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# An Improved SVM-Based Spatial Spectrum Sensing Scheme via Beamspace at Low SNRs

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**ABSTRACT** Most spectrum sensing algorithms mainly use the characteristics of frequency, time, and geographical dimensions to detect spectrum holes. In this paper, we propose a novel spectrum sensing scheme from the space domain by using beamspace transformation and the support vector machine technology. First, a model of beamspace transformation is proposed for the case of complex calculations in a sizeable multi-antenna system. This beamspace transformation has the ability of spatial filtering, which can not only decrease the dimension of the receive matrix but also enhance the signal to noise ratio of the received signal. Then, we employ the support vector machine classification to overcome the problems caused by the inherent threshold of traditional sensing algorithms. We only need to train the historical samples to distinguish between noise and primary user signals effectively. This classification algorithm has self-learning ability, which can adaptively adjust the classification hyperplane according to environmental changes without complex threshold calculation. Finally, simulation results show that the proposed scheme outperforms other related multi-antenna sensing algorithms, especially under low signal to noise ratio and low snapshot.

**INDEX TERMS** Cognitive radio, spatial spectrum sensing, support vector machine, beamspace transformation.

## I. INTRODUCTION

In recent decades, with the popularity of Internet-of-Things (IoT) technology, the scarce spectrum resources have become more valuable. In order to advocate the concept of green communication and green IoT, network resource sharing has become a new trend. Cognitive radio (CR) has come into being to solve the shortage of spectrum resources [1], [2]. CR [3] can dynamically sense the spectrum allocation of the surrounding environment and utilize the idle spectrum accordingly, thereby improving spectrum utilization. An efficient and reliable IoT system model can be constructed based on CR technology [4]. Therefore, CR technology can provide substantial spectrum opportunities for IoT devices for efficient large-scale IoT deployment [5]. In recent years, CR has been also widely used in vehicular network and communication security [6]–[8].

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Under the traditional policy, primary users (PUs) own fixed spectrums for exclusive use, while secondary users (SUs) cannot access those spectrums even when they are unoccupied. As one of the significant technologies in CR, spectrum sensing can help SUs to detect whether PUs are using the current spectrum. Once the PU signal does not exist, the SU can access the current spectrum for communication, and the spectrum utilization will also be increased. Although the theory of spectrum sensing has matured, with the increasing demand for communication quality, the study of spectrum sensing technology in low signal to noise ratio (SNR) and low sampling snapshot environment has become one of the current topics.

Traditional spectrum sensing algorithms include matched filter, energy detection (ED), and cyclostationary feature detection. The ED algorithm is widely employed because it has low computational complexity and does not require any prior knowledge about PUs [9]. However, at low SNR, its detection capability is severely degraded due to the influence of noise uncertainty [10]. Many recent approaches were introduced to surmount the effects of noise uncertainty. Authors in [11] proposed to decrease the noise uncertainty to minimal level by co-estimating the noise intensity [12]. Matching filtering [13] and cyclostationary detection [14] have high sensing performance, but both of them require prior information. Such algorithms are difficult to apply to actual scenarios because the information of PUs is generally unknown. The relevant characteristics of the received signal can be reflected by the sample covariance matrix and its eigenvalues with the development of multi-antenna technology, which can be used as the test statistic of spectrum sensing [15], [16]. The maximum-minimum eigenvalue detection (MME) [17] is robust to noise and does not require any prior information from the PU. Assuming that the dimension of the covariance matrix and the sampling number are infinite, the performance of the MME algorithm is optimal. However, this impractical assumption makes the actual detection threshold and the real threshold have errors, which led the MME algorithm is restricted in practice [18]. Authors in [19] presented a dynamic matching scheme to overcome the problem of fixed threshold. The spectrum sensing schemes [20], [21] based on Cholesky decomposition were proposed to overcome the difficulty of decision thresholds [22]. Authors in [15] designed a semi-blind maximum eigenvalue-based goodness-of-fit (GoF) detection scheme using the ratio of the maximum eigenvalue to the noise power. A multiple antenna sensing scheme was proposed in [23] using the higher-order moments of eigenvalues.

In the concept of CR, cognitive devices have the capacity to self-learn and recognize the surrounding environment. So, researchers naturally apply machine learning and neural networks to spectrum sensing. Authors in [24] trained the Artificial Neural Network model for spectrum sensing with the test statistic obtained by the ED algorithm and the cyclic characteristic algorithm. A blind spectrum sensing method based on deep learning was proposed that used three kinds of neural networks together, namely convolutional neural networks, long short-term memory, and fully connected neural networks [25]. In [26], the authors introduced Support Vector Machine (SVM) algorithm to distinguish the presence or absence of signals. Thilina et al. applied SVM classification and $K$-Nearest Neighbors (KNN) to spectrum sensing [27]. However, [26] and [27] do not make full use of the characteristics of the signal. Therefore, authors in [22] trained the characteristics obtained by Cholesky decomposition to achieve better performance. Genetic algorithm was also used for spectrum sensing in [28].

The aforementioned methods are analyzed from the frequency or time domain, but the spatial properties are not fully utilized. The spatial sensing algorithm is proposed to detect spectrum holes while acquiring relevant information of spectrum holes. SUs can access from different angles at the same frequency and time, so as not to interfere with the primary user. Traditional methods [29]–[31] divided detection and positioning into two phases. However, these algorithms only combine traditional spectrum sensing algorithms with spatial positioning algorithms, and they do not fully consider the inherent characteristics of the spatial signal [32]. In order to overcome these problems, authors in [32] proposed a new spatial spectrum sensing scheme by constructing new test statistic using the noise features in angle estimation. A novel spectrum sensing technique based on the higher-order statistics of spatial samples was proposed in [33]. Similarly, multiple signal classification (MUSIC) was applied to spatial spectrum sensing in [34]. However, authors in [34] did not give a reasonable threshold derivation scheme, and the computational complexity would increase exponentially as the number of array elements increases.

A novel spatial spectrum sensing scheme based on beamspace transformation and SVM classification algorithm is proposed in our paper, considering the problems of the above-mentioned spectrum sensing algorithms, especially the poor detection performance under low SNRs and low sampling snapshots. Specifically, the main contributions of this paper are as follows.

- Beamspace transformation is performed on the received signal matrix, based on [34]. The proposed beam transformation model can improve the output signal-to-noise ratio in the observation range while reducing the matrix dimension. On the other hand, it has the effect of suppressing out-of-band interference.
- Employing the SVM classification algorithm not only solves the threshold problem in [34] but also improves the classification accuracy by adjusting the parameters. The proposed scheme can adapt to various environments and can effectively distinguish between signals and noise because of its self-learning ability.
- The simulation results show that the proposed scheme has more significant detection performance under low SNRs and low snapshots conditions. The method can obtain the angle information of PUs while detecting the spectrum hole, which can greatly improve spectrum utilization.

The rest of the research is organized as follows. A multiple-antenna system model of spatial spectrum sensing is presented in section II. In section III, we first propose a beamspace transformation model and its construction method. Secondly, we analyze the shortcomings of the traditional threshold construction and present the SVM classification algorithm. Finally, the specific steps of our scheme are proposed. Section IV verifies the significant performance of the proposed algorithm through simulation comparisons and analyses. The conclusions are summarized in Section V.

## II. SPATIAL SPECTRUM SENSING

### A. SYSTEM MODEL OF SPATIAL SPECTRUM SENSING

Suppose that there is an isotropic uniform linear array (ULA) with $M$ antennas, and the spacing of array elements is $d \leq \lambda_s/2$, where $\lambda_s$ denoting the wavelength of the source signal. When $K$ narrow-band far-field signals are incident on the uniform linear array, they can be approximately regarded

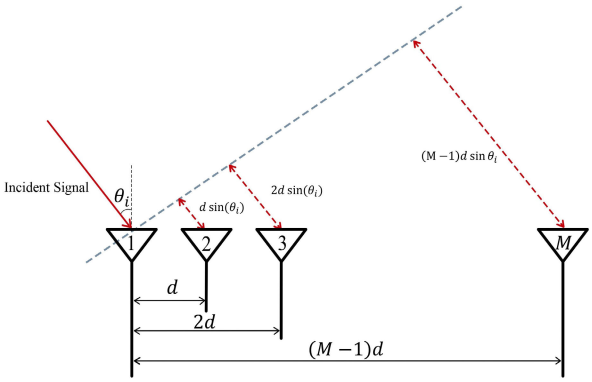


**FIGURE 1.** **The receive model of the multi-antenna system.**

as plane waves. Therefore, when signals arrive at different array elements, they will generate equidistant wave-path differences, resulting in equal interval delays. A typical receive model of the multi-antenna system is shown in Fig.1, and we can use this time delay characteristics for array signal processing.

$\theta_i(i = 1, 2, \cdots, K)$ denotes the direction of arrival (DOA) of the source signals in Fig 1. So the model of the received signals can be expressed as

$$\mathbf{Y}(t) = \mathbf{AS}(t) + \mathbf{N}(t), \tag{1}$$

where $t$ indicates the time index for sampled signals. In addition, $\mathbf{A} = [\mathbf{a}(\theta_1), \mathbf{a}(\theta_2), \ldots, \mathbf{a}(\theta_K)]$ is the steering matrix composed of steering vectors. The steering vector is given by $\mathbf{a}(\theta_i) = \left[1, e^{-j\frac{2\pi d}{\lambda}\sin(\theta_i)}, \ldots, e^{-j\frac{2\pi d}{\lambda}(M-1)\sin(\theta_i)}\right]^T$, where $[\cdot]^T$ denotes the transpose operator. $\mathbf{S}(t) = [s_1(t), s_2(t), \ldots, s_K(t)]^T$ and $\mathbf{N}(t) = [n_1(t), n_2(t), \ldots n_M(t)]^T$ denote the source signals and the zero-mean white Gaussian noise vectors whose variance is $\sigma^2$. Similarly, $\mathbf{Y}(t) = [y_1(t), y_2(t), \ldots, y_M(t)]^T$ represents the received signals matrix, and $y_i(t)$ denotes the signal received by the $i$-th array element. Meanwhile, we generally assume that the source signals are not correlated with noise.

In general, spectrum sensing can be replaced by a binary hypothesis test problem, that is, condition $H_0$ indicates that the PU signal does not exist, and $H_1$ stands for the opposite. According to the above system model, the following judgment can be obtained

$$\mathbf{Y}(t) = \begin{cases} \mathbf{N}(t), & H_0 \\ \mathbf{AS}(t) + \mathbf{N}(t), & H_1 \end{cases} \quad t = 1, 2, \ldots N. \tag{2}$$

$N$ is the number of sampling snapshots.

## B. WEIGHTED SUBSPACE MULTIPLE SIGNAL CLASSIFICATION ALGORITHM

The weighted subspace multiple signal classification (WMUSIC) algorithm improves the classical DOA estimation algorithm-MUSIC algorithm to achieve spatial spectrum sensing without any prior knowledge. This algorithm eigen-decomposes the covariance matrix of the received signals and sorts the eigenvalues and the corresponding eigenvectors according to the eigenvalue size. The eigenvectors corresponding to the first $K$ large eigenvalues constitute the signal subspace, and the rest of the eigenvectors is the noise subspace, which is orthogonal to the signal subspace.

According to (1), the covariance matrix of the received signals is

$$\mathbf{R}_y = \mathbf{AR}_s\mathbf{A}^H + \sigma^2\mathbf{I}_M, \tag{3}$$

where $\mathbf{R}_s$ and $[\cdot]^H$ denote the covariance matrix of the source signals and the conjugate transposition, respectively. Ideally, if we sort the eigenvalues obtained by eigen-decomposing $\mathbf{R}_y$, we can get $K$ large eigenvalues and $M-K$ small eigenvalues. Correspondingly,$\mathbf{U}_s = [\mathbf{u}_1, \mathbf{u}_2, \ldots \mathbf{u}_K]$ and $\mathbf{U}_n = [\mathbf{u}_{K+1}, \mathbf{u}_{K+2}, \ldots \mathbf{u}_M]$ represent the signal subspace and noise subspace spanned by the signal eigenvectors and the noise eigenvectors, respectively. Because the noise subspace is orthogonal to the signal subspace, we can easily derive from the derivation in [34]

$$\mathbf{A}^H\mathbf{U}_n = 0. \tag{4}$$

So, the expression of MUSIC algorithm can be expressed as

$$P_{MUSIC} = \frac{1}{\mathbf{a}^H(\theta)\mathbf{U}_n\mathbf{U}_n^H\mathbf{a}(\theta)}. \tag{5}$$

Traditional MUSIC algorithm needs to know the number of source signals to get accurate noise subspace $\mathbf{U}_n$, but for spectrum sensing, it is difficult to know the number of sources. Therefore, we can adjust the proportion of noise subspace by weighting eigenvectors according to [34]. The eigenvectors space of the received signals are redefined as

$$\mathbf{U} = [\frac{1}{\lambda_1^\alpha}\mathbf{u}_1, \frac{1}{\lambda_2^\alpha}\mathbf{u}_2, \ldots, \frac{1}{\lambda_M^\alpha}\mathbf{u}_M]. \tag{6}$$

where $\alpha(\alpha > 0)$ represents the weighted coefficient and $\lambda_i(i = 1, 2, \ldots M)$ is eigenvalue. Because the eigenvalues of the noise subspace are extremely smaller than those corresponding to the signal subspace, multiplying the $i$-th eigenvector by $\frac{1}{\lambda_i^\alpha}$ can suppress the signal subspace components and enhance the noise subspace components at the same time. Increasing $\alpha$ can suppress the signal subspace, but reduce the peak value at the same time. Therefore, a reasonable $\alpha$ should be set according to actual needs. Then we can replace $\mathbf{U}_n$ in (5) by the weighted eigenvector space $\mathbf{U}$ to avoid estimation of the number of sources. Similarly, the expression of WMUSIC algorithm can be expressed as

$$P_{WMUSIC} = \frac{1}{\mathbf{a}^H(\theta)\mathbf{U}\mathbf{U}^H\mathbf{a}(\theta)}. \tag{7}$$

The geometric meaning of this expression is that once a signal is present, its spatial spectrum curve will show a significant peak at the incident angle of the signal. The curve approaches zero when there is no incident signal. According to the difference of spatial spectrum curve in the presence or absence of signals, the maximum-minimum spectrum

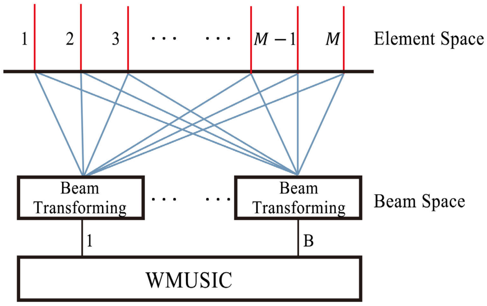


**FIGURE 2.** The model of beamspace transformation.

ratio detection algorithm can be designed as

$$T_{WMUSIC} = \frac{\max(P_{WMUSIC})}{\min(P_{WMUSIC})} \begin{matrix} > \tau & H_1 \\ \leq \tau & H_0 \end{matrix}. \tag{8}$$

That is to say, the test statistic $T_{WMUSIC}$ is maximum-minimum spectrum ratio obtained by WMUSIC algorithm. When $T_{WMUSIC}$ is greater than the threshold $\tau$, $H_1$ is proved to be true. Otherwise it is determined that there is no signal in the current spectrum.

## III. IMPROVED SPECTRUM SENSING SCHEME USING BEAMSPACE AND SVM

The improved spectrum sensing scheme is proposed in this section. The contribution of the improved scheme mainly includes beamspace transformation and SVM classification. Therefore, relevant theories about SVM and beamspace will be introduced below respectively. Finally, the implementation steps of the improved scheme are proposed.

### A. BEAMSPACE WMUSIC ALGORITHM

The WMUSIC algorithm needs to decompose the covariance matrix of the received signals, and its computational complexity is $O(M^3)$. Therefore, for large arrays and few signal sources, such algorithms are difficult to implement in real-time and are susceptible to interference signals. Beamspace transformation can effectively solve the above problems. The beamspace transformation refers to synthesizing the $M$-dimensional array element signal into a B-dimensional beamspace signal by beamforming technology, and then replacing the array element signal with the beamspace signal for subsequent processing. The algorithm model is shown in Fig 2.

In brief, beamspace transformation can be seen as a spatial domain filter, which can effectively receive the target signal of the sector of interest angle while suppressing noise and interference in other directions (out-of-band), thus improving the signal-to-noise ratio. At the same time, for large arrays (the number of array elements is as high as tens or even hundreds), beamspace transformation can effectively reduce the signal dimension and reduce the complexity of the operation, which is of great significance in engineering practice.

The MUSIC algorithm requires that the number of array elements is larger than the number of source signals to estimate the directions of the signals accurately. Assuming $B$ is the number of beams, then $B$ should satisfy $K \leq B \leq M$. Beamspace transformation of received signals can be expressed as

$$\mathbf{Y}_B(t) = \mathbf{T}^H \mathbf{Y}(t). \tag{9}$$

$\mathbf{T}$ is an $M \times B$-dimensional beam transformation matrix. Its function is to transform the original $M \times N$-dimensional received signal $\mathbf{Y}(\mathbf{t})$ into $B \times N$-dimensional beamspace signal through beamspace preprocessing. It should be emphasized that the beam transformation matrix $\mathbf{T}$ should be an orthogonal matrix, which should satisfy $\mathbf{T}^H\mathbf{T} = \mathbf{I}$. In some applications, the beam transformation matrix does not satisfy the orthogonal condition, so the following transformation should be used to turn it into an orthogonal matrix

$$\mathbf{T}_0 = \mathbf{T}\left(\mathbf{T}^H\mathbf{T}\right)^{-\frac{1}{2}}. \tag{10}$$

#### 1) BEAMSPACE WMUSIC

According to the model in Fig. 2, an improved WMUSIC algorithm based on beamspace transformation is proposed. The beam transformed received signal matrix can be expressed as

$$\mathbf{Y}_B(t) = \mathbf{T}^H\mathbf{A}\mathbf{S}(t) + \mathbf{T}^H\mathbf{N}(t). \tag{11}$$

Accordingly, the covariance matrix of the received signals can also be expressed as

$$\mathbf{R}_y = \mathbf{T}^H\mathbf{A}\mathbf{R}_s\mathbf{A}^H\mathbf{T} + \sigma^2\mathbf{I}. \tag{12}$$

Then the expression of the beamspace WUISC algorithm (BWUSIC) is

$$P_{BWMUSIC} = \frac{1}{\mathbf{a}(\theta)^H\mathbf{T}\mathbf{U}\mathbf{U}^H\mathbf{T}^H\mathbf{a}(\theta)}. \tag{13}$$

It is not difficult to see that the performance of the algorithm is affected by the beam transformation matrix $\mathbf{T}$. Constructing a reasonable beam transformation matrix can effectively suppress interference and improve the accuracy of the algorithm. So, it is necessary to discuss how to construct the beam transformation matrix $\mathbf{T}$ in the following part.

#### 2) CONSTRUCTION OF BEAM TRANSFORMATION MATRIX

Assuming that $\sin(\theta_i) = v_i$, the steering vector can be written as

$$\mathbf{a}(\theta_i) = [1, e^{-j\frac{2\pi d}{\lambda}v_i}, \ldots, e^{-j\frac{2\pi d}{\lambda}(M-1)v_i}]^T. \tag{14}$$

In addition, consider the vector consisting of the $M$-point discrete Fourier transform factors

$$\mathbf{F} = [1, e^{-j2\pi/M}, \ldots e^{-j2\pi(M-1)/M}]^T. \tag{15}$$

The steering vector is also a form of DFT, and the DFT of the $t$ snapshots data can be expressed as

$$f(v,t) = \sum_{k=0}^{M-1} x_k(t)e^{-jk\pi v} = \mathbf{a}_M^H(v)\mathbf{x}(t), \tag{16}$$

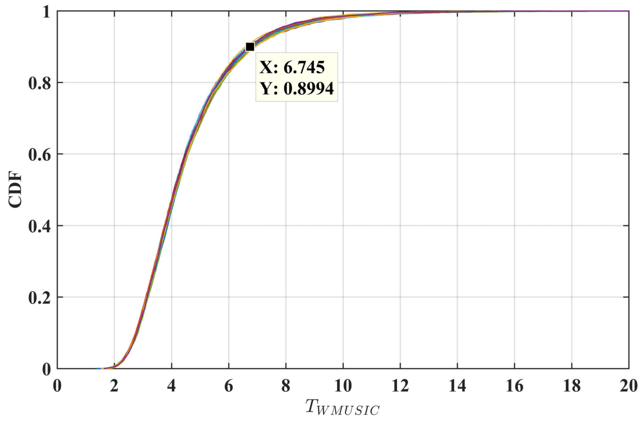


**FIGURE 3.** The CDF of $T_{BWMUSIC}$.

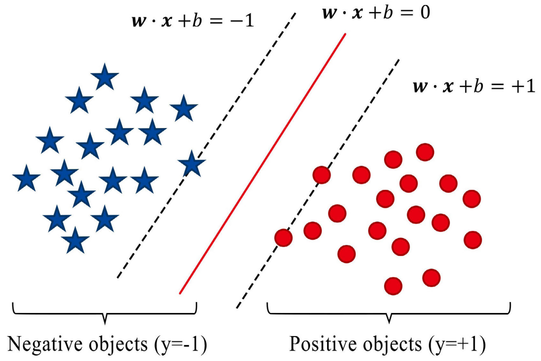


**FIGURE 4.** The model of the support vector machine.

where $x_k(t)$ is the data received by the $k$-th element at the $t$-th snapshot. The steering vector is actually a beamformer with the main lobe pointing to $v = \sin(\theta)$. When the angle interval is $-90 \leq \theta \leq 90$, the interval corresponding to $v$ is $-1 \leq v \leq 1$. Apparently, $f(v;t)$ is a periodic function of $v$ with a period of 2, assuming that $t$ is fixed. If the spacing of array elements is not half wavelength, the period should be $\lambda/d$.

A beamspace transformation $\mathbf{T}$ matrix can be constructed by continuously extracting $B$ DFT beamforming vectors from (15) and performing normalized weighting.

$$\mathbf{T} = \frac{1}{\sqrt{M}}[\mathbf{a}(m\frac{2}{M}), \mathbf{a}((m+1)\frac{2}{M}), \cdots, \mathbf{a}((m+B-1)\frac{2}{M}))]. \tag{17}$$

$m$ represents the position of the starting beam. The pointing angle interval of each beam is $\Delta v = 2/M$.

### B. SUPPORT VECTOR MACHINE

Traditional spectrum sensing algorithms need to set a fixed decision threshold that was restricted in practice. It is commonly used to estimate the corresponding decision threshold by giving a false alarm probability $P_f$. The definition of false alarm is as follows

$$P_f = P(H_1|H_0) = P(T_{BWMUSIC} > \tau|H_0). \tag{18}$$

The cumulative distribution function(CDF) of $T_{BWMUSIC}$ is

$$\begin{aligned} F_{H_0}(T_{WMUSIC} = \tau) &= P(T_{WMUSIC} \leq \tau|H_0) \\ &= 1 - P(T_{WMUSIC} > \tau|H_0) \\ &= 1 - P_f. \end{aligned} \tag{19}$$

Therefore, assuming $P_f = 0.1$, the decision threshold is the value of the abscissa corresponding to $F_{H_0}(T_{WMUSIC} = \tau) = 0.9$ under $H_0$ condition. The CDF curve can be obtained by multiple Monte Carlo simulations assuming that there are only different intensity noises. Fig. 3 is the CDF curve of $T_{WMUSIC}$.

It can be seen from Fig. 3 that the decision threshold $\tau$ is 6.745 under the condition of $P_f = 0.1$. The detection accuracy of the algorithm is related to the accuracy of the decision threshold. However, the decision threshold is easily influenced by surroundings so that the method needs huge calculation complexity to adapt to the real changing environment. All in all, the traditional threshold selection method can neither adaptively adjust the threshold value with environmental changes nor guarantee a high detection accuracy for each threshold due to artificial selection error. Therefore, an adaptive decision method is presented in this paper that exploits SVM theory to implement spectrum sensing.

SVM is a supervised classification algorithm in machine learning with the purpose of finding the optimized hyperplane of linearly separable feature vectors to maximize margin for generalization ability while minimizing the misclassification error [35].

As is shown in Fig.4, the binary hypothesis problem in spectrum sensing can be replaced with binary classification. The red circle and the blue star in Fig.4 represent the samples that indicate the existence or absence of the signals, respectively. The SVM trains the original data set containing the state information of the signal and optimizes the hyperplane by tuning the parameters to obtain the optimal classification accuracy.

Suppose the training set can be represented as $\mathbf{D} = \{(T_{WMUSIC_i}, f_i)\,|i = 1, 2, \cdots, L\}$, where $L$ denotes the number of training set. $f_i \in \{-1, 1\}$ is called label, indicating the hypothesis $H_0$ or $H_1$ corresponding to the test statistic $T_{WMUSIC}$. The classification hyperplane can be represented as

$$\mathbf{w} \cdot \varphi(T_{WMUSIC}) + b = 0, \tag{20}$$

where $b$ and $\mathbf{w}$ denote the bias and the weighting vector respectively. $\varphi(T_{WMUSIC})$ denotes the mapping function which maps $T_{WMUSIC}$ into a high dimensional space. Therefore, the conditions below are satisfied by the classifier for

$$\mathbf{w} \cdot \varphi(T_{WMUSIC_i}) + b \geq 1, \quad if\ f_i = 1. \tag{21}$$

$$\mathbf{w} \cdot \varphi(T_{WMUSIC_i}) + b \leq -1, \quad if\ f_i = -1. \tag{22}$$

The received signal is inevitably affected by noise, so the data set satisfying linear separability is not practically feasible. A slack variable $\xi_i$ is introduced in [36] to form the soft margin hyperplane to accommodate linear indivisible data. Assuming the slack variable $\xi_i \geq 0$, the constraint condition after introducing $\xi_i$ is amended as

$$f_i\left[\left(\mathbf{w}\cdot\varphi(T_{WMUSIC_i})+b\right)\right] \geq 1-\xi_i,\quad \xi_i \geq 0, i=1,2,\cdots L. \tag{23}$$

When the classification is wrong, $\xi_i > 0$. Therefore, $\sum_{i=1}^{L}\xi_i$ is the upper bound of the classification error in the training set. Then, the above constraint problem can be transformed into a convex optimization problem

$$\min_{\mathbf{w}} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{L}\xi_i$$
$$s.t. f_i\left[\left(\mathbf{w}\cdot\varphi(T_{WMUSIC_i})+b\right)\right] \geq 1-\xi_i,\quad \xi_i \geq 0,\quad i=1,2,\cdots L, \tag{24}$$

where $C$ is the penalty factor that can be used to control the degree of penalty for classification error. It takes into account the empirical risk and confidence range, and it can also compromise the minimize misclassified samples and the maximum classification interval. The solution to the optimization problem is the saddle point of the following Lagrangian norm function

$$L_a(\mathbf{w},b,\alpha,\beta) = \frac{1}{2}\|\mathbf{w}\|^2 + C\left(\sum_{i=1}^{L}\xi_i\right) - \sum_{i=1}^{L}\alpha_i\left\{f_i\left[\left(\mathbf{w}\cdot\varphi(T_{WMUSIC_i})\right)+b\right]-1+\xi_i\right\} - \sum_{i=1}^{L}\beta_i\xi_i. \tag{25}$$

$\alpha_i$ and $\beta_i$ are Lagrangian multipliers, which are non-negative. Calculate the partial derivative of $L_a$ with respect to $\mathbf{w}$, $b$,and $\xi$. From $\frac{\partial L_a}{\partial \mathbf{w}} = 0$, $\frac{\partial L_a}{\partial b} = 0$, and $\frac{\partial L_a}{\partial \xi} = 0$ we can get

$$\mathbf{w} = \sum_{i=1}^{L}\alpha_i f_i\varphi(T_{WMUSIC_i}) \tag{26}$$

$$\sum_{i=1}^{L}\alpha_i f_i = 0 \tag{27}$$

$$\alpha_i + \beta_i = C,\quad i=1,2,\cdots,L \tag{28}$$

So, the above problem can be replaced by following dual optimization problem

$$\max_a -\frac{1}{2}\sum_{i=1}^{L}\sum_{j=1}^{L}\alpha_i\alpha_j f_i f_j K(T_i,T_j) + \sum_{i=1}^{L}\alpha_i$$
$$s.t. 0 \leq \alpha_i \leq C, i=1,2,\cdots L \quad and \sum_{i=1}^{L}\alpha_i f_i = 0, \tag{29}$$

where $K(T_i,T_j) = \varphi(T_{WMUSIC_i})\cdot\varphi(T_{WMUSIC_j})$ is the kernel function which denotes a legitimate inner product in eigen space. In practical applications, most of the data are linearly inseparable, but nonlinearly separable. Therefore, a kernel function $K(T_i,T_j)$ is the best way to solve the problem of nonlinear classification by transforming the original train set into a higher dimensional space. Some commonly used kernel functions are linear, polynomial, sigmoid, and Gaussian radial basis function (RBF).

The problem at hand has a unique solution due to applying the Karush-Kuhn-Tucker (KKT) conditions. After solving (29), the final decision function is given as

$$F(T_{WMUSIC}) = sgn[\sum_{i=1}^{L} f_i\alpha_i K(T_i,T_j)+b], \tag{30}$$

where $sgn$ denotes the Signum function. Finally, we can give a specific spectrum sensing algorithm scheme.

Step 1: Perform beamspace transform on the received signal matrix according to (9) to obtain $\mathbf{Y}_B$.

Step 2: Calculate the covariance matrix of $\mathbf{Y}_B$. Due to the finite number of snapshots in practice, we can only obtain the sample covariance matrix $\hat{\mathbf{R}}_B$

$$\hat{\mathbf{R}}_B = \frac{1}{N}\sum_{n=0}^{N}\mathbf{Y}_B(n)\mathbf{Y}_B^H(n). \tag{31}$$

Step 3: Eigen-decomposes the covariance matrix $\mathbf{Y}_B$ and calculate the weighted signal space $\mathbf{U}$ according to (6).

Step 4: Calculate the value $P_{WMUSIC}(\theta_i)$ of each search angle $\theta_i$ by peak search, and then find out the maximum and minimum values of $P_{WMUSIC}(\theta_i)$. Then, calculate the statics $T_{test}$ according to (8).

Step 5: Generate the SVM classification model using the training set $\mathbf{D} = \left\{\left(T_{WMUSIC_i}, f_i\right)|i=1,2,\cdots,L\right\}$ obtained by simulation experiments. Make the model achieves higher classification accuracy by selecting the kernel function and adjusting the related parameters.

Step 6: Generate the prediction model with the statistic $T_{test}$ and trained model. If the predicted result is "+1", the PU signal exists. Otherwise, "-1" indicates no signal.

## IV. SIMULATION COMPARISONS AND ANALYSES

This section provides the numerical simulations and result analyses based on the ULA system. All of the simulations are assumed to be implemented in an ideal wireless environment. Wireless signals are simulated in BPSK modulation. The element spacing of the receive array defaults to half-wavelength ($d = \lambda/2$). The noise at the receive antenna is additive white Gaussian noise. Some simulation results which need to do the Mentor Carlo experiment are obtained by at least 1000 times independent experiments.

### A. PERFORMANCE ANALYSIS OF BEAM TRANSFORM ALGORITHMS

Generally speaking, for beamspace transformation, it is hoped that the signal can be well received in the range of observation angle, while the signal outside the range of observation angle can be suppressed. We can evaluate the

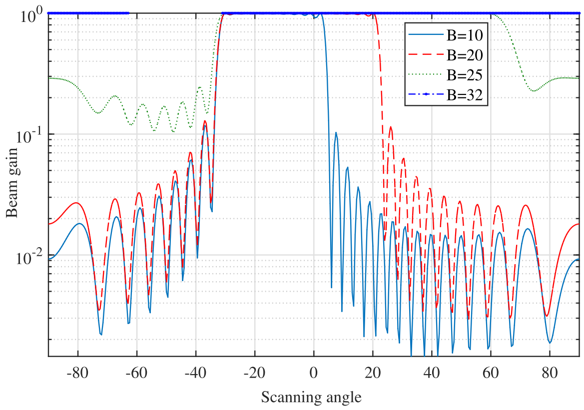


**FIGURE 5.** The beam gain curve of the proposed algorithm with different beam numbers.

performance of the beam transformation based on the beam gain, which is defined as follows

$$g(\theta) = \frac{\mathbf{a}^H(\theta)\mathbf{T}\mathbf{T}^H\mathbf{a}(\theta)}{\mathbf{a}^H(\theta)\mathbf{a}(\theta)}. \tag{32}$$

Since the beam transformation matrix $\mathbf{T}$ satisfies $\mathbf{T}^H\mathbf{T} = \mathbf{I}$, the beam gain is generally less than 1. Therefore, a good beam transform matrix should be such that the beam gain of the detection range approaches 1 and is as small as possible outside the detection range.

Figure 5 shows the beam gain curve of the proposed method in different beam numbers. Assuming that the starting angle is constant, increasing the number of beams can increase the range of observation angles. However, the slide lobes outside the observation range also increase as the number of beams increases, and the performance of interference suppression will reduce. We can flexibly set a reasonable number of beams and observation range according to the needs of the real detection environment. If we know the approximate angle of the prime user signal, we can set a small angle range for very accurate detection. We can also achieve blind spectrum sensing by setting multiple sectors. For example, the total azimuth coverage of the array is restricted to $[-90°, 90°]$ so that we can set 6 sectors with an angle range of 30° to cover the whole observation range.

On the other hand, as is shown in Fig. 5, beam transformation is equivalent to a spatial domain filter. Interference outside the observation angle range can be suppressed by lower side lobes. Assuming that the beam direction and the signal incident angle are $\theta_0$, the received signal model can be expressed as

$$y(t) = \mathbf{a}^H(\theta_0)\mathbf{a}(\theta_0)s(t) + \mathbf{a}^H(\theta_0)n(t). \tag{33}$$

On any array element, the input power of the signal is assumed to be

$$P_s = E(|s(t)^2|). \tag{34}$$

Similarly, the input power of noise is

$$P_n = E(|n(t)^2|) = \sigma^2. \tag{35}$$

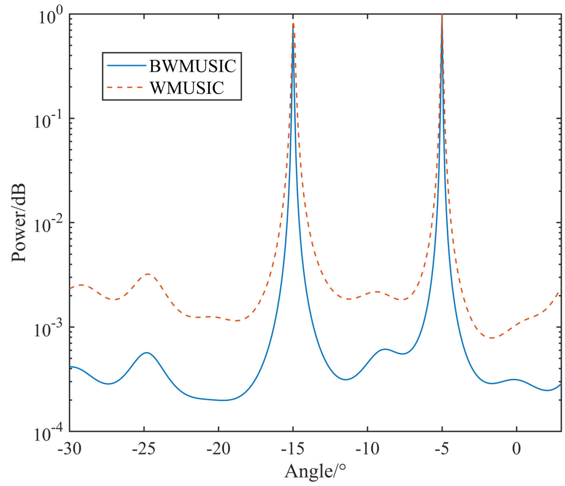


**FIGURE 6.** The spatial spectral curve without interference.

Then input SNR of the array signal can be expressed as

$$SNR_{in} = \frac{P_s}{P_n} = \frac{p_s}{\sigma^2}. \tag{36}$$

According to the expression of the steering vector, it is not difficult to get

$$\mathbf{a}^H(\theta)\mathbf{a}(\theta) = M. \tag{37}$$

The output power of the array signal after beamspace transformation can be expressed as

$$P_{sout} = E\left\{|\mathbf{a}^H(\theta_0)\mathbf{a}(\theta_0)s(t)|^2\right\} = M^2 \cdot P_s. \tag{38}$$

The output power of the array noise is

$$P_{nout} = E\left\{|\mathbf{a}^H(\theta_0)\mathbf{n}(t)|^2\right\} = M \cdot \sigma^2. \tag{39}$$

Then the output SNR is

$$SNR_{out} = M\frac{P_s}{\sigma^2} = M \cdot SNR_{in}. \tag{40}$$

According to the above analysis, for the signal within the observation angle, the signal-to-noise ratio can be improved by beam transform preprocessing. Then, we will analyze from the angle of arrival (AoA). Suppose there are two signals incident from $-5°$ and $-15°$ respectively, and the observation range is $[-30°, 0°]$. The number of beams and the number of array elements are 10 and 32, respectively. The sampling snapshot is set to 2000, and the SNR is 0 $dB$.

Fig. 6 shows the spatial spectrum curve drawn according to (7) and (13). The value of the abscissa corresponding to the peak is the angle of arrival of the incident signal. Compared with the original algorithm, the peak of BWMUSIC is sharper. The sharpness of the peak indicates the angular resolution of the algorithm. The sharper the peak, the higher the resolution. On the other hand, after normalizing the curve, the peak value of the proposed algorithm is higher than that of the original algorithm. In other words, the maximum-minimum spectral ratio has a more significant difference,

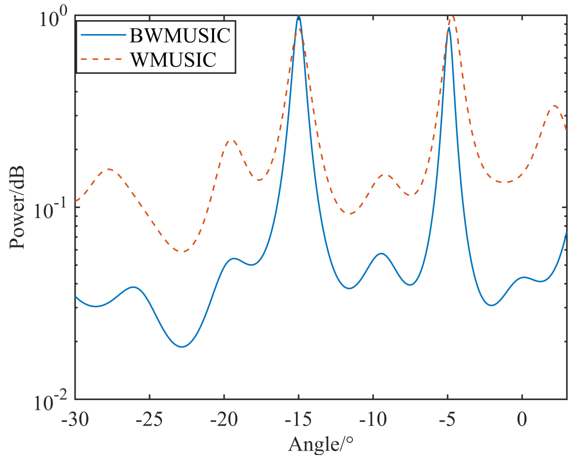


**FIGURE 7.** The spatial spectral curve with interference.

**TABLE 1.** The estimation of the AoA using different algotithms in Fig.7.

| Incident angle of the real signal | WMUSIC | BWMUSIC |
|---|---|---|
| $-5°$ | $-5.2°$ | $-4.9°$ |
| $-15°$ | $-14.8°$ | $-15.1°$ |

which indicates that its detection sensitivity is higher than the original algorithm. All of these results show that the output signal-to-noise ratio can be increased by beamspace transformation, and the detection accuracy can be improved.

Fig. 7 shows the spatial spectrum curve when a strong interfering signal is added outside the observation range. It is not difficult to find the proposed algorithm has better anti-interference performance than the original algorithm. By comparing the data in Table. 1, the angle estimation of the proposed algorithm is more accurate under strong interference conditions.

### B. DETECTION PERFORMANCE ANALYSIS AND COMPARISONS

The proposed scheme is based on multi-antenna system, so we mainly compare the performance with other spectrum sensing scheme of multi-antenna system. The RBF kernel function is used for SVM classification through theoretical analysis and practice. The parameters in RBF are obtained by the grid search method.

Fig. 8 shows the variation of detection probability with different SNRs under different sampling snapshots. Under the same sampling snapshot condition, the detection probability of the proposed scheme is better than the traditional WMUSIC and MME algorithms. When $N = 100$, the proposed algorithm significantly outperforms others and even reaches the performance of MME at $N = 500$. The detection probability approaches 1 at $-16$ $dB$. These are obvious indicators that the proposed algorithm has excellent performance under low SNRs and low snapshots conditions. Good performance is attributed to the beam transformation and SVM classification. Firstly, through the analysis in the previous section,

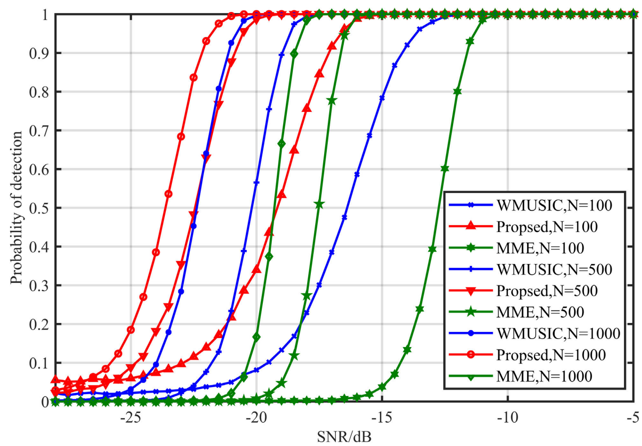


**FIGURE 8.** The detection probability curves of different algorithms with different snapshots.

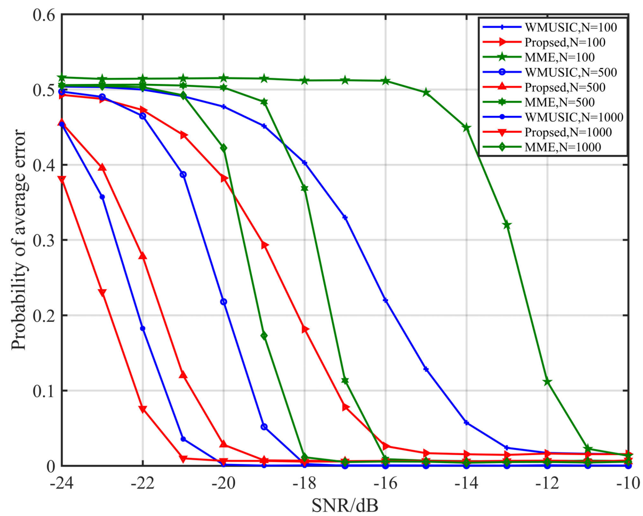


**FIGURE 9.** The average error rate curves of different algorithms with different snapshots.

beamforming can improve the output SNRs of the received signals. Therefore, under low SNR conditions, beamforming has higher detection accuracy. On the other hand, the decision threshold of the traditional spectrum sensing algorithm is fixed. The WMUSIC algorithm does not even specify the calculation method of the threshold in [34]. A fixed decision threshold is often inaccurate in real environments, so the detection performance is seriously deteriorated. The SVM algorithm trains the historical data in the current environment to obtain the optimal classification hyperplane. The SVM algorithm does not need to set a fixed decision threshold. SVM can adaptively adjust the hyperplane as the environment changes to ensure its classification accuracy. Therefore, the proposed sensing algorithm can achieve significant performance under low SNRs and low snapshots conditions.

Fig. 9 shows the average error rate curve with increased SNRs under different sampling snapshots. Compared with other sensing algorithms, the proposed sensing algorithm decreases more rapidly and has a lower average error rate under the same conditions. The reason for the high average error rate of traditional algorithms is due to inaccurate threshold settings. Under low SNR conditions, the calculated test statistic is generally close to the threshold. Therefore, inaccurate thresholds increase the probability of missed or false alarm. The performance of the proposed solution benefits from the optimal decision boundary established by the SVM maximizes the margin between the separated hyperplane and the received data.

## V. CONCLUSION

We have proposed an improved spatial spectrum sensing algorithm based on beamspace transformation and SVM. The proposed algorithm can obtain the angle information of the PU signal while detecting the spectrum hole. Even if the PU exists, SUs can access from other angles by beamforming technology. Spectrum utilization would increase significantly. Beamspace transformation has been used to reduce the dimensionality of the predecessor algorithm. Both theories and simulations have shown that beamspace transformation could improve detection accuracy while reducing dimensionality. In order to solve the problem caused by the fixed threshold in the traditional algorithm, we have exploited the features of the spatial-spectral curve to generate the SVM training model. SVM algorithm presents a superior performance in small sample conditions and can adapt to the sensing environment for real-time. Under low SNRs conditions, beamspace transformation can improve the SNRs of received signals, which also makes the SVM classification accuracy improve. Therefore, simulation results have demonstrated that the proposed algorithm outperforms the conventional multi-antenna spectrum sensing schemes at low SNRs and low sampling snapshots.

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