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Antenna selection for MIMO system based on pattern recognition

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ABSTRACT

This paper proposes a novel Multiple-Input Multiple-Output (MIMO) transmission scheme based on Pattern Recognition (PR), which is termed as the PR aided Transmission Antenna Selection MIMO (PR-TAS aided MIMO). As the conventional TAS algorithms need to search all possible legitimate antenna subsets, they may impose some redundant calculations. In order to avoid this problem, we employ some pattern recognition methods to carry out the TAS algorithm in this paper. To be specific, two PR algorithms, namely the K-Nearest Neighbor (KNN) algorithm and the Support Vector Machine (SVM) algorithm, are introduced and redesigned to obtain a TAS with lower complexity but higher efficiency. Moreover, in order to improve the performance of the SVM, we propose a new feature extraction of channel matrix for the TAS. Our simulation results show that the proposed KNN and SVM based PR-TAS algorithms are capable of striking a flexible tradeoff between the complexity and the Bit Error Rate (BER), and the new feature can effectively improve the BER performance compared with the conventional feature extraction method.

1. Introduction

In recent years, the Multiple-Input Multiple-Output (MIMO) technology has been regarded as a promising technology for the cellular systems because of its high system capacity and attractive Bit Error Rate (BER) performance [1–3]. One of the high-rate MIMO technologies is the Vertical-Bell Laboratories Layered Space Time (V-BLAST) scheme [4–6], which divides the serial data into several sub-streams and transmits them through different transmitting antennas respectively.

Generally, not all the transmitting antennas are needed in practical implementation, sometimes only part of antennas are utilized to transmit information. Therefore, the Transmission Antenna Selection (TAS) was proposed to select the transmitting antennas that can achieve the best performance [7]. In the TAS, the Euclidean Distance Antenna Selection (EDAS) criterion is most often used [7], whose main idea is to maximize the minimum Euclidean distance of the received signal constellation. However, the classic EDAS algorithm and its variants usually impose high computational complexity. Many pervious contributions have been devoted to circumvent the issue of complexity in the operation of the EDAS, such as the low-complexity designs of [8–10], but there still exist some redundant calculations and there seems to be no more improvement using traditional methods. In order to search for a new breakthrough, Ref. [11] applied the pattern recognition to the TAS research, which helps to build a learning system [12] based on some classic classifiers. In this new framework, the antenna combination that achieves the best performance is obtained by classification instead of tedious calculation, therefore, the redundant calculations in the conventional search-based TAS algorithms are effectively avoided. However, just as shown in Ref. [12], the training samples need to be real-valued vectors, which means that the channel matrices need to be manipulated for real-value features, and the feature extraction would affect the results of classification. It is worth noting that Ref. [11] only extracted one kind of features, i.e., the modulus of the channel matrix, which may be unsuitable for the TAS and will lead to some BER loss compared with the traditional EDAS.

In this paper, we optimize the feature extraction for the TAS algorithm based on the pattern recognition demonstrated in Ref. [11]. We employ the SVM to operate the antenna selection algorithm and effectively reduce the redundant calculations in the antenna-set search process. To be specific, firstly we use the optimized feature of the training samples, i.e., channel matrices, as the training feature matrix, which also needs to be normalized. Secondly, we label the samples based on the Key Performance Indicator (KPI), which is designed by the predefined objective function of the TAS. Then, a learning system could be built based on the label vectors and the normalized feature matrix by using the SVM algorithm. Once a learning system is built, the TAS for a new-coming channel matrix could be operated on this well-trained

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learning system.

The rest of this paper is organized as follows: Section 2 introduces the background of machine learning and the V-BLAST system model. Section 3 introduces the conventional TAS algorithm and the proposed TAS based on pattern recognition, where a new feature extraction of training samples is proposed to improve the performance. Section 4 presents the simulation results of the proposed TAS algorithm. Finally, Section 5 draws the conclusion of the whole paper.

Notation: $|a|$ is the absolute value of a, $\|\mathbf{a}\|$ denotes the norm of vector or matrix $\mathbf{a}$, $\mathbb{C}^{a\times b}$ denotes the set of $a\times b$-dimensional matrixes with complex value entries, $\mathbb{R}^{a\times b}$ denotes the set of $a\times b$-dimensional matrixes with real value entries, $(.)^T$ denotes the transpose, and $(.)^H$ denotes the conjugate transpose. $\mathscr{CN}(a,b)$ denotes the distributions of the complex Gaussian random vector, which has the mean value a and the covariance value b.

2. Background

2.1. Machine learning and its applications in wireless communications

In this section, we give a review of some basic knowledge concerning machine learning and some applications of the machine learning techniques in communications.

Machine learning can be classified into three types: the unsupervised learning, the supervised learning, and the reinforcement learning.

1) Unsupervised Learning: The label information of clusters is unknown in unsupervised learning, i.e., we know that some samples in one cluster have the same or familiar features, but we do not know what these samples actually are. The common methods of unsupervised learning are K-Means Clustering (KMC) and affinity propagation.

Application: Ref [13] proposed a blind detector for the Space Shift Keying (SSK) system based on the KMC algorithm, which does not need any channel state information. Ref. [14] proposed a blind detector for the SM system based on an improved KMC algorithm and an affinity propagation algorithm, which can respectively avoid the error floor effect and improve the BER performance.

2) Supervised Learning: Supervised learning utilizes training samples with known labels to build a learning system before making classification. The common methods of supervised learning are regression models, K-nearest neighbor, Support Vector Machines (SVM) and Bayesian learning.

Ref. [15] proposed an energy learning system based on the regression algorithm and the K-nearest neighbor algorithm, which is capable of enhancing the accuracy of prediction by 50% and achieving an average improvement of 24% energy savings. Ref. [16] proposed a blind detector based on the K-Nearest Neighbor (KNN) algorithm, which does not need channel state information, but still can improve the BER performance compared with some conventional blind detectors. Ref. [17] proposed a MIMO channel learning based on hierarchical support vector machines, which is able to reduce the complexity compared with the conventional SVM. Ref. [18] proposed a massive MIMO learning based on Bayesian learning, which can achieve much better performance in terms of channel estimation accuracy and achievable rates. Refs. [19–21] proposed a cognitive spectrum learning based on Bayesian learning, which can successfully estimate the true channel parameters and considerably improve the performance of spectrum detection by exploiting the diversity of the spatially distributed single users equipped with multiple antennas.

3) Reinforcement Learning: Reinforcement learning was inspired by behavioral psychology. Its common methods include: Markov decision processes, partially observable Markov decision process, Q-learning, and multi-armed bandits.

Application: Ref. [22] proposed an energy harvesting algorithm based on (partially observable) Markov decision processes, which can outperform the conventional ad hoc approaches. Refs. [23,24] proposed a novel interference management method for Femto and small cells based on Q-learning. To be specific, in Ref. [23], the intra/inter-tier interference can be significantly reduced, and higher cell throughputs can be achieved. The method proposed in Ref. [24] is able to detect both data and control cell outage and compensate for the detected outage in a reliable manner. Ref. [25] proposed a device-to-device network based on multi-armed bandits, which not only yields vanishing regret in comparison to the global optimal solution, but also guarantees that the empirical joint frequencies of the game converge into the set of correlated equilibria.

2.2. System model

We consider a V-BLAST system with N_t transmitting antennas and N_r receiving antennas [4–6], where the data is divided into N_t sub-streams, which are transmitted by N_t transmitting antennas respectively. Let $\mathbf{X}\in\mathbb{C}^{N_t\times 1}$ denote the transmitting signal, then the received signal can be expressed as

$$Y = HX + N \tag{1}$$

where $H\in\mathbb{C}^{N_r\times N_t}$ is the channel matrix, and $N\in\mathbb{C}^{N_r\times 1}$ is the additive white Gaussian noise. H and N have independent and identically distributed (i.i.d) entries according to $\mathscr{CN}(0,1)$ and $\mathscr{CN}(0,\ N_0)$, respectively.

3. Antenna selection based on pattern recognition

In order to solve the problem that only part of transmitting antennas are needed to transmit information in practice, some antenna selection algorithms are proposed to select the transmitting antennas that can achieve the best performance.

3.1. Conventional antenna selection

Among the traditional antenna selection algorithms, the EDAS method is most often used [7]. The main idea of the EDAS method is to maximize the minimum Euclidean distance.

Assume we need to select N_s transmitting antennas among N_t transmitting antennas, and $\mathbb{A}=\{a_1,\ldots,a_{N_c}\}$ is the set of all possible antenna combinations, where N_c is the number of antenna combinations, i.e., $N_c=\binom{N_t}{N_s}$. Assume that $\mathbb{X}$ is the set of all possible transmitting signal vectors, then the objective function of the EDAS can be written as

$$I_{ED} = \arg\max_{I\in\mathbf{A}}\left\{\min_{\mathbf{x}_1\neq\mathbf{x}_2}\|H_I(x_1-x_2)\|_2^2\right\} \tag{2}$$

where $H_I\in\mathbb{C}^{N_r\times N_s}$ is the submatrix that selects N_s columns from the channel matrix $H\in\mathbb{C}^{N_r\times N_t}$.

Though the EDAS can achieve an attractive BER performance in MIMO systems, its complexity is very high because of its exhaustive search process and large-dimensional signal space. Many related contributions have been made to reduce the complexity of the EDAS. For example, Ref. [8] proposed an EDAS with low complexity based on pairwise error probability; Ref. [9] reduced the search complexity based on the greedy incremental algorithm; Ref. [10] proposed an EDAS algorithm with low complexity based on the rotational symmetry of digital modulation constellations. However, some redundant computations still exist in the search process of these algorithms because all conventional TAS algorithms need to compute Eq. (2) at each time slot, and that may lead to repetitive computation when the channel matrixes of some time slots are the same or similar, which obviously means that these calculations are redundant.

3.2. Antenna selection based on pattern recognition

In order to avoid these redundant operations, Ref. [11] proposed a novel TAS algorithm based on pattern recognition, which is capable of obtaining the suitable antenna subset by classification instead of tedious calculation. The main process of this new TAS can be described as follows:

Firstly, the channel matrix samples are regarded as training data. Then a multiclass classification algorithm is employed to classify the channel matrix into some corresponding classes, where each class represents an antenna combination that provides the best performance. Finally, a classification model can be obtained and the classes of the new channel matrix can be predicted by this trained model.

To obtain the training set, there are three procedures: (a) design the training samples from channel matrixes; (b) design the KPI; (c) label based on the KPI.

(a) Generate Training Data: As mentioned above, the channel matrix is utilized to design the training samples, but it is hard to classify a two-dimensional complex-valued channel matrix accurately, so all channel matrices need to be manipulated for L real-valued features. Assume that there are M_s channel matrixes $H_{m_s} \in \mathbb{C}^{N_r \times N_t}$ as training samples, and each sample generates an $N_f \times 1$ dimensional real-valued feature vector d_{m_s}, then a training data matrix $D \in \mathbb{R}^{M_s \times L}$ is obtained by

$$D = \left[d_1^T, \ldots, d_{M_s}^T\right]^T$$

Finally, we normalize matrix D and generate a normalized feature matrix T, whose elements are normalized values of the elements of D as

$$t_{i,j} = \left(d_{i,j} - E_i\left(d_{i,j}\right)\right) \Big/ \left(\max_i\left\{d_{i,j}\right\} - \min_i\left\{d_{i,j}\right\}\right)$$

(b) Design KPI: The KPI is used to label the training samples. It can be defined as spectral efficiency, energy efficiency, BER, and so on. In this paper, the Euclidean distance of Eq. (2) is used as the KPI.

(c) Label: Assume that $\mathbb{L}$ is the set of labels, and we need to establish a one-to-one correspondence between $\mathbb{L}$ and $\mathbb{A}$, i.e., each antenna combination corresponds to one unique label. As Ref. [11] has pointed out, the less correlated antennas are more likely to be selected, so the antenna combinations could be reduced according to this principle. An example of mapping between labels and antenna combinations is shown in Table 1, where the bold typeface refers to the antenna combinations with less correlation. If the correlation information is unknown or the channels are uncorrelated, then all antenna combinations need to be included. For each channel matrix $\mathbf{H}_{m_s}$, we need to calculate the KPI of each antenna combination, then choose the antenna combination $a_{n^*} \in \mathbb{A}$ which can achieve the best KPI, and let the corresponded label l^* be the m_s-th element c_{m_s} of the label vector $\mathbf{c} \in \mathbb{R}^{M_s \times 1}$.

Table 1
Example of mapping between labels and antenna combinations, where $(N_t, N_r, N_s) = (6, 2, 2)$.

$l = 1, a_1 = [1, 2]$	$l = 2, a_2 = [1, 3]$	$l = 3, a_3 = [1, 4]$
$l = 4, a_4 = [1, 5]$	$l = 5, a_5 = [1, 6]$	$l = 6, a_6 = [2, 3]$
$l = 7, a_7 = [2, 4]$	$l = 8, a_8 = [2, 5]$	$l = 9, a_9 = [2, 6]$
$l = 10, a_{10} = [3, 4]$	$l = 11, a_{11} = [3, 5]$	$l = 12, a_{12} = [3, 6]$
$l = 13, a_{13} = [4, 5]$	$l = 14, a_{14} = [4, 6]$	$l = 15, a_{15} = [5, 6]$

With the normalized feature matrix T and the label vector $\mathbf{c}$ obtained by the above steps, we can build a learning system. In this paper, we make $\mathbf{t}_r[m_s]$ be the m_s-th row of $\boldsymbol{T}$ and employ the KNN and SVM algorithms to classify data, which are detailed as follows:

1) KNN: the KNN classifier finds k nearest training samples from the new sample t_r among M_s training samples, where the distance is defined as

$$d(t_r[m_s], t_r) = \|t_r[m_s] - t_r\|^2$$

Then, the KNN assigns the new sample into the class which has the most samples among the k training samples. It should be noted that the value of k would affect the performance of the KNN.

2) SVM: Assume that T_l is the submatrix of T, which is made of the rows of $\mathbf{T}$ that correspond to label l, then we generate a binary label vector:

$$b_l = [b_l[1], \ldots, b_l[M_s]]^T$$

where

$$b_l\left[m_s\right] = \begin{cases} 1, c_{m_s} = l \\ 0, else \end{cases} \tag{3}$$

Then the classification problem can be solved as follows:

$$\theta_l = \min_{\theta_l} C \sum_{m=1}^{M} \left[b_l\left[m\right] g_1\left(\theta_l^T f(t_r[m])\right) + (1 - b_l[m]) g_0\left(\theta_l^T f(t_r[m])\right)\right] + \frac{\|\theta_l\|^2}{2} \tag{4}$$

where C is the penalty parameter, and $g_k(z)$ is the cost function, which is defined as:

$$g_k(z) = \begin{cases} (-1)^k z + 1, (-1)^k z \geq -1 \\ 0, \text{else} \end{cases} \tag{5}$$

$\theta_l \in \mathbb{R}^{M \times 1}$ is the learning parameter vector, $\mathbf{f}(\mathbf{t}_r[m]) \in \mathbb{R}^{M \times 1}$ is the Gaussian radial-based kernel function vector, whose q-th element $f_q(\mathbf{t}_r[m])$ shows the similarity score between $\mathbf{t}_r[q]$ and $\mathbf{t}_r[m_s]$, and $f_q(\mathbf{t}_r[m])$ is defined as:

$$f_q(t_r[m]) = \exp\left(-\|t_r[q] - t_r[m]\|^2 / \left(2\sigma^2\right)\right) \tag{6}$$

The kernel function can affect the performance of the SVM algorithm, but the optimization of kernel function is beyond the scope of this paper and can be discussed in future work.

When all θ_l values are obtained, we can build a learning system based on Eq. (4). Once a new channel matrix is input, we can manipulate it to $t_r \in \mathbb{R}^{1 \times L}$ and output its label according to the SVM classifier, then the corresponding antenna combination is the final result we need.

It should be noted that the construction of feature d_{m_s} can affect the performance of classification. In Ref. [11], $\left|h_{i,j}\right|^2$ is used to construct d_{m_s}; and in this paper, we find a better construction. To be specific, we use $\left|h'_{i,j}\right|^2$ to construct the feature d_{m_s}, where $h'_{i,j}$ is the element of matrix $H^H H$. It is worth noting that $H^H H$ is similar to the definition of channel correlation matrix. Based on this feature, the procedures of the antenna selection algorithm based on the KNN and SVM algorithms are shown in Table 2.

Compared with the conventional antenna selection algorithms, the proposed antenna selection algorithm based on pattern recognition is capable of reducing many redundant computations, and hence can reduce the complexity imposed by the set search. Moreover, it does not need repetitive training unless the distribution of channel is changed.

Table 2
Antenna selection based on pattern recognition.

Algorithm 1. Antenna selection based on pattern recognition
Step 1. Build a map between labels and antenna combinations.
Step 2. Input M_s channel matrix samples, and manipulate them to normalized feature matrix **T**.
Step 3. For each sample $\mathbf{H}_{m_s}$, calculate the KPI according to Eq. (3), and obtain a label vector **c** according to the KPI.
Step 4. Build a learning system based on the KNN and SVM algorithms with the normalized feature matrix **T** and the label vector **c**.
Step 5. Input a new channel matrix, and manipulate it to the normalized feature vector $\mathbf{t}_r$, and obtain a label by the learning system.
Step 6. Output the label obtained in Step 5, and find the corresponding antenna combination according to the map built in Step 1, and the antenna combination we find is the final result.

Table 3
Comparison of the complexity of different antenna selection algorithms.

Algorithms	Complexity order
Conventional AS	$o(N_c N_r N_s + N_c \log N_c)$
AS based on KNN	$o(N_f)$
AS based on SVM	$o(N_f^2)$

4. Simulation results

In this section, the simulation results of some conventional TAS algorithms and the proposed PR-TAS aided MIMO algorithms are presented. The results are given as follows: Feature 1 means that the element norm of **H** is used as features, and Feature 2 means that the element norm of $\mathbf{H}^H\mathbf{H}$ is used as features in the classifiers. Moreover, the Zero-Forcing Successive Interference Cancellation (ZF-SIC) detection for the V-BLAST system [26–28] is applied in this paper.

The complexities of different TAS algorithms are compared in Table 3, where N_f is the length of feature vector. In our simulation, we have $N_f = N_r N_t$. It can be observed in Table 3 that the complexity of the TAS based KNN and SVM algorithms is lower than that of the conventional AS algorithm, especially when the number of antenna combinations N_c is large. Moreover, the complexity orders of the SVM and KNN based PR-TAS can be reduced by reducing the length of feature vector.

Fig. 1 shows the BER performance of the KNN-based PR-TAS with different values of k, where Feature 1 is used and the number of training samples is 5000. In this simulation, the setup is $(N_t, N_r, N_s) = (4, 2, 2)$ and the BPSK is adopted. It can be observed in Fig. 1 that the performance of the KNN-based PR-TAS would fluctuate when the value of k is changed, but the fluctuation is not obvious.

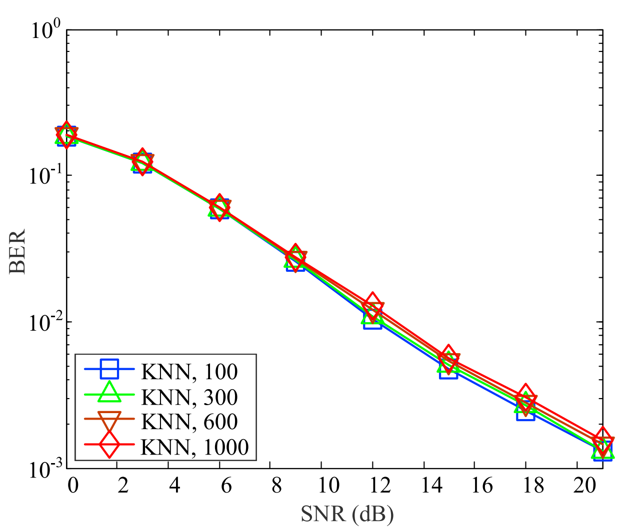

Fig. 1. BER performance of KNN with different k, $(N_t, N_r, N_s) = (4, 2, 2)$, BPSK.

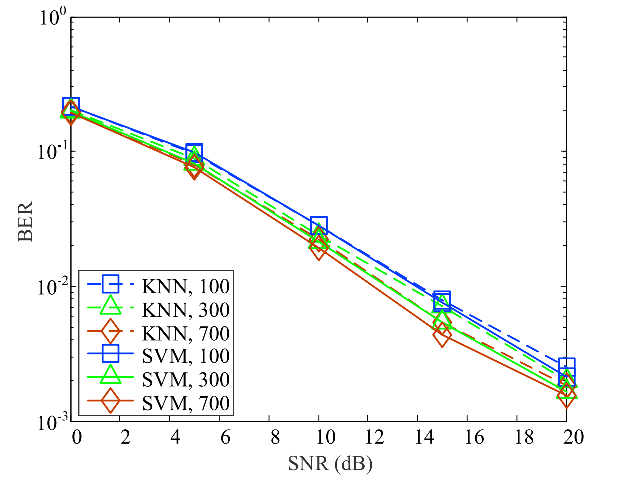

Fig. 2. BER performance of KNN and SVM with different numbers of training samples, $(N_t, N_r, N_s) = (4, 2, 2)$, BPSK.

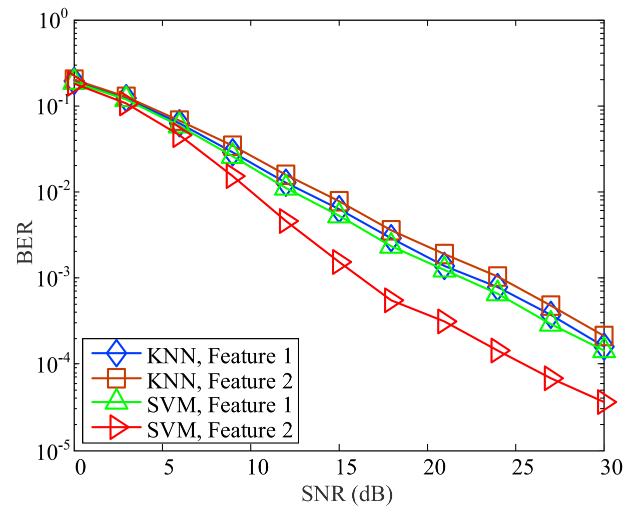

Fig. 3. BER performance of KNN and SVM with different features, $(N_t, N_r, N_s) = (4, 2, 2)$, BPSK.

Fig. 2 gives the BER performance of the KNN algorithm and SVM algorithm with different number of training samples, where Feature 1 is used, $(N_t, N_r, N_s) = (4, 2, 2)$, the BPSK is adopted, and k is set as one-fifth of the training samples for the KNN. It can be observed that the BER performance can be improved with the increase of the number of training samples. In the rest of the simulation, we set the number of training samples as 5000 in order to guarantee the performance.

The antenna selection based on the KNN and the SVM with different features are shown in Figs. 3 and 4, and the parameters are set as: $k = 100$ for the KNN, $(N_t, N_r, N_s) = (4, 2, 2)$, and the modulations are BPSK and QPSK respectively. In this paper, the correlation of channels is not considered, i.e., the set $\mathbb{A}$ is constructed with all antenna combinations. From Figs. 3 and 4, it can be observed that the performance of the SVM-based PR-TAS is better than that of the KNN-based PR-TAS, and the performance of the SVM-based PR-TAS with Feature 2 is much better than that of the SVM-based PR-TAS with Feature 1, but for the KNN algorithm, the performance generated by these two features is similar.

Figs. 5 and 6 compare the BER performance of different TAS algorithms for the V-BLAST system, where the parameters are given as $(N_t,$

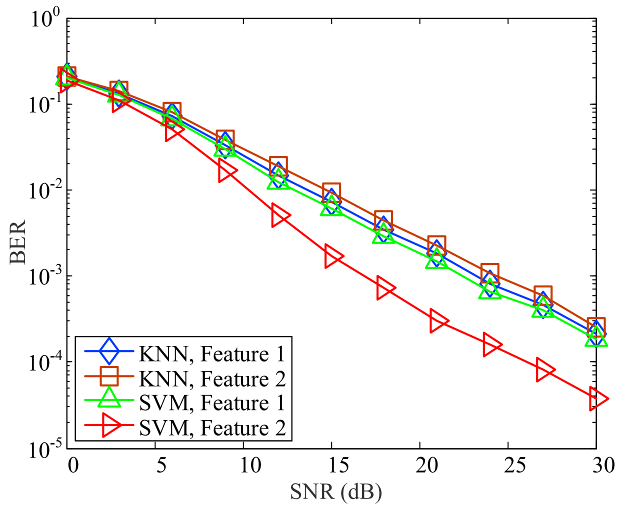

Fig. 4. BER performance of KNN and SVM with different features, $(N_t, N_r, N_s) = (4, 2, 2)$, QPSK.

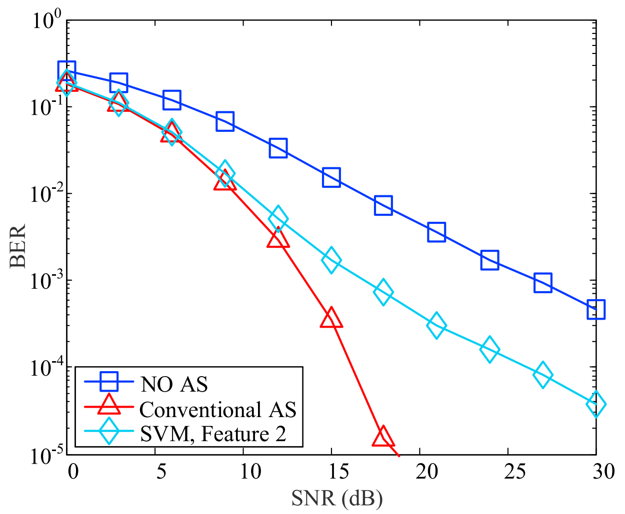

Fig. 5. BER performance of different AS algorithms, $(N_t, N_r, N_s) = (4, 2, 2)$, QPSK.

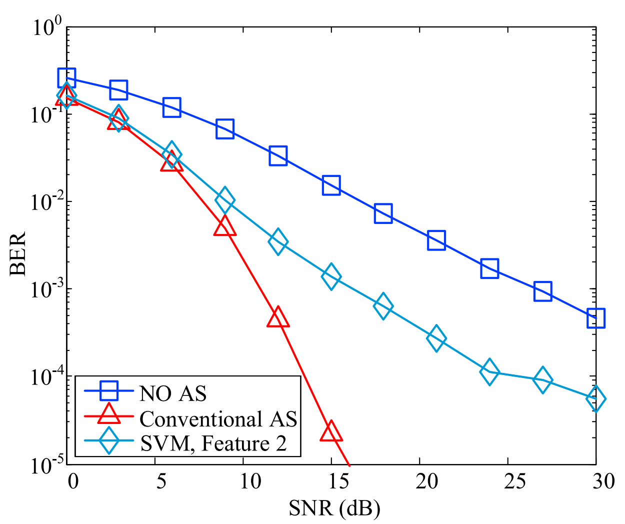

Fig. 6. BER performance of different AS algorithms, $(N_t, N_r, N_s) = (6, 2, 2)$, QPSK.

$N_r, N_s) = (4, 2, 2)$ and $(N_t, N_r, N_s) = (6, 2, 2)$, respectively. Moreover, QPSK is employed in these figures. The legendary "NO AS" is the conventional V-BLAST system with $(N_t, N_r) = (2, 2)$. It can be observed from Figs. 5 and 6 that the performance of the proposed antenna selection based on the SVM is much better than that of the conventional multiplexing scheme without TAS. Also, we find that the PR-based TAS may produce some performance loss compared with the exhaustive-search based TAS, but it can be improved by using more efficient feature vectors and more powerful classifiers. This topic will be considered in our future research.

5. Conclusion

In this paper, we optimize the feature extraction for the antenna selection algorithm based on pattern recognition. The simulation results show that the new feature can achieve a better performance. Moreover, it is found that the complexity of the PR-TAS aided MIMO is much lower than that of the conventional AS algorithm, therefore it can be an attractive candidate for the future link adaptive MIMO systems.

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