

$$\mathbf{C} = \begin{bmatrix} 1 & \sqrt{\rho_I} & \cdots & \sqrt{\rho_I} \\ \sqrt{\rho_I} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \sqrt{\rho_I} \\ \sqrt{\rho_I} & \cdots & \sqrt{\rho_I} & 1 \end{bmatrix}, \quad (2.31)$$

where $\rho_I = E[(d^2(\tau(o)) - L)(d^2(\tau(\hat{o})) - L)]/L$ denotes the Pearson product-moment correlation coefficient for any two different Gamma random variables (RVs) $d^2(\tau(o))$ and $d^2(\tau(\hat{o}))$ in $\mathbf{D}^2$. The parameter δ_k is given by

$$\begin{cases} \delta_0 = 1, \\ \delta_{k+1} = \frac{L}{k+1} \sum_{l=1}^{k+1} \sum_{j=1}^{N_F} \left(1 - \frac{\beta_1}{\beta_j}\right)^l \delta_{k+1-l}, \quad k = 0, 1, \dots \end{cases}$$

By averaging (2.28) with (2.30), we have

$$\begin{aligned}\Pr(\mathbf{x}_I \rightarrow \hat{\mathbf{x}}_I) &= E_{\lambda_I} \left[Q \left(\sqrt{\frac{\lambda_I}{2}} \gamma \right) \right] \\ &\leq E_{\lambda_I} \left[\frac{1}{2} e^{-\lambda_I \gamma / 4} \right],\end{aligned}\quad (2.32)$$

where the Chernoff bound $Q(x) \leq \frac{1}{2} e^{-x^2/2}$ is applied. Using the integration formula [12, Eq. (3.381, 4)], (2.32) can be calculated as

$$\begin{aligned}\Pr(\mathbf{x}_I \rightarrow \hat{\mathbf{x}}_I) &\leq \frac{1}{2} \prod_{j=1}^{N_F} \left(\frac{\beta_1}{\beta_j} \right)^L \sum_{k=0}^{+\infty} \frac{\delta_k \beta_1^{-N_F L - k}}{\Gamma(N_F L + k)} \int_0^{+\infty} y^{N_F L + k - 1} e^{-(\frac{\gamma}{4} + \frac{1}{\beta_1})y} dy \\ &= \frac{1}{2} \prod_{j=1}^{N_F} \left(\frac{\beta_1}{\beta_j} \right)^L \left(\frac{\beta_1 \gamma}{4} + 1 \right)^{-N_F L} \sum_{k=0}^{+\infty} \frac{\delta_k}{(\beta_1 \gamma / 4 + 1)^k}.\end{aligned}\quad (2.33)$$

At high SNR ($\gamma \rightarrow +\infty$), the PEP can be simplified as

$$\Pr(\mathbf{x}_I \rightarrow \hat{\mathbf{x}}_I) \approx \frac{\prod_{j=1}^{N_F} \left(\frac{\beta_1}{\beta_j} \right)^L}{2} \left(\frac{\beta_1 \gamma}{4} + 1 \right)^{-N_F L}, \quad (2.34)$$

where (2.34) is obtained by $\sum_{k=0}^{+\infty} \frac{\delta_k}{(\beta_1 \gamma / 4 + 1)^k} = 1$.

With the PEP, the upper bound on ABEP P_E^I for the n_1 bits now can be evaluated by (2.27). It can be observed that a high SNR approximation of P_E^I is the linear combination of PEP, which is only dominated by the smallest exponent of γ with $N_F = 1$. Therefore, at very high SNR we have

$$P_E^I \approx \frac{1}{2^{n_1+1} n_1} \sum_{\mathbf{x}^I} \sum_{\hat{\mathbf{x}}^I \neq \mathbf{x}^I} N(\mathbf{x}^I, \hat{\mathbf{x}}^I) \left(\frac{\beta_1 \gamma}{4} + 1 \right)^{-L}. \quad (2.35)$$

In the same manner, an upper bound on ABEP P_E^Q for the n_2 bits can be obtained. Finally, an upper bound on ABEP for GPQSM can be expressed as

$$P_E = \frac{n_1 P_E^I + n_2 P_E^Q}{n_1 + n_2}, \quad (2.36)$$

where it reveals that the diversity order of our scheme is L . We see that the diversity order depends on the system configuration only and is independent of N_p and M .

2.2.3 Performance Evaluation

In this subsection, we conduct computer simulations to examine the ABEP performance of GPQSM and make comparison with that of the conventional generalised pre-coding aided spatial modulation (GPSM) and MIMO schemes.

In Fig. 2.5, the ABEP performances of various GPQSM schemes under spectral efficiencies of 8 and 32 bps/Hz are drawn with $m = 1$. In order to match 8 bps/Hz for 8×4 MIMO setup, 4-QAM is chosen for GPQSM with $N_p = 2$ and the MIMO scheme while 16-QAM is chosen for GPQSM with $N_p = 1$. On the other hand, to match 32 bps/Hz for 10×8 MIMO setup, 16-QAM is adopted for both the GPQSM with $N_p = 6$ and MIMO schemes. It can be seen that GPQSM schemes obtain an overwhelming performance gain over the MIMO schemes in the high SNR regime. Note that the performance of the MIMO scheme becomes better than the GPQSM scheme with $N_p = 1$ for the 8×4 system. This is because using 16-QAM for GPQSM leads to a worse performance than using 4-QAM for the MIMO scheme, which cannot be compensated for by the performance gain from the spatial domain.

Figure 2.6 investigates the ABEP performance of a 8×4 GPQSM scheme using 4-QAM modulation and a 8×4 GPSM scheme using 8-QAM modulation both with $N_p = 2$ and $m = 2$. The performance of the proposed suboptimal detector is also examined. At $\text{ABEP} = 10^{-5}$, it can be seen that the proposed GPQSM scheme achieves about a 3.5 dB SNR gain with respect to the GPSM scheme under the

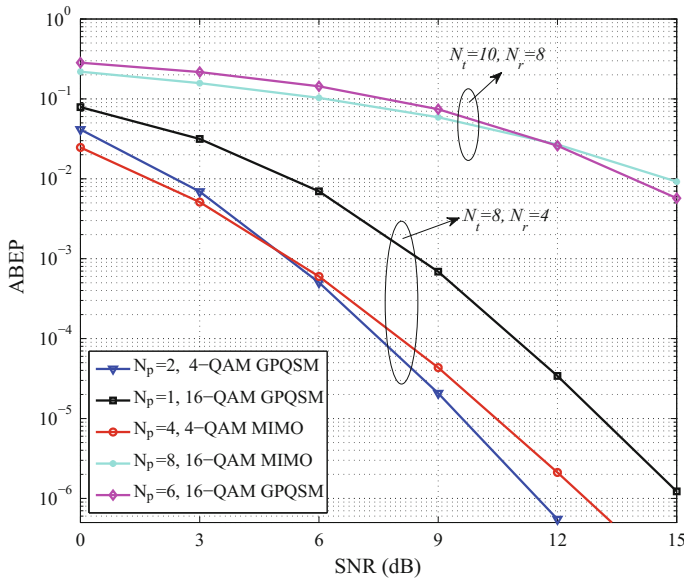


Fig. 2.5 ABEP performance of the GPQSM scheme in comparison to the MIMO scheme with $m = 1$

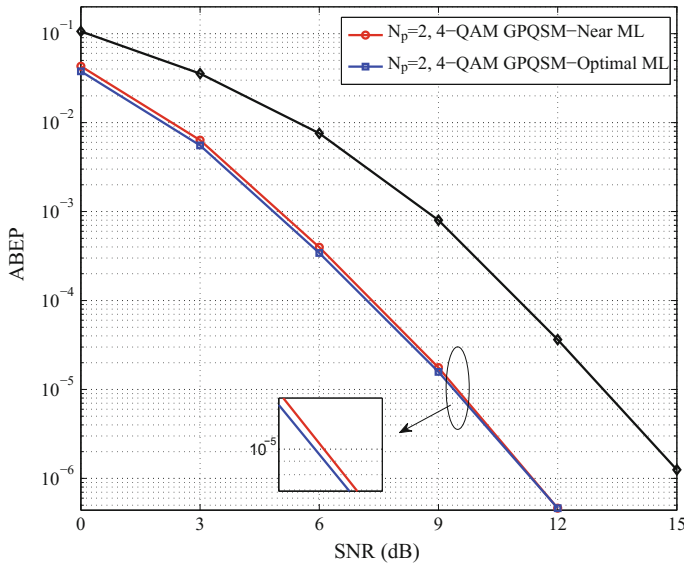


Fig. 2.6 ABEP performance of GPQSM and GPSM with $N_t = 8$ and $N_r = 4$ for $m = 2$

spectral efficiency of 8 bps/Hz. From Fig. 2.6, we can see that the proposed detector achieves nearly the same performance as the ML detector.

Figure 2.7 shows the ABEP performance of GPQSM for $N_t = \{8, 12\}$, $N_r = \{4, 8\}$ and $m = 1$ with different values of N_p and M . In Fig. 2.7a, 4-QAM and 16-QAM are applied for a 8×4 GPQSM scheme with $N_p = 1, 2$, and 3, respectively. It can be seen that the theoretical results well match the simulation counterparts in the high SNR regime. Similar results can be found in Fig. 2.7b, where a 12×8 GPQSM scheme with 4-QAM and 16-QAM for $N_p = 2, 3$, and 4 are considered. The simulation curves of GPQSM also perfectly match the theoretical curves in the high SNR regime. From Fig. 2.7, we can see that the diversity order does not change with N_p and M , which verifies the analysis in Sect. 2.2.2.

2.3 Virtual Spatial Modulation

In this section, we propose the VSM scheme that operates on the virtual parallel channels resulting from the singular value decomposition (SVD) of MIMO channels. The VSM scheme conveys information through both the indices of the virtual parallel channels and the M -ary modulated symbols, applying to any configuration of transceiver antennas. We derive a closed-form upper bound on the ABEP of the VSM scheme, which takes into account the impact of imperfect channel estimation. Moreover, the asymptotic ABEP is also studied, which characterizes the ABEP error

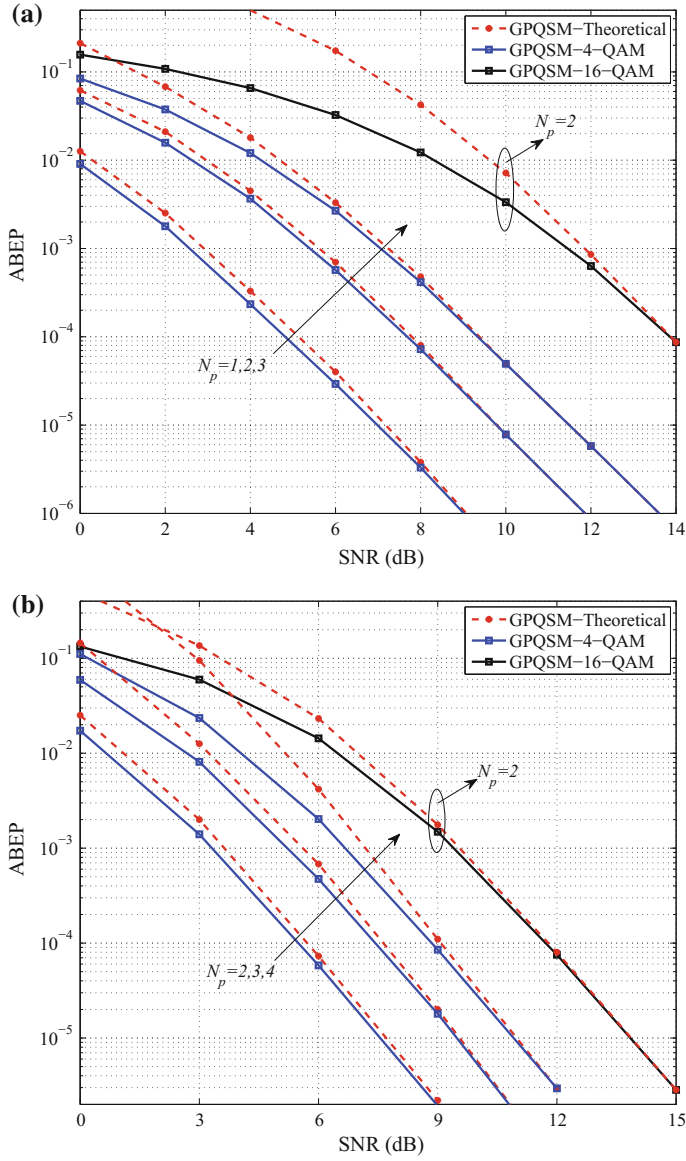


Fig. 2.7 ABEP performance of GPQSM with $m = 1$ for different configurations. **a** $N_t = 8$ and $N_r = 4$. **b** $N_t = 12$ and $N_r = 8$

floor in the presence of channel estimation error and the resulting diversity order and the coding gain under perfect channel estimation.

2.3.1 System Model

The received signal vector for all schemes with pre-coding can be expressed in a general form as

$$\mathbf{y} = \mathbf{H}\mathbf{P}\mathbf{x} + \mathbf{w}, \quad (2.37)$$

where $\mathbf{x}$ is the signal vector, $\mathbf{P}$ is the pre-coding matrix and $\mathbf{w} \in \mathbb{C}^{N_r \times 1}$ is an AWGN vector with zero mean and covariance matrix $N_0 \mathbf{I}_{N_r}$.

The well-known parallel decomposition of $\mathbf{H}$ using SVD is given by

$$\mathbf{H} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^H, \quad (2.38)$$

where $\mathbf{U} \in \mathbb{C}^{N_r \times N_r}$ and $\mathbf{V} \in \mathbb{C}^{N_t \times N_t}$ are unitary matrices, and $\mathbf{\Sigma} \in \mathbb{C}^{N_r \times N_t}$ is the singular value matrix, which contains singular values $\{\sigma_i\}_{i=1}^m$ with $m = \min\{N_t, N_r\}$. Inspired by SVD, we aim to transmit the spatial bits through the virtual parallel channels in $\mathbf{\Sigma}$. If we have perfect channel estimation at the receiver and perfect feedback of the CSI from the receiver to the transmitter, the pre-coding matrix can be simply set to be $\mathbf{P} = \mathbf{V}$. However, the perfect CSI is always unavailable at the receiver in practical systems. Therefore, to be practical we take into account the imperfect channel estimation. The estimated channel with errors at the receiver can be modeled as $\tilde{\mathbf{H}} = \mathbf{H} + \mathbf{H}_e$, where $\mathbf{H}_e$ denotes the channel estimation error matrix whose entries are independent and identically distributed complex Gaussian RVs with zero mean and variance δ_e^2 . Note that $\mathbf{H}_e$ is independent of $\mathbf{H}$ and $\tilde{\mathbf{H}}$ depends on $\mathbf{H}$ with the correlation coefficient $\rho = 1/(1 + \delta_e^2)$. It can be seen that the perfect channel estimation is the special case of $\delta_e^2 = 0$ ($\rho = 1$). In Sect. 2.3.3, we will consider two situations for determining ρ : (1) fixed ρ : the value of estimation error is fixed for all SNRs; (2) unfixed ρ : the estimation error changes with the given SNR as $\delta_e^2 = 1/(L\gamma)$, where $\gamma = 1/N_0$ denotes the SNR and L denotes the number of pilot symbols used for channel estimation [13]. Note that the feedback error can be incorporated into $\mathbf{H}_e$. For ease of exposition, we simply consider perfect feedback.

Due to channel estimation, the receiver knows $\tilde{\mathbf{H}}$ instead of $\mathbf{H}$. Performing SVD to $\tilde{\mathbf{H}}$, we have

$$\tilde{\mathbf{H}} = \tilde{\mathbf{U}}\tilde{\mathbf{\Sigma}}\tilde{\mathbf{V}}^H, \quad (2.39)$$

where $\tilde{\mathbf{U}} \in \mathbb{C}^{N_r \times N_r}$ and $\tilde{\mathbf{V}} \in \mathbb{C}^{N_t \times N_t}$ are the unitary matrices, and $\tilde{\mathbf{\Sigma}} \in \mathbb{C}^{N_r \times N_t}$ is the singular value matrix. The right unitary matrix $\tilde{\mathbf{V}}$ is fed back to the transmitter for pre-coding purposes. Under a rich scattering environment assumption, $\tilde{\mathbf{\Sigma}} \in \mathbb{C}^{N_r \times N_t}$

contains non-zero singular values $\{\tilde{\sigma}_i\}_{i=1}^m$, which can also provide m virtual parallel channels for carrying spatial bits. To perform index modulation on the m virtual parallel channels, however, the signal vector $\mathbf{x}$ has to be carefully designed to match the pre-coding matrix $\tilde{\mathbf{V}}$. To this end, we have to classify the SVD of $\tilde{\mathbf{H}}$ into two situations. When $N_t \leq N_r$, the SVD of $\tilde{\mathbf{H}}$ can be rewritten as

$$\tilde{\mathbf{H}} = [\tilde{\mathbf{U}}_1, \tilde{\mathbf{U}}_0][\tilde{\mathbf{\Sigma}}_1, \mathbf{0}]^T \tilde{\mathbf{V}}^H, \quad (2.40)$$

where $\tilde{\mathbf{U}}_1 \in \mathbb{C}^{N_r \times N_t}$ and $\tilde{\mathbf{U}}_0 \in \mathbb{C}^{N_r \times (N_r - N_t)}$ are the sub-matrices of $\tilde{\mathbf{U}}$, which collect the left-singular vectors corresponding to nonzero and zero singular values, respectively, and $\tilde{\mathbf{\Sigma}}_1 \in \mathbb{C}^{N_t \times N_t}$ is the non-zero singular value matrix. In this case, the signal vector (a.k.a., the information vector) is set to be $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$. On the other hand, when $N_t > N_r$, the SVD of $\tilde{\mathbf{H}}$ can be rewritten as

$$\tilde{\mathbf{H}} = \tilde{\mathbf{U}}[\tilde{\mathbf{\Sigma}}_1, \mathbf{0}][\tilde{\mathbf{V}}_1, \tilde{\mathbf{V}}_0]^H, \quad (2.41)$$

where $\tilde{\mathbf{V}}_1 \in \mathbb{C}^{N_t \times N_r}$ and $\tilde{\mathbf{V}}_0 \in \mathbb{C}^{N_t \times (N_t - N_r)}$ are sub-matrices of $\tilde{\mathbf{V}}$, which collect the right-singular vectors corresponding to nonzero and zero singular values, respectively. In this case, the signal vector is set to be $\tilde{\mathbf{x}} \in \mathbb{C}^{N_t \times 1} = [\mathbf{x}^T, \mathbf{z}_0^T]^T$, where $\mathbf{x} \in \mathbb{C}^{N_r \times 1}$ is the information vector corresponding to the m virtual parallel channels and $\mathbf{z}_0 \in \mathbb{C}^{(N_t - N_r) \times 1}$ denotes the all-zero vector.

VSM Transmitter

The transmitter structure of VSM is depicted in Fig. 2.8. In VSM, N_p out of m virtual parallel channels are activated for transmitting the real (imaginary) parts of the modulated symbols. In order to modulate the spatial bits, only $N = 2^{\lfloor \log_2(C(m, N_p)) \rfloor}$ combinations are selected as the legitimate antenna combinations. Note that the number of virtual parallel channels is m , which equals the minimum between the numbers of transmit and receive antennas. Therefore, the VSM scheme contains both benefits of transmitter and receiver PSM schemes.

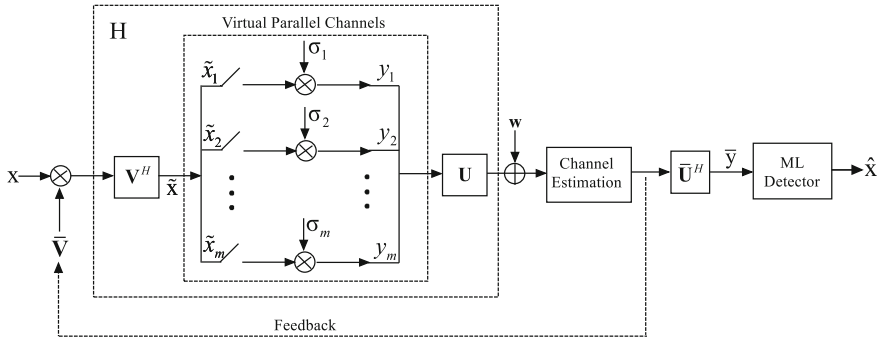


Fig. 2.8 The schematic of VSM

Specifically, VSM works as follows. At each time slot, $d = N_p \log_2(M) + 2\lfloor \log_2(C(m, N_p)) \rfloor$ information bits are fed into the transmitter and divided into three parts. The first part of $N_p \log_2(M)$ bits are mapped into a symbol vector $\mathbf{s} = [s_1, \dots, s_{N_p}]^T$, where $s_\varphi = s_\varphi^I + js_\varphi^Q$, $\varphi \in \{1, \dots, N_p\}$, with s_φ^I and s_φ^Q denoting the in-phase and quadrature parts of s_φ , respectively. Note that $s_i^I \in \mathcal{X}^I$ and $s_i^Q \in \mathcal{X}^Q$, where $\mathcal{X}^I$ and $\mathcal{X}^Q$ denote the in-phase and quadrature sets of $\mathcal{X}$, respectively. The second part of $\lfloor \log_2(C(m, N_p)) \rfloor$ bits select an active channel combination $I_v^I = \{i_v^I(1), \dots, i_v^I(N_p)\}$, where $i_v^I(\alpha) \in \{1, \dots, m\}$ with $v \in \{1, \dots, N\}$ and $\alpha \in \{1, \dots, N_p\}$, for transmitting the real part of $\mathbf{s}$, yielding $\mathbf{x}^I = [\dots, s_1^I, \dots, s_{N_p}^I, \dots]$. Similarly, the third part of $\lfloor \log_2(C(m, N_p)) \rfloor$ bits select an active channel combination $I_\mu^Q = \{i_\mu^Q(1), \dots, i_\mu^Q(N_p)\}$, where $i_\mu^Q(\varsigma) \in \{1, \dots, m\}$ with $\mu \in \{1, \dots, N\}$ and $\varsigma \in \{1, \dots, N_p\}$, for transmitting the imaginary part of $\mathbf{s}$, yielding $\mathbf{x}^Q = [\dots, s_1^Q, \dots, s_{N_p}^Q, \dots]$. Finally, the information vector is generated by combining the in-phase and quadrature parts:

$$\mathbf{x} = \mathbf{x}^I + j\mathbf{x}^Q. \quad (2.42)$$

As an example, we present a mapping table of VSM for $N_t = 4$, $N_r = 2$, $N_p = 1$, and 4-QAM in Table 2.1. In this example, we have $d = 4$. Suppose that the information bits $q = [0 \ 1 \ 1 \ 0]$ are transmitted at a given time slot. The first $N_p \log_2(M) = 2$ bits $[0 \ 1]$ are mapped into $\mathbf{s} = [-1 - j]$. Then, $\mathbf{s}$ is divided into in-phase and quadrature parts $\mathbf{s}^I = [-1]$ and $\mathbf{s}^Q = [-1]$, respectively. The second $\lfloor \log_2(C(N_r, N_p)) \rfloor = 1$ bit $[1]$ indicates the active channel combination $I_2^I = \{2\}$ to transmit $\mathbf{s}^I$, resulting in the vector $\mathbf{x}^I = [0, -1]^T$. The last $\lfloor \log_2(C(N_r, N_p)) \rfloor = 1$ bit $[0]$ indicates the active channel combination $I_1^Q = \{1\}$ to transmit $\mathbf{s}^Q$ resulting in the vector $\mathbf{x}^Q = [1, 0]^T$. Finally, the information vector is obtained as $\mathbf{x} = [-j, -1]^T$.

Before transmitted into the wireless channel, the information vector is pre-coded by $\mathbf{P} = \tilde{\mathbf{V}}$, which represents $\tilde{\mathbf{V}}$ for $N_t \leq N_r$ and $\tilde{\mathbf{V}}_1$ for $N_t > N_r$, respectively.

Table 2.1 Mapping table for VSM with $N_t = 4$, $N_r = 2$, $N_p = 1$ and 4-QAM

Input bits	Signal vector	Input bits	Signal vector
0000	$[-1 + j, 0]^T$	1000	$[1 + j, 0]^T$
0001	$[-1, j]^T$	1001	$[1, j]^T$
0010	$[j, -1]^T$	1010	$[j, 1]^T$
0011	$[0, -1 + j]^T$	1011	$[0, 1 + j]^T$
0100	$[-1 - j, 0]^T$	1100	$[1 - j, 0]^T$
0101	$[-1, -j]^T$	1101	$[1, -j]^T$
0110	$[-j, -1]^T$	1110	$[-j, 1]^T$
0111	$[0, -1 - j]^T$	1111	$[0, 1 - j]^T$

VSM Receiver

The receiver structure of VSM is depicted in Fig. 2.8. The received signal vector after receiver shaping can be expressed in a general form as

$$\bar{\mathbf{y}} = \bar{\mathbf{U}}^H \mathbf{y} = \bar{\mathbf{U}}^H \mathbf{H} \bar{\mathbf{V}} \mathbf{x} + \bar{\mathbf{U}}^H \mathbf{w}, \quad (2.43)$$

where $\bar{\mathbf{U}}$ represents $\tilde{\mathbf{U}}_1$ or $\tilde{\mathbf{U}}$ for $N_t \leq N_r$ or $N_t > N_r$, respectively.

Based on (2.43), we propose two detection methods corresponding to whether or not the receiver has the knowledge of the correlation coefficient ρ . When ρ is known to the receiver, the optimal ML detector can be derived as

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\bar{\mathbf{y}} - \rho \tilde{\Sigma}_1 \mathbf{x}\|^2. \quad (2.44)$$

The reason why (2.44) is optimal will be clarified later. On the other hand, when ρ is unknown to the receiver, it is reasonable to assume perfect channel estimation for detection, under which the detector follows from (2.44) by setting $\rho = 1$:

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\bar{\mathbf{y}} - \tilde{\Sigma}_1 \mathbf{x}\|^2. \quad (2.45)$$

However, both detectors in (2.44) and (2.45) impose great computational burden to the receiver when N_r or M goes to a very large value. To solve this problem, we can resort to the idea proposed in Sect. 2.2.1.

2.3.2 Average Bit Error Probability Analysis

We derive a closed-form upper bound on the ABEP of VSM that employs the detector in (2.44). To study the diversity order and coding gain, we further derive the asymptotic ABEP of VSM. We note that it may be difficult to obtain closed-form upper bounded and asymptotic ABEPs of VSM that adopts the detector in (2.45). Fortunately, as will be verified in Sect. 2.3.3 that both detectors achieve nearly the same ABEP performance, the analysis for the detector in (2.44) suffices.

Analysis of ABEP

Based on the first-order autoregressive model, we can express the true channel with the estimated one as $\mathbf{H} = \rho \tilde{\mathbf{H}} + \mathbf{G}$, where $\mathbf{G} \in \mathbb{C}^{N_r \times N_t}$ is a complex Gaussian matrix independent of $\tilde{\mathbf{H}}$, whose entries have zero mean and variance $1 - \rho$. Accordingly, $\bar{\mathbf{y}}$ can be rewritten from (2.43) as

$$\bar{\mathbf{y}} = \rho \tilde{\Sigma}_1 \mathbf{x} + \mathbf{q}, \quad (2.46)$$

where $\mathbf{q} = \bar{\mathbf{U}}^H \mathbf{G} \bar{\mathbf{V}} \mathbf{x} + \bar{\mathbf{U}}^H \mathbf{w}$. Since multiplying a matrix by any unitary matrix does not change the probability distribution, we can conclude that $\tilde{\mathbf{U}}^H \mathbf{G} \tilde{\mathbf{V}}$ and $\bar{\mathbf{U}}^H \mathbf{w}$ have the same distribution as $\mathbf{G}$ and $\mathbf{w}$, respectively. In addition, since $\mathbf{G}$ and $\mathbf{w}$ are

mutually independent, each entry of $\mathbf{q}$ follows the complex Gaussian distribution with zero mean and variance

$$\psi = N_0 + (1 - \rho)||\mathbf{x}||^2. \quad (2.47)$$

At this point, it is straightforward to arrive at (2.44) from (2.46), which is optimal for detection.

Denote $\mathbf{c} \triangleq [c_1, \dots, c_m]^T = \mathbf{x} - \hat{\mathbf{x}}$. In light of (2.44) and (2.46), the conditional PEP of detecting $\hat{\mathbf{x}}$ when $\mathbf{x}$ is transmitted on $\tilde{\Sigma}_1$ can be calculated as

$$\begin{aligned} \Pr(\mathbf{x} \rightarrow \hat{\mathbf{x}} | \tilde{\Sigma}_1) &= \Pr(||\tilde{\mathbf{y}} - \rho \tilde{\Sigma}_1 \mathbf{x}||^2 > ||\tilde{\mathbf{y}} - \rho \tilde{\Sigma}_1 \hat{\mathbf{x}}||^2) \\ &= Q \left(\sqrt{\frac{||\rho \tilde{\Sigma}_1 (\mathbf{x} - \hat{\mathbf{x}})||^2}{2\psi}} \right) \\ &= Q \left(\sqrt{\frac{\sum_{i=1}^m \lambda_i |c_i|^2}{2\psi}} \right), \end{aligned} \quad (2.48)$$

where $\lambda_i = \rho^2 \tilde{\sigma}_i^2$, $i \in \{1, \dots, m\}$. From (2.48), it can be seen that the derivation of PEP needs the joint PDF of $\Lambda = [\lambda_1, \dots, \lambda_m]^T$, which is given by [14]

$$\begin{aligned} f(\Lambda) &= \frac{1}{K_{m,n}} e^{-\sum_{i=1}^m \lambda_i} \underbrace{\prod_{i=1}^m \lambda_i^{n-m} \prod_{j=i+1}^m (\lambda_i - \lambda_j)^2}_{\gamma} \\ &= \frac{1}{K_{m,n}} \sum_{\kappa=1}^L a_{\kappa} e^{-\sum_{i=1}^m \lambda_i} \lambda_1^{b_{\kappa}^1} \dots \lambda_m^{b_{\kappa}^m}, \end{aligned} \quad (2.49)$$

where $n = \max\{N_r, N_t\}$, $K_{m,n}$ is a normalizing coefficient, L denotes the number of monomials in γ , a_{κ} denotes the coefficient of the κ -th monomial in γ with $\kappa \in \{1, \dots, L\}$, and $\{b_{\kappa}^i\}_{i=1}^m$ denote the power coefficients of $\{\lambda_i\}_{i=1}^m$ in the κ -th monomial in γ . An example for all values of $(K_{m,n}, a_{\kappa}, b_{\kappa}^1, \dots, b_{\kappa}^m)$ with $N_t = 4$ and $N_r = 3$ is given in Table 2.2. By averaging (2.48) with (2.49), we have

$$\begin{aligned} \Pr(\mathbf{x} \rightarrow \hat{\mathbf{x}}) &= E_{\Lambda} \left[Q \left(\sqrt{\frac{\sum_{i=1}^m \lambda_i |c_i|^2}{2\psi}} \right) \right] \\ &\cong E_{\Lambda} \left[\frac{1}{12} e^{-\sum_{i=1}^m \frac{\lambda_i |c_i|^2}{4\psi}} + \frac{1}{4} e^{-\sum_{i=1}^m \frac{\lambda_i |c_i|^2}{3\psi}} \right] \end{aligned} \quad (2.50)$$

$$= \frac{1}{12} \int e^{-\sum_{i=1}^m \frac{\lambda_i |c_i|^2}{4\psi}} f(\Lambda) d\Lambda + \frac{1}{4} \int e^{-\sum_{i=1}^m \frac{\lambda_i |c_i|^2}{3\psi}} f(\Lambda) d\Lambda, \quad (2.51)$$

where (2.50) is obtained by [15]

$$Q(x) \cong \frac{1}{12}e^{-\frac{x^2}{2}} + \frac{1}{4}e^{-\frac{2x^2}{3}}. \quad (2.52)$$

According to [12, Eq. (8.312.2)], the first integral of (2.51) can be calculated as

$$\begin{aligned} & \frac{1}{12} \int e^{-\sum_{i=1}^m \frac{\lambda_i |c_i|^2}{4\psi}} f(\Lambda) d\Lambda \\ &= \frac{1}{12K_{m,n}} \sum_{\kappa=1}^L a_{\kappa} \int e^{-\sum_{i=1}^m \left(\frac{|c_i|^2}{4\psi} + 1\right) \lambda_i} \lambda_1^{b_{\kappa}^1} \dots \lambda_m^{b_{\kappa}^m} d\Lambda \\ &= \frac{1}{12K_{m,n}} \sum_{\kappa=1}^L a_{\kappa} \int e^{-(\frac{|c_1|^2}{4\psi} + 1) \lambda_1} \lambda_1^{b_{\kappa}^1} d\lambda_1 \dots \int e^{-(\frac{|c_m|^2}{4\psi} + 1) \lambda_m} \lambda_m^{b_{\kappa}^m} d\lambda_m \\ &= \frac{1}{12K_{m,n}} \sum_{\kappa=1}^L a_{\kappa} \prod_{i=1}^m \left(\frac{|c_i|^2}{4\psi} + 1 \right)^{-(b_{\kappa}^i + 1)} \Gamma(b_{\kappa}^i + 1). \end{aligned} \quad (2.53)$$

In the same manner, the second integral of (2.51) is given by

$$\frac{1}{4K_{m,n}} \sum_{\kappa=1}^L a_{\kappa} \prod_{i=1}^m \left(\frac{|c_i|^2}{3\psi} + 1 \right)^{-(b_{\kappa}^i + 1)} \Gamma(b_{\kappa}^i + 1). \quad (2.54)$$

By substituting (2.53) and (2.54) into (2.51), the unconditional PEP can be expressed as

$$\begin{aligned} \Pr(\mathbf{x} \rightarrow \hat{\mathbf{x}}) &= \frac{1}{4K_{m,n}} \sum_{\kappa=1}^L a_{\kappa} \left(\prod_{i=1}^m \Gamma(b_{\kappa}^i + 1) \right) \\ &\quad \times \left[\frac{1}{3} \prod_{i=1}^m \left(\frac{|c_i|^2}{4\psi} + 1 \right)^{-(b_{\kappa}^i + 1)} + \prod_{i=1}^m \left(\frac{|c_i|^2}{3\psi} + 1 \right)^{-(b_{\kappa}^i + 1)} \right]. \end{aligned} \quad (2.55)$$

After obtaining the PEP, an upper bound on the ABEP can be readily derived according to the union bounding technique as

$$P_e \leq \frac{1}{d^{2d}} \sum_{\mathbf{x}} \sum_{\hat{\mathbf{x}} \neq \mathbf{x}} N(\mathbf{x}, \hat{\mathbf{x}}) \Pr(\mathbf{x} \rightarrow \hat{\mathbf{x}}). \quad (2.56)$$

Asymptotic ABEP Analysis

Recall $\psi = N_0 + (1 - \rho) \|\mathbf{x}\|^2$. If we have channel estimation error ($\rho \neq 1$), $N_0 = 1/\gamma$ tends to be zero and $\psi \rightarrow \psi^* = (1 - \rho) \|\mathbf{x}\|^2$ as $\gamma \rightarrow +\infty$. The asymptotic ABEP can be thus expressed from (2.56) as

$$P_e \rightarrow \frac{1}{d2^{d+2}K_{m,n}} \sum_{\mathbf{x}} \sum_{\hat{\mathbf{x}}} N(\mathbf{x}, \hat{\mathbf{x}}) \sum_{\kappa=1}^L a_{\kappa} \left(\prod_{i=1}^m \Gamma(b_{\kappa}^i + 1) \right) \times \left[\frac{1}{3} \prod_{i=1}^m \left(\frac{|c_i|^2}{4\psi^*} + 1 \right)^{-(b_{\kappa}^i+1)} + \prod_{i=1}^m \left(\frac{|c_i|^2}{3\psi^*} + 1 \right)^{-(b_{\kappa}^i+1)} \right]. \quad (2.57)$$

The above equation reveals that the ABEP tends to be a constant irrelevant to the SNR in the high SNR region, which, as reflected in the ABEP performance, creates an error floor.

On the other hand, if no channel estimation error exists ($\rho = 1$), we have $\psi = 1/\gamma$ and the asymptotic ABEP can be derived as

$$P_e \rightarrow \frac{1}{d2^{d+2}K_{m,n}} \sum_{\mathbf{x}} \sum_{\hat{\mathbf{x}}} N(\mathbf{x}, \hat{\mathbf{x}}) \sum_{\kappa=1}^L a_{\kappa} \left(\prod_{i=1}^m \Gamma(b_{\kappa}^i + 1) \right) \times \left[\frac{1}{3} \prod_{i=1}^m \left(\frac{|c_i|^2 \gamma}{4} \right)^{-(b_{\kappa}^i+1)} + \prod_{i=1}^m \left(\frac{|c_i|^2 \gamma}{3} \right)^{-(b_{\kappa}^i+1)} \right]. \quad (2.58)$$

From (2.58), we see that the high SNR approximation of P_e turns out to be a linear combination of PEPs, which are dominated by the sum of the terms associated with the largest exponent (equivalently the smallest value among $\{b_{\kappa}^i\}_{i=1}^m$ for all $\kappa(s)$) of γ . For instance, from Table 2.2 with $N_t = 4$ and $N_r = 3$, the smallest coefficient is 1. From the above analysis, the asymptotic ABEP in (2.58) can be further approximated as

$$P_e \rightarrow \frac{\gamma^{-d_{\min}}}{d2^{d+2}K_{m,n}} \sum_{\kappa, d_{\min}} \sum_{s, \hat{s} \in \mathcal{X}} a_{\kappa} \left(\prod_{i=1}^m \Gamma(b_{\kappa}^i + 1) \right) \times N(\mathbf{x}, \hat{\mathbf{x}}) \left(\frac{|s - \hat{s}|^{-2d_{\min}}}{3 \cdot 4^{-d_{\min}}} + \frac{|s - \hat{s}|^{-2d_{\min}}}{3^{-d_{\min}}} \right), \quad (2.59)$$

Table 2.2 A look-up table for $N_t = 4$, $N_r = 3$ ($K_{3,4} = 144$)

κ	a_{κ}	b_{κ}^1	b_{κ}^2	b_{κ}^3	κ	a_{κ}	b_{κ}^1	b_{κ}^2	b_{κ}^3	κ	a_{κ}	b_{κ}^1	b_{κ}^2	b_{κ}^3
1	1	1	3	5	8	2	3	4	2	15	1	3	1	5
2	-2	1	4	4	9	1	3	5	1	16	-2	4	1	4
3	1	1	5	3	10	-2	2	2	5	17	1	5	1	3
4	2	2	3	4	11	2	3	2	4	18	-2	5	2	2
5	2	2	4	3	12	2	4	2	3	19	1	5	3	1
6	-2	2	5	2	13	2	4	3	2					
7	-6	3	3	3	14	-2	4	4	1					

where $d_{\min} = n - m + 1$ is the diversity order achieved by the VSM scheme and $\sum_{\kappa, d_{\min}}$ denotes the sum applying to all $\kappa(s)$ for which there exists the coefficient $d_{\min}$. From (2.59), we see that similar to the existing pre-coding schemes, the diversity order of VSM is determined by the configuration of the transceiver antennas only and is irreverent to N_p . By definition [16], the coding gain achieved by the VSM scheme can be derived from (2.59) as

$$G_c = \left[\frac{1}{K_{m,n} d 2^{d+2}} \sum_{\kappa, d_{\min}} \sum_{s, \hat{s} \in \mathcal{X}} a_{\kappa} \left(\prod_{i=1}^m \Gamma(b_{\kappa}^i + 1) \right) \right. \\ \left. \times N(\mathbf{x} \rightarrow \hat{\mathbf{x}}) \left(\frac{|s - \hat{s}|^{-2d_{\min}}}{3 \cdot 4^{-d_{\min}}} + \frac{|s - \hat{s}|^{-2d_{\min}}}{3^{-d_{\min}}} \right) \right]^{-\frac{1}{d_{\min}}}, \quad (2.60)$$

which satisfies

$$P_e \cong (G_c \gamma)^{-d_{\min}}, \quad (2.61)$$

in the high SNR region.

2.3.3 Performance Evaluation

In this subsection, we conduct computer simulations to evaluate the ABEP performance of VSM. The 4-QAM is assumed for all schemes.

Performance Comparison with Existing Pre-coding Schemes

We evaluate the ABEP performance of VSM for the case of $N_t > N_r$ in Figs. 2.9 and 2.10, where the GPQSM scheme is considered for comparison. The simulation parameters for Fig. 2.9 are chosen as $N_t = 4$, $N_r = 2$, and $N_p = 1$, and those for Fig. 2.10 are $N_t = 8$, $N_r = 4$, and $N_p = 2$. Since the proposed low-complexity detector achieves almost the same performance as the optimal ML detector, we have removed its ABEP curves for figure clarity. To examine the effect of channel estimation, we consider $\rho = 1, 0.95$, and 0.91 , which correspond to $\delta_e^2 = 0, 0.01$, and 0.05 , respectively. The situation of unfixed ρ will be discussed later. For references, the analytical ABEP upper bounds and asymptotic results of VSM are also added in the figures. It is observed from Figs. 2.9 and 2.10 that, as expected, under imperfect channel estimation, error floors appear, whose levels are accurately characterized by the analytical results. In addition, the error floor increases with the channel estimation error, applying to both schemes. However, the floor level for VSM is much lower. The above observation can be explained by (2.46), which reveals that the power of the equivalent noise $\mathbf{q}$ scales with the channel estimation error instead of the SNR. On the other hand, under perfect channel estimation, VSM achieves a diversity order of $N_t - N_r + 1$ as GPQSM while obtaining a much larger coding gain. For example,

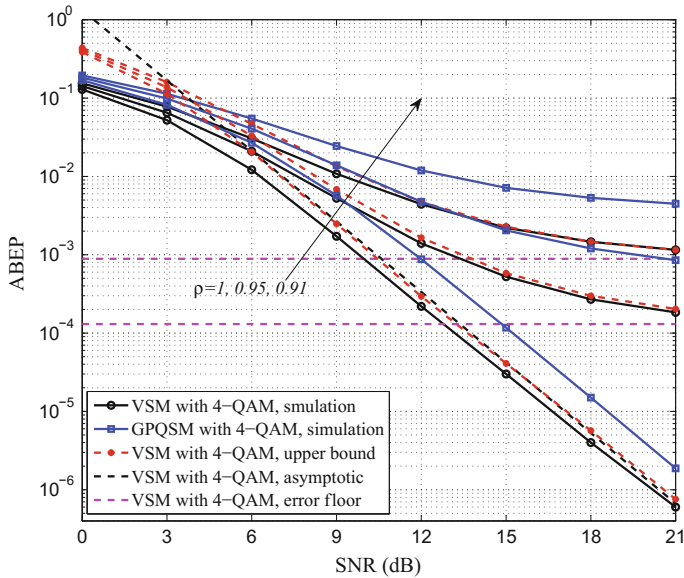


Fig. 2.9 Comparison between VSM and GPQSM in terms of ABEP with $\rho = 1, 0.95, 0.91$ for $N_t = 4$, $N_r = 2$, $N_p = 1$, and 4-QAM

as seen from Fig. 2.9, about 2 dB SNR gain is obtained at an ABEP value of 10^{-5} . This superiority can be accounted for the more diverse channels resulting from the SVD.

The case of $N_t < N_r$ is considered in Fig. 2.11, where $N_t = 2$, $N_r = 4$, $N_p = 1$, and the generalized SM (GSM) scheme is chosen as a comparison representative. For fair comparison, we deprive VSM of the index modulation on the real(imaginary) parts of the received signals, which means VSM activates a single channel to convey a 4-QAM symbol as GSM. It should be noted that as only a single channel is active, GSM degenerates to SM. For figure clarity, only the upper bounded ABEP curve with $\rho = 1$ for VSM is added. From the figure, we see that under perfect channel estimation, GSM outperforms VSM in the low-to-high SNR region. This can be understood since a diversity order of $N_r - N_t + 1$ is achieved by VSM, while a higher diversity order, i.e., N_r , is achieved by GSM. On the other hand, we see that under imperfect channel estimation both VSM and GSM result in error floors, while the level for GSM is much lower. This can be accounted for the SVD used in VSM, which converts MIMO channels into parallel channels by scarifying some copies of transmitted signals. Since besides its worse performance, VSM requires an additional feedback link, VSM is not recommended to be used as a transmitter-side SM scheme in practice.

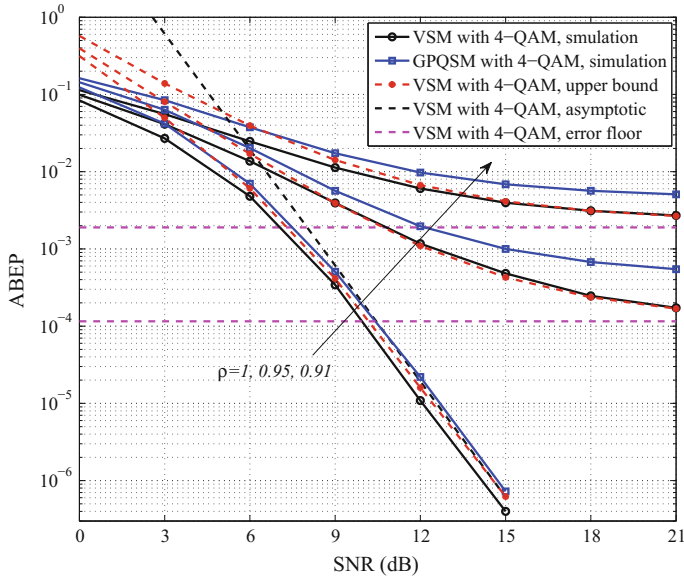


Fig. 2.10 Comparison between VSM and GPQSM in terms of ABEP with $\rho = 1, 0.95, 0.91$ for $N_t = 8, N_r = 4, N_p = 2$, and 4-QAM

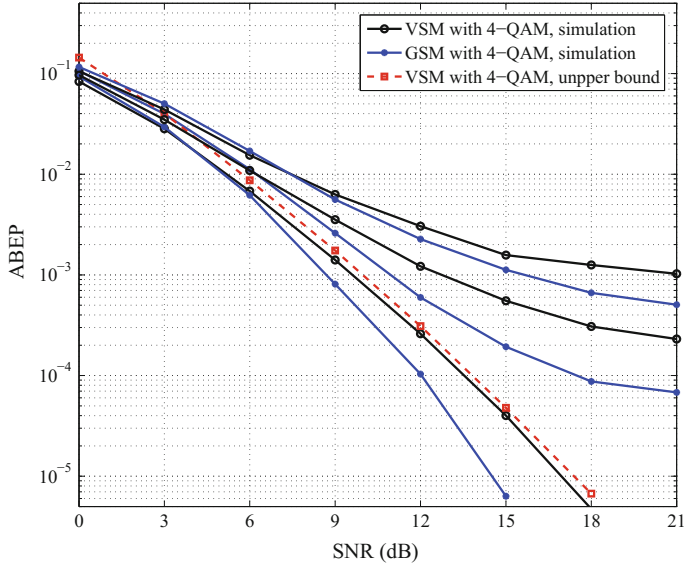


Fig. 2.11 Comparison between VSM and GSM in terms of ABEP with $\rho = 1, 0.95, 0.91$ for $N_t = 2, N_r = 4, N_p = 1$, and 4-QAM

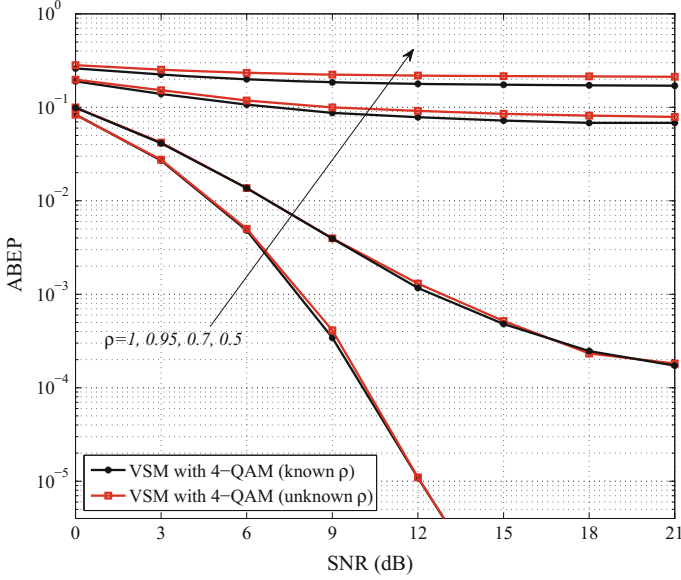


Fig. 2.12 Comparison of the performances of VSM receivers (2.25) and (2.26) in terms of ABEP with $\rho = 1, 0.95, 0.7, 0.5$ for $N_t = 8$, $N_r = 4$, and $N_p = 2$

Impact of ρ on The Receiver Performance

We examine the impact of the knowledge of ρ to the receiver on the performance of VSM systems. Figure 2.12 shows the comparison results between the ABEPs of the detectors (2.44) and (2.45) with $\rho = 1, 0.95, 0.7, 0.5$ for $N_t = 8$, $N_r = 4$, $N_p = 2$ and 4QAM. From the figure, we see that for large correlation coefficients such as $\rho = 1$ and 0.95 , nearly the same performance is resulted no matter whether ρ is known to the receiver or not. For smaller correlation coefficients such as $\rho = 0.7, 0.5$, the performance with the knowledge of ρ to the receiver is superior to that without the knowledge of ρ . This can be easily understood since the influence of channel estimation becomes more significant as ρ becomes smaller and the knowledge of ρ helps the receiver tract the true channel more accurately. However, we note that as the performance gap becomes apparent, the ABEP value also goes very large, e.g., on an order of 10^{-1} for $\rho = 0.7, 0.5$, which is intolerable for most applications of wireless communications. Therefore, in practice the receiver (2.45) is preferred for VSM systems in consideration of its simplicity in implementation, since usually the true value of ρ is difficult to obtain.

Then, we consider the impact of a different channel estimation model on the ABEP performance of VSM. It is assumed that ρ changes with the SNR according to $\rho = l\gamma/(l\gamma + 1)$, where l is chosen to be 2. Figure 2.13 shows the comparison results between performances of VSM and GPQSM with unfixed ρ for two different system configurations, which are (1) $N_t = 4$, $N_r = 2$, and $N_p = 1$; (2) $N_t = 8$,

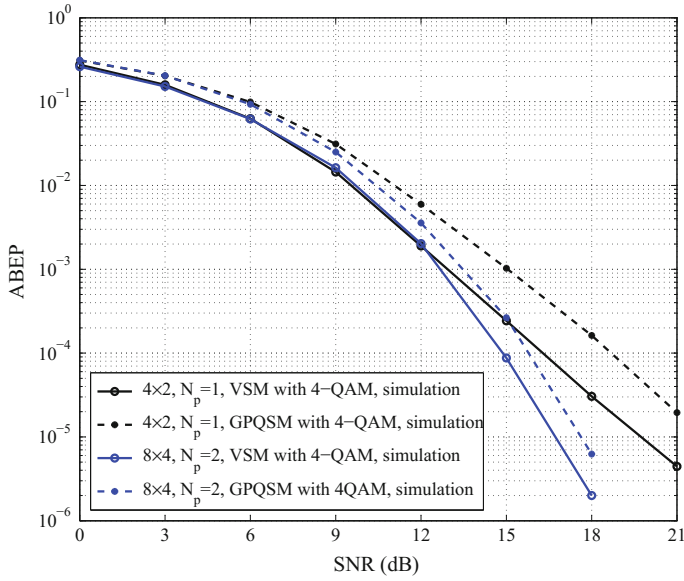


Fig. 2.13 Comparison between VSM and GSM in terms of ABEP with unfixed ρ for two different configurations: (1) $N_t = 4$, $N_r = 2$, and $N_p = 1$; (2) $N_t = 8$, $N_r = 4$, and $N_p = 2$

$N_r = 4$, and $N_p = 2$. From the figure, it can be seen that different from what we observe under the situation of fixed ρ , the error floors never appear for both VSM and GPQSM. This is because ρ approaches one, which happens to be the perfect channel estimation case, in the high SNR region. Therefore, the asymptotic results also apply to the situation of unfixed ρ , which are not shown for figure clarity. On the other hand, from Fig. 2.13, we see that similarly VSM is superior to GPQSM in the whole SNR region.

2.4 Applications to Cooperative Communications

In this section, we demonstrate the potentials and advantages of space domain index modulation techniques in the applications to cooperative communications. We take SSK modulation as a demonstrative example. Specifically, a pragmatic communication strategy for the use of SSK modulation in two-way amplify-and-forward (AF) relaying is proposed. By considering a Nakagami- m fading environment, upper bounded and asymptotic ABEPs are both derived in closed form. The optimal power allocation problem in the minimization of the ABEP is also addressed.

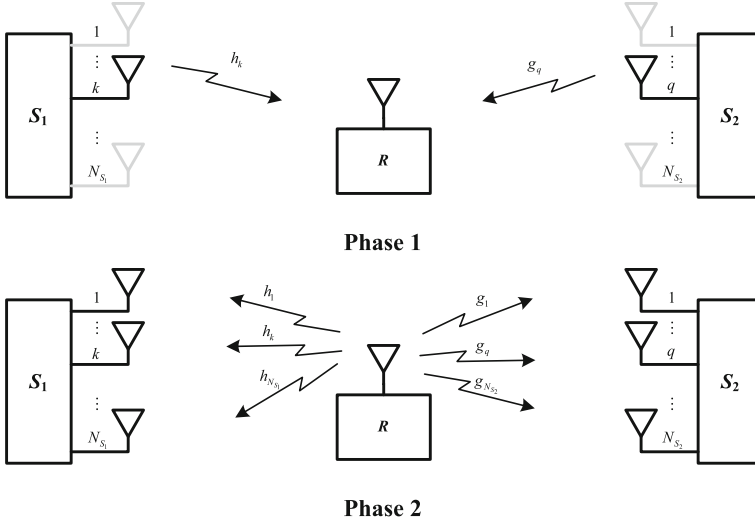


Fig. 2.14 The schematic of the two-way relaying with SSK modulation

2.4.1 System Model

We consider a bidirectional relay network, which is comprised of two source nodes, denoted by S_1 and S_2 , and a relay node, denoted by R , as depicted in Fig. 2.14. We assume that both source nodes adopt SSK modulation such that the numbers of antennas at these nodes, N_{S_1} and N_{S_2} , are no less than 2, and the relay node with a single antenna serves as a non-regenerative repeater. The channel vectors for the $S_1 - R$ and $S_2 - R$ links, respectively, are represented by $\mathbf{h}$ and $\mathbf{g}$, where the magnitudes of the entries of $\mathbf{h}$ and $\mathbf{g}$, $|h_i|$, $i = 1, \dots, N_{S_1}$ and $|g_l|$, $l = 1, \dots, N_{S_2}$, are assumed to follow Nakagami- m distributions with parameters (Ω_h, m_h) and (Ω_g, m_g) , respectively. We further presume that m_g and m_h are integers, the channels are mutually independent and reciprocal, and each node is subjected to AWGN of variance N_0 . Each message exchange between two source nodes takes place in two phases. In the first phase, both sources simultaneously send the information and the following superimposed signal is received at the relay node

$$y_R = \sqrt{P_{S_1}} h_k + \sqrt{P_{S_2}} g_q + n_R, \quad (2.62)$$

where P_I is the transmit power of node I ($I \in \{S_1, S_2, R\}$), n_R is the AWGN at the relay, and without loss of generality, it is assumed that the k -th indexed antenna of S_1 and the q -th indexed antenna of S_2 are activated for transmission. In the second phase, the relay first processes the received signal by multiplying an amplification factor G and then forward it to the two source nodes. Due to symmetry, in what follows only the signal flowchart at S_1 will be detailed. The received signal at the

i -th antenna of S_1 can be expressed by

$$y_{S_1,i} = \sqrt{P_{S_1} P_R} G h_i h_k + \sqrt{P_{S_2} P_R} G h_i g_q + \sqrt{P_R} G h_i n_R + n_{S_1,i}, \quad (2.63)$$

where

$$G = \frac{1}{\sqrt{(P_{S_1} \Omega_h + P_{S_2} \Omega_g + N_0)}}, \quad (2.64)$$

is chosen to fix the average transmit power of relay and $n_{S_1,i}$ is the AWGN at the i -th antenna of S_1 . Here, the fixed-gain AF relay mode is considered. We note that it is quite difficult to implement the CSI-assisted AF relay mode since the instantaneous CSI which carries on information due to SSK modulation is unavailable at the relay during the message transmission. Since the source acquires the knowledge of the activated antenna index for the previous transmission phase and the CSI during the pilot transmission phase, it is able to eliminate the self-interference as

$$\tilde{y}_{S_1,i} = \sqrt{P_{S_2} P_R} G h_i g_q + \underbrace{\sqrt{P_R} G h_i n_R + n_{S_1,i}}_{\text{Effective noise}}. \quad (2.65)$$

Finally, based on the ML principle, the optimum detection for the transmit antenna index can be given by

$$\begin{aligned} \hat{q} &= \arg \max_{1 \leq q \leq N_{S_2}} f_{\tilde{y}_{S_1}}(\tilde{\mathbf{y}}_{S_1} | \mathbf{g}_q, \mathbf{h}) \\ &= \arg \min_{1 \leq q \leq N_{S_2}} (\tilde{\mathbf{y}}_{S_1} - \mathbf{d}_{g_q})^H \mathbf{C}_{\mathbf{n}_{eff}, S_1}^{-1} (\tilde{\mathbf{y}}_{S_1} - \mathbf{d}_{g_q}), \end{aligned} \quad (2.66)$$

where

$$f_{\tilde{y}_{S_1}}(\tilde{\mathbf{y}}_{S_1} | \mathbf{g}_q, \mathbf{h}) = \pi^{-N_{S_1}} |\mathbf{C}_{\mathbf{n}_{eff}, S_1}|^{-\frac{1}{2}} e^{-(\tilde{\mathbf{y}}_{S_1} - \mathbf{d}_{g_q})^H \mathbf{C}_{\mathbf{n}_{eff}, S_1}^{-1} (\tilde{\mathbf{y}}_{S_1} - \mathbf{d}_{g_q})},$$

$\tilde{\mathbf{y}}_{S_1}$, of dimension N_{S_1} , is the received signal vector, whose i -th entry is given by (2.65), $\mathbf{d}_{g_q}$, of dimension N_{S_1} , is the useful signal vector, whose i -th entry is $\sqrt{P_{S_2} P_R} G h_i g_q$, and $\mathbf{C}_{\mathbf{n}_{eff}, S_1}$, of dimensions $N_{S_1} \times N_{S_1}$, is the covariance matrix of the effective noise, whose (i, i') -th entry is $N_0 (P_R G^2 h_i^* h_{i'} + \delta(i - i'))$.

As indicated in (2.66), the optimum ML detector invokes an inverse of a positive definite matrix $\mathbf{C}_{\mathbf{n}_{eff}, S_1}$, resulting in a cubic increase in the dimension of the matrix instead of the linear increase with the number of received antennas in previous SSK modulation schemes [17, 18]. This is due to the fact that by incurring the relay retransmission, the effective noise at different antennas of either source become highly correlated. To solve this problem, we propose a suboptimal detector, which enables not only a largely reduced detection but also a near-ML performance as will be validated in Sect. 2.4.3. The idea is motivated by the discovery of the underlying

spatial constellation for SSK modulation in [17] and can be realized based on the MRC principle [9, pp. 821–823] as follows,

$$\hat{q} = \arg \min_{1 \leq q \leq N_{S_2}} \left| \frac{\mathbf{h}^H \tilde{\mathbf{y}}_{S_1}}{\|\mathbf{h}\|_F^2} - \mathbf{g}_q \right|. \quad (2.67)$$

It is clear that the evaluation of (2.67) requires $(4N_{S_1} + 2N_{S_2} - 1)$ complex operations, which is much less than the $\mathcal{O}(N_{S_2} N_{S_1}^3)$ required in (2.66). It is worth noting that the powers of the effective noise processes at all antennas are simply treated as equal while performing MRC in (2.67), which greatly helps relieve the burden on the source nodes in estimating the noise power at different antennas. Also note that unlike the MRC detection in [3], which only operates under special channel assumption, the one in (2.67) holds regardless of the channel realization.

2.4.2 ABEP Analysis and Power Allocation

In this subsection, we derive upper bounded and asymptotic ABEPs of the system. Based on the asymptotic ABEP, we further solve the power allocation problem.

PEP Derivation

The PEP $\Pr(q \rightarrow \hat{q})$, which is defined as the probability of the error event that occurs when the q -th antenna of S_2 is activated but antenna index $\hat{q}$ is detected, is derived in closed form in the following.

When conditioned upon the instantaneous CSI, the PEP can be readily expressed from (2.65) and (2.67) as

$$\begin{aligned} \Pr(q \rightarrow \hat{q} | \mathbf{h}, \mathbf{g}) &= \Pr \left(\left| \mathbf{h}^H \tilde{\mathbf{y}}_{S_1} / \|\mathbf{h}\|^2 - \mathbf{g}_q \right|^2 > \left| \mathbf{h}^H \tilde{\mathbf{y}}_{S_1} / \|\mathbf{h}\|^2 - \mathbf{g}_{\hat{q}} \right|^2 \right) \\ &= \Pr \left(\frac{|\mathbf{g}_q - \mathbf{g}_{\hat{q}}|^2}{2} < \Re \{ (\mathbf{g}_{\hat{q}} - \mathbf{g}_q)^* n_{eq} \} \right) \\ &= Q \left(\sqrt{\frac{\gamma_{R-S_1} \cdot \gamma_{S_2-R}}{\gamma_{R-S_1} + C_{S_1}}} \right), \end{aligned} \quad (2.68)$$

where $C_{S_1} = 1/(N_{S_1} G^2 N_0)$, $n_{eq} = n_R / \sqrt{P_{S_2}} + \mathbf{h}^H \mathbf{n}_{S_1} / (\sqrt{P_{S_2} P_R} G \|\mathbf{h}\|^2)$ is the equivalent noise after MRC, $\mathbf{n}_{S_1}$ is the noise vector at S_1 , and $\gamma_{R-S_1} = P_R \|\mathbf{h}\|^2 / (N_{S_1} N_0)$ and $\gamma_{S_2-R} = P_{S_2} |\mathbf{g}_q - \mathbf{g}_{\hat{q}}|^2 / (2N_0)$ are defined as the instantaneous received SNR for the $R - S_1$ link and the $S_2 - R$ link, respectively. From (2.68), we see that to obtain the PEP dispensing with the channels, it is necessary to characterize the distributions of γ_{R-S_1} and γ_{S_2-R} first.

By considering an integer-fading-parameter Nakagami- m environment, the PDF of γ_{R-S_1} can be expressed from [19, Eq. (7)] as

$$f_{\gamma_{R-S_1}}(\gamma) = \frac{\gamma^{m_h N_{S_1}-1}}{\Gamma(m_h N_{S_1})} \left(\frac{m_h N_{S_1}}{\bar{\gamma}_{R-S_1}} \right)^{m_h N_{S_1}} e^{-\frac{m_h N_{S_1}}{\bar{\gamma}_{R-S_1}} \gamma}, \quad (2.69)$$

where $\bar{\gamma}_{R-S_1} = \frac{P_R \Omega_h}{N_0}$ is the average received SNR for the $R - S_1$ link. On the other hand, since the PDF of $|g_q - g_{\hat{q}}|$ is given by [20, Eq. (8)] of a form

$$f_{|g_q - g_{\hat{q}}|}(u) = \wp_{\mathbf{g}} \left\langle \frac{m_g^{z+1}}{2^z \Omega_g^{z+1}} u^{2z+1} e^{-\frac{m_g u^2}{2\Omega_g}} \right\rangle, \quad (2.70)$$

where the operator $\wp_{\mathbf{g}} \langle \cdot \rangle$ is defined as

$$\wp_{\mathbf{g}} \langle \chi \rangle = \sum_{i_0=0}^{m_g-1} \sum_{i_1=0}^{m_g-1} \frac{(i_0 + i_1)! (-m_g + 1)_{i_0} (-m_g + 1)_{i_1}}{(i_0!)^2 (i_1!)^2 2^{i_0+i_1}} \sum_{z=0}^{i_0+i_1} \frac{(-i_0 - i_1)_z}{(z!)^2} \chi, \quad (2.71)$$

from basic probability theory [9, p. 30–32] we have

$$\begin{aligned} f_{\gamma_{S_2-R}}(\gamma) &= \sqrt{\frac{N_0}{2P_{S_2}\gamma}} f_{|g_q - g_{\hat{q}}|} \left(\sqrt{\frac{2N_0}{P_{S_2}}} \gamma \right) \\ &= \wp_{\mathbf{g}} \left\langle \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} \right)^{z+1} \gamma^z e^{-\frac{m_g}{\bar{\gamma}_{S_2-R}} \gamma} \right\rangle, \end{aligned} \quad (2.72)$$

where $\bar{\gamma}_{S_2-R} = \frac{P_{S_2} \Omega_g}{N_0}$ is the average received SNR for the $S_2 - R$ link. Accordingly, given the PDF in (2.72), the cumulative distribution function (CDF) of γ_{S_2-R} can be readily derived as

$$\begin{aligned} F_{\gamma_{S_2-R}}(\gamma) &= \wp_{\mathbf{g}} \left\langle \Gamma(z+1) - \Gamma\left(z+1, \frac{m_g}{\bar{\gamma}_{S_2-R}} \gamma\right) \right\rangle \\ &= 1 - \wp_{\mathbf{g}} \left\langle z! e^{-\frac{m_g}{\bar{\gamma}_{S_2-R}} \gamma} \sum_{m=0}^z \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} \right)^m \frac{\gamma^m}{m!} \right\rangle, \end{aligned} \quad (2.73)$$

where the property $\wp_{\mathbf{g}} \langle \Gamma(z+1) \rangle = 1$ and the series representation of the incomplete gamma function in [12, Eq. (8.352.2)] are used in obtaining the last equation.

Therefore, by analogy with the mathematics in [18], the CDF of the equivalent received SNR in (2.68), i.e., $\gamma_{eq} = \frac{\gamma_{R-S_1} \gamma_{S_2-R}}{\gamma_{R-S_1} + C_{S_1}}$, can be readily derived as

$$\begin{aligned}
F_{\gamma_{eq}}(\gamma) &= \int_0^{+\infty} F_{\gamma_{S_2-R}} \left(\left(1 + \frac{C}{x}\right) \gamma \right) f_{\gamma_{R-S_1}}(x) dx \\
&= 1 - \frac{e^{-\frac{m_g}{\bar{\gamma}_{S_2-R}} \gamma}}{\Gamma(m_h N_{S_1})} \left(\frac{m_h N_{S_1}}{\bar{\gamma}_{R-S_1}} \right)^{m_h N_{S_1}} \wp_g \left\langle z! \sum_{m=0}^z \frac{\gamma^m}{m!} \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} \right)^m \right. \\
&\quad \times \left. \int_0^{+\infty} x^{m_h N_{S_1}-1} \left(1 + \frac{C}{x}\right)^m e^{-\frac{m_g C \gamma}{\bar{\gamma}_{S_2-R}} \cdot \frac{1}{x} - \frac{m_h N_{S_1}}{\bar{\gamma}_{R-S_1}} x} dx \right\rangle. \quad (2.74)
\end{aligned}$$

Next, by resorting to the binomial expansion of $(1 + \frac{C}{x})^m$ and the integral result in [12, Eq. (3.471.9)], (2.74) can be further simplified as

$$\begin{aligned}
F_{\gamma_{eq}}(\gamma) &= 1 - \frac{2e^{-\frac{m_g}{\bar{\gamma}_{S_2-R}} \gamma}}{\Gamma(m_h N_{S_1})} \wp_g \left\langle \sum_{m=0}^z \sum_{n=0}^m \frac{z!}{(m-n)!n!} D_{S_1}^{\frac{m_h N_{S_1}+n}{2}} \right. \\
&\quad \times \left. \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} \right)^{m-n} \gamma^{\frac{m_h N_{S_1}-n}{2}+m} K_{m_h N_{S_1}-n} \left(2\sqrt{D_{S_1}} \gamma \right) \right\rangle, \quad (2.75)
\end{aligned}$$

where $D_{S_1} = \frac{m_g m_h C_{S_1} N_{S_1}}{\bar{\gamma}_{S_2-R} \bar{\gamma}_{R-S_1}} = m_g m_h \frac{\bar{\gamma}_{S_1-R} + \bar{\gamma}_{S_2-R} + 1}{\bar{\gamma}_{S_2-R} \bar{\gamma}_{R-S_1}}$ and $\bar{\gamma}_{S_1-R} = \frac{P_{S_1} \Omega_h}{N_0}$ is the average received SNR for the $S_1 - R$ link. Finally, by using the partial integral, the PEP can be expressed as

$$\begin{aligned}
\Pr(q \rightarrow \hat{q}) &= \frac{1}{2\sqrt{2\pi}} \int_0^{+\infty} \frac{1}{\sqrt{\gamma}} e^{-\frac{\gamma}{2}} F_{\gamma_{eq}}(\gamma) d\gamma \\
&= \frac{1}{2} - \frac{1}{\sqrt{2\pi} \Gamma(m_h N_{S_1})} \wp_g \left\langle \sum_{m=0}^z \sum_{n=0}^m \frac{z!}{(m-n)!n!} D_{S_1}^{\frac{m_h N_{S_1}+n}{2}} \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} \right)^{m-n} \right. \\
&\quad \times \left. \int_0^{+\infty} \gamma^{\frac{m_h N_{S_1}-n-1+2m}{2}} e^{-\left(\frac{m_g}{\bar{\gamma}_{S_2-R}} + \frac{1}{2}\right)\gamma} K_{m_h N_{S_1}-n} \left(2\sqrt{D_{S_1}} \gamma \right) d\gamma \right\rangle. \quad (2.76)
\end{aligned}$$

Closed-form solution exists by changing the integral variable with $t = \sqrt{\gamma}$ in the last equation of (2.76) and applying the identity in [12, Eq. (6.631.3)], yielding

$$\begin{aligned}
\Pr(q \rightarrow \hat{q}) &= \frac{1}{2} - \frac{e^{D_{S_1} / \left(\frac{2m_g}{\bar{\gamma}_{S_2-R}} + 1 \right)}}{2\sqrt{2\pi} D_{S_1} \Gamma(m_h N_{S_1})} \wp_g \left\langle \sum_{m=0}^z \sum_{n=0}^m \frac{z! D_{S_1}^{\frac{m_h N_{S_1}+n}{2}}}{(m-n)!n!} \right. \\
&\quad \times \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} \right)^{m-n} \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} + \frac{1}{2} \right)^{-\frac{m_h N_{S_1}-n+2m}{2}} \Gamma\left(\frac{1}{2} + m_h N_{S_1} + m - n \right) \\
&\quad \times \left. \Gamma\left(\frac{1}{2} + m \right) W_{-\frac{m_h N_{S_1}-n+2m}{2}, \frac{m_h N_{S_1}-n}{2}} \left(\frac{D_{S_1}}{\frac{m_g}{\bar{\gamma}_{S_2-R}} + \frac{1}{2}} \right) \right\rangle, \quad (2.77)
\end{aligned}$$

which with the help of [21, Eqs. (13.1.10) and (13.1.33)] can be also expressed in terms of ${}_2F_0$ as

$$\begin{aligned} \Pr(q \rightarrow \hat{q}) &= \frac{1}{2} - \frac{\Gamma^{-1}(m_h N_{S_1})}{2\sqrt{2\pi}} \wp_{\mathbf{g}} \left\langle \sum_{m=0}^z \sum_{n=0}^m \frac{z! D_{S_1}^{n-m-\frac{1}{2}}}{(m-n)!n!} \right. \\ &\times \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} \right)^{m-n} \Gamma\left(\frac{1}{2} + m_h N_{S_1} + m - n\right) \Gamma\left(\frac{1}{2} + m\right) \\ &\times {}_2F_0\left(m_h N_{S_1} + m - n + \frac{1}{2}, m + \frac{1}{2}; -\left(\frac{m_g}{D_{S_1} \bar{\gamma}_{S_2-R}} + \frac{1}{2D_{S_1}}\right)\right) \Bigg\rangle. \end{aligned} \quad (2.78)$$

For a Rayleigh fading environment, where $m_g = m_h = 1$, (2.78) reduces to

$$\begin{aligned} \Pr(q \rightarrow \hat{q}) &= \frac{1}{2} - \frac{\Gamma(N_{S_1} + \frac{1}{2})}{4\Gamma(N_{S_1})} \sqrt{\frac{2\bar{\gamma}_{R-S_1}\bar{\gamma}_{S_2-R}}{\bar{\gamma}_{S_1-R} + \bar{\gamma}_{S_2-R} + 1}} \\ &\times {}_2F_0\left(N_{S_1} + \frac{1}{2}, \frac{1}{2}; -\frac{\bar{\gamma}_{R-S_1} + \frac{1}{2}\bar{\gamma}_{R-S_1}\bar{\gamma}_{S_2-R}}{\bar{\gamma}_{S_1-R} + \bar{\gamma}_{S_2-R} + 1}\right). \end{aligned} \quad (2.79)$$

Upper-Bounded and Asymptotic ABEPs

When $N_{S_2} = 2$, one can readily determine that the exact ABEP at S_1 , i.e., P_{b,S_1} , turns out to be (2.78). As for $N_{S_2} > 2$, the union bounding technique is used here to derive an upper bound on the ABEP at S_1 :

$$P_{b,S_1} \leq \frac{1}{N_{S_2} \log_2(N_{S_2})} \sum_{q=1}^{N_{S_2}} \sum_{\hat{q}=q+1}^{N_{S_2}} 2N(q, \hat{q}) \Pr(q \rightarrow \hat{q}) \quad (2.80)$$

where $N(q, \hat{q})$ is the Hamming distance between the bit sequences mapped to antenna indexes q and $\hat{q}$. In the case in which N_{S_2} is equal to a power of 2, which is of great interest in practice, it follows that $\sum_{q=1}^{N_{S_2}} \sum_{\hat{q}=q+1}^{N_{S_2}} 2N(q, \hat{q}) = \frac{1}{2} N_{S_2}^2 \log_2(N_{S_2})$ and (2.80) becomes [22]

$$P_{b,S_1} \leq \frac{N_{S_2}}{2} \Pr(q \rightarrow \hat{q}). \quad (2.81)$$

Furthermore, greater insight ABEP about the effects of the different system parameters can be gained from the following asymptotic expression for the ABEP:

$$\begin{aligned} P_{b,S_1} &\approx \frac{m_g N_{S_2}}{4} (1 - \wp_{\mathbf{g}} \langle z! U(z-1) \rangle) \\ &\times \left(\frac{1}{\bar{\gamma}_{S_2-R}} + \frac{m_h}{m_h N_{S_1} - 1} \frac{\bar{\gamma}_{S_1-R} + \bar{\gamma}_{S_2-R} + 1}{\bar{\gamma}_{R-S_1} \bar{\gamma}_{S_2-R}} \right). \end{aligned} \quad (2.82)$$

Proof According to [23], the asymptotic error probability is closely related to the first non-zero higher order derivative of the CDF of γ_{eq} at the origin, which is contained in the first term of the Taylor's series of this CDF. By using the series representation of $K_{m_h N_{S_1} - n} (2\sqrt{D_{S_1} \gamma})$ in (2.75) according to [12, Eq. (8.446)], one can determine that two parts in (2.75) contribute to the aforementioned first term, where the first part corresponds to the case when $m = 0$, given by

$$\begin{aligned} F_{\gamma_{eq}}^{(1)}(\gamma) &= 1 - \frac{2}{\Gamma(m_h N_{S_1})} \left(1 - \frac{m_g}{\bar{\gamma}_{S_2-R}} \gamma + O(\gamma) \right) \\ &\quad \times \left(\frac{\Gamma(m_h N_{S_1})}{2} - \frac{\Gamma(m_h N_{S_1} - 1)}{2} D_{S_1} \gamma + O(\gamma) \right) \\ &= \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} + \frac{D_{S_1}}{m_h N_{S_1} - 1} \right) \gamma + O(\gamma), \end{aligned} \quad (2.83)$$

and the second part corresponds to the case when $m = 1$, yielding

$$\begin{aligned} F_{\gamma_{eq}}^{(2)}(\gamma) &= - \frac{2 \left(1 - \frac{m_g}{\bar{\gamma}_{S_2-R}} \gamma + O(\gamma) \right)}{\Gamma(m_h N_{S_1})} [\wp_g \langle z! U(z-1) \rangle] \\ &\quad \times \left(\frac{m_g \Gamma(m_h N_{S_1})}{2 \bar{\gamma}_{S_2-R}} + \frac{\Gamma(m_h N_{S_1} - 1)}{2} D_{S_1} \right) \gamma + O(\gamma) \\ &= - \wp_g \langle z! U(z-1) \rangle \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} + \frac{D_{S_1}}{m_h N_{S_1} - 1} \right) \gamma + O(\gamma). \end{aligned} \quad (2.84)$$

Then, by incorporating (2.83) and (2.84), we obtain the first non-zero higher order derivative of $F_{\gamma_{eq}}(\gamma)$ at the origin as

$$\begin{aligned} \frac{\partial F_{\gamma_{eq}}(\gamma=0)}{\partial \gamma} &= f_{\gamma_{eq}}(0) \\ &= (1 - \wp_g \langle z! U(z-1) \rangle) \left(\frac{m_g}{\bar{\gamma}_{S_2-R}} + \frac{D_{S_1}}{m_h N_{S_1} - 1} \right), \end{aligned} \quad (2.85)$$

where $f_{\gamma_{eq}}(\gamma)$ is the PDF of γ_{eq} . Finally, the application of the identity in [23, Eq. (10)] completes the proof. $\square$

Specifically, for a Rayleigh fading environment, we have

$$P_{b, S_1} \approx \frac{N_{S_2}}{4} \left(\frac{1}{\bar{\gamma}_{S_2-R}} + \frac{1}{N_{S_1} - 1} \frac{\bar{\gamma}_{S_1-R} + \bar{\gamma}_{S_2-R} + 1}{\bar{\gamma}_{R-S_1} \bar{\gamma}_{S_2-R}} \right). \quad (2.86)$$

From (2.82) and (2.86), it is clear that an increase in the number of received antennas in two-way relay systems with SSK modulation always achieves unit diversity order but results in an improvement of the coding gain. This is different from the case of

conventional SSK modulation, where N_{S_1} diversity order can be gained [17]. When relay retransmission is introduced, the received signal versions at all antennas become dependent and completely unresolvable.

Power Allocation

By excluding all parameters irrelevant to power allocation (PA) and after some manipulation, the PA problem based on the minimization of the average ABEP $P_e = (P_{e,S_1} + P_{e,S_2})/2$, subject to total and individual power constraints, can be formulated as

$$\begin{aligned} \{P_{S_1}^*, P_R^*, P_{S_2}^*\} = & \min_{\{P_{S_1}, P_R, P_{S_2}\}} \left\{ \frac{1 - \wp_{\mathbf{g}} \langle z!U(z-1) \rangle}{m_h N_{S_1} \Omega_g} \right. \\ & \times \left(\frac{1}{P_{S_2}} + \frac{m_h}{m_h N_{S_1} - 1} \frac{P_{S_1} \Omega_h + P_{S_2} \Omega_g}{P_R P_{S_2} \Omega_h} \right) \\ & + \frac{1 - \wp_{\mathbf{h}} \langle z!U(z-1) \rangle}{m_g N_{S_2} \Omega_h} \\ & \left. \times \left(\frac{1}{P_{S_1}} + \frac{m_g}{m_g N_{S_2} - 1} \frac{P_{S_1} \Omega_h + P_{S_2} \Omega_g}{P_R P_{S_1} \Omega_g} \right) \right\} \\ \text{s.t. } & P_{S_1} + P_R + P_{S_2} \leq P_{tot} \quad \& \quad P_{S_1}, P_R, P_{S_2} > 0, \end{aligned} \quad (2.87)$$

where P_{e,S_2} is the ABEP at S_2 , $\wp_{\mathbf{h}} \langle \cdot \rangle$ is the operator defined similar to (2.71) but with all related parameters extracted from the $S_1 - R$ link, P_{tot} is the upper bound on the system power, and $\{P_{S_1}^*, P_R^*, P_{S_2}^*\}$ are the optimum values of $\{P_{S_1}, P_R, P_{S_2}\}$, which satisfy the constrained optimization problem in (2.87). A careful inspection of (2.87) reveals the convex property of the objective function with respect to the decision variables, i.e., P_{S_1} , P_R , and P_{S_2} , and thus unique solutions, i.e., $\{P_{S_1}^*, P_R^*, P_{S_2}^*\}$, exist for the above non-linear programming problem. Unfortunately, to the best of our knowledge, closed-form expressions for $\{P_{S_1}^*, P_R^*, P_{S_2}^*\}$ are unavailable. To this end, numerical searching algorithms should be relied on, and this can be easily realized by standard mathematical software platforms, e.g., Matlab, Mathematica, etc.

2.4.3 Performance Evaluation

In this subsection, BER simulations are conducted to validate the analysis given in Sect. 2.4.2. Without loss of generality, in the simulations we let $\Omega_h = \Omega_g = 1$ and the number of antennas at both sources be powers of 2. Unless otherwise specified, the transmit powers of all three nodes are set equal and the proposed MRC detector is applied.

Figure 2.15 depicts the BER performance for two different channel scenarios, where we choose $N_{S_1} = 8$ and $N_{S_2} = 2$. It is clear that the proposed MRC detector expresses nearly the same performance as the optimum ML detector. Moreover,

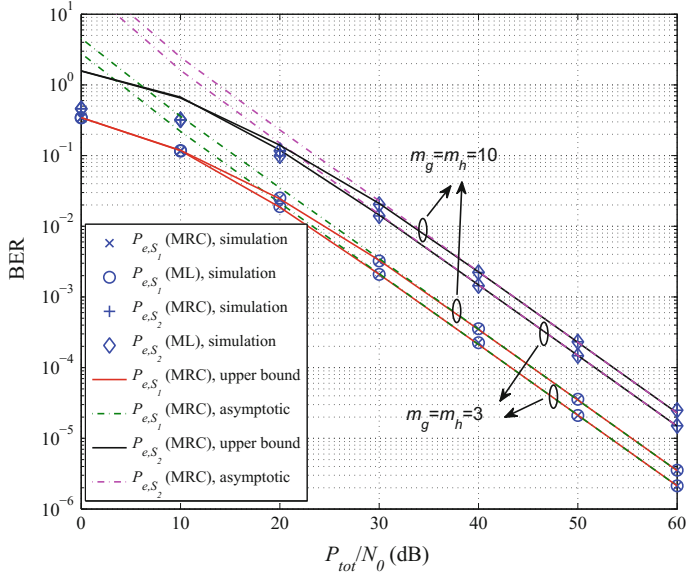


Fig. 2.15 BER performance in the case of $N_{S1} = 8$ and $N_{S2} = 2$

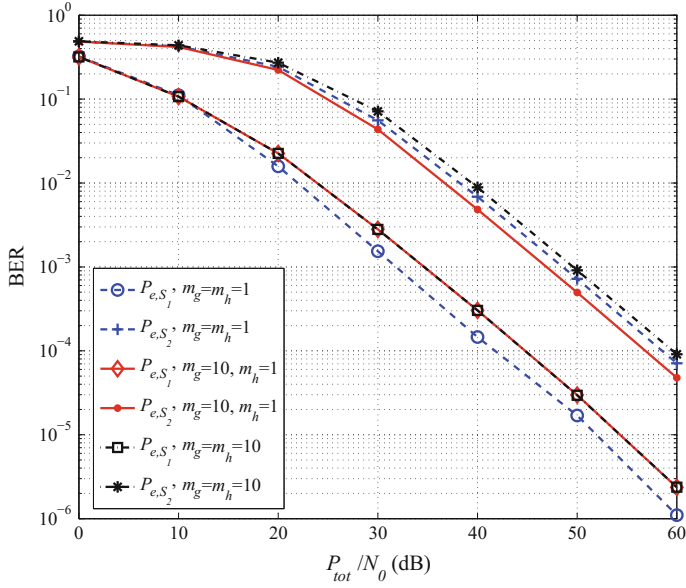


Fig. 2.16 Effects of fading parameters on the BER performance

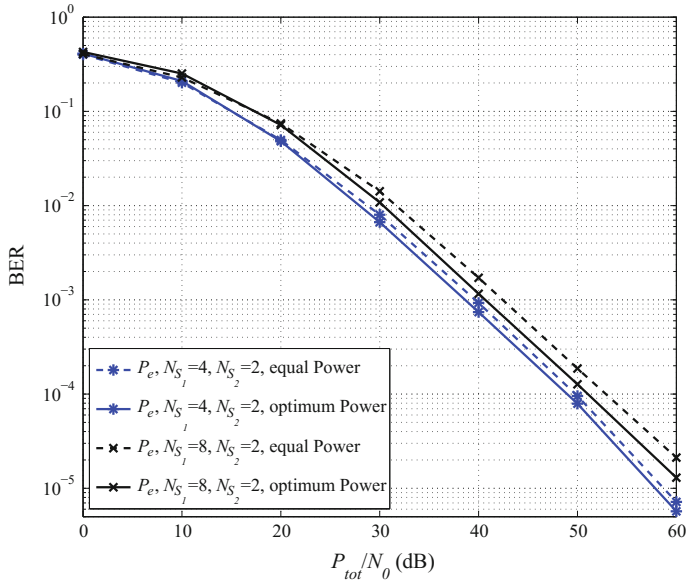


Fig. 2.17 BER performance comparison between equal power allocation and optimum power allocation

as expected, the analytical exact, upper bounded, and asymptotic ABEPs are all in perfect agreement with their simulation counterparts. On the other hand, as predicted in (2.82), the systems always gain a diversity order of unity.

Figure 2.16 shows the effects of fading parameters on the BER performance, where we choose $N_{S_1} = 32$ and $N_{S_2} = 2$. For the purpose of figure clarity, the analytical curves are removed. We see that as the fading of the link between one source and the relay becomes less severe, i.e., the value of the corresponding parameter $m_{h/g}$ becomes larger, the BER performance of this source will be somewhat improved, whereas that of the other source will deteriorate. The improvement in the BER performance is due to the improvement of the channel quality, which fulfils our intuition. However, deterioration of the BER performance seems counter-intuitive at first but can be explained reasonably after further consideration as follows: the improvement of the channel quality at one link will result in the shrinking of the spatial constellation for the source at this link, and thus will lead to the detection at the other source becoming harder. Moreover, from Fig. 2.16, it is clear that compared with the increase of the BER, the decrease of the BER is more serious. This can be easily accounted for from the positions of the two fading parameters in the BER expression in (2.82), which implies the dominant effect of the shrinking of the spatial constellation over the improvement of channel quality. Therefore, it is not surprising to see from Figs. 2.15 and 2.16 that the improvement of the fading severities for both links produces a reverse effect on the overall system performance, i.e., results in the deterioration of the overall system performance.

Figure 2.17 illustrates the feasibility of adopting the proposed PA strategy in lowering the average BER, where the fading parameters are fixed as $m_g = 1$ and $m_h = 10$. In Fig. 2.17, we consider two different system situations, i.e., (1) $N_{S_1} = 4$, $N_{S_2} = 2$; and (2) $N_{S_1} = 8$ and $N_{S_2} = 2$. The optimum PA strategies, according to (2.87), for the above two system settings in order are (1) $P_{S_1}^* = 0.4113P_{tot}$, $P_R^* = 0.4317P_{tot}$, $P_{S_2}^* = 0.1570P_{tot}$; and (2) $P_{S_1}^* = 0.4398P_{tot}$, $P_R^* = 0.4457P_{tot}$, $P_{S_2}^* = 0.1144P_{tot}$. Both BER values for the equal PA and optimum PA strategies are depicted in Fig. 2.17, while their analytical results are not shown for the purpose of figure clarity. One can observe that by adopting the proposed PA strategy, the system can even benefit about 2 dB SNR reduction with respect to the equal power distribution strategy at some specific level of P_e , e.g., $P_e = 10^{-3}$. We note that as the proposed PA strategy focuses on the minimization of average BER for a moderate-to-high SNR regime, it may worsen the average BER compared with the equal PA strategy for a very low SNR regime, where $P_e > 10^{-1}$.

2.5 Summary

In this chapter, we began with the introduction of the first space domain index modulation technique, which is well known as SM. Then, we proposed a receiver-side SM scheme, i.e., GPQSM, which relies on the ZF/MMSE pre-coding operation at the transmitter. The advantages of GPQSM were revealed through both theoretical analysis and simulations. However, similar to the other pre-coding SM schemes, the performance of GPQSM is limited by the correlated channels. To solve this problem, we further proposed the VSM scheme, which embeds additional information into the indices of the virtual parallel channels resulting from the SVD of the MIMO channel and can be regarded as either a transmitter-side or receiver-side SM scheme. VSM was shown to be favorable especially for low data rate transmission. Finally, we took SSK as a representative to examine the potential of space domain index modulation techniques in the application to cooperative communications.

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