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Research Article

A High-Precision Spectrum-Detection Algorithm Based on the Normalized Variance of Nonreconstruction Compression Sensing

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The traditional energy detection algorithm has been widely used in the field of signal detection, and a variety of improved algorithms have been derived. In the case of low signal-to-noise ratio, existing methods have shortcomings on achieving fast and accurate spectrum sensing that need to be resolved. This work proposes a normalized-variance-detection method based on compression sensing measurements of received signal. The discrete cosine transform sensing matrix is used to compress the signal, whose normalized variance is then calculated before being used as the testing variable for detecting the primary user signal. Taking the detection results as historical data into consideration, the classification model is obtained after training by applying a support vector machine for classifying and predicting test signals. Simulation results show that the proposed method outperforms the current state-of-the-art approaches by achieving faster and more accurate spectrum occupancy decisions.

1. Introduction

Many spectrum-detection algorithms have been proposed and developed. Conventional energy detection (ED) is one of the most widely used methods for spectrum sensing due to its simplicity and cost-effectiveness, from which many improved algorithms have been developed, such as maximum-minimum ED [1]. Unfortunately, the performance of ED is dramatically degraded in low signal-to-noise (SNR) ratio regimes and in the presence of noise uncertainty [2]. Alternative spectrum-sensing methods have been investigated to address these problems. Eigenvalue-based spectrum-sensing algorithms as proposed in [3] are currently the most attractive solution [4], while spectrum-sensing algorithms based on statistical covariance of the received signal have been proposed in [5], and a spectrum-sensing scheme using the sample covariance matrix was proposed in [6]. Regrettably, the computational cost and the implementation burden of these methods are overwhelming. More recently, certain spectrum-sensing methods based on high-order statistics of the received signal have been proposed [7] to overcome the drawbacks of ED under noise uncertainty without dramatically increasing the overall computational complexity, but their method cannot be applied to signals that conform to a symmetric distribution. In [8], the authors first estimate the second- and fourth-order moments of the received signal to avoid problems.

However, the traditional spectrum-sensing techniques—especially those for wideband spectrum sensing due to problems with hardware circuit and complexity—have major limitations such as high cost, high power consumption, and insufficient digital signal processing speed [9] and possibly even infeasibility with existing devices. These challenges can be addressed by exploiting compression sensing (CS) [10], and several sub-Nyquist wideband-sensing techniques have been proposed recently. Following the ideas in [11], spectrum sensing and sharing based on cyclic prefix autocorrelation have been proposed based on a low-order matrix of the received signal [12]. In [13], based on higher order cumulants and kurtosis spectrum-sensing methods are proposed, in a real-world communication channel, simulation results have verified improvement of the performances. All of these algorithms aim to reduce the computational complexity and shorten the average detection time. However, it would be very expensive to directly apply CS methods for spectrum sensing due to high-computational complexity of signal recovery. Moreover, it is not necessary to completely reconstruct the signal because its existence can be detected based on the main features of the signal. The possibility of using compressed signals for detection without reconstruction was proposed in [14]. Eigenvalue-based spectrum detection for compressed nonreconstructed signals was proposed in [15], which not only greatly reduces the computational complexity but also does not affect the probability of signal detection. The discrete cosine transform (DCT) is increasingly being applied to CS because it is capable of compressing most of the energy of a signal into low frequencies [16].

Nevertheless, as mentioned above, most existing methods are based on the assumption of an asymptotic distribution and apply limit theory to calculate the threshold value and detection probability, which are approximate values that are not good representations of the real environment. This situation prompted a proposal for a machine-learning-based spectrum-sensing algorithm [17]. A machine-learning algorithm based on the traditional sample covariance matrix detection was used in [18], the Bayesian algorithm was introduced in [19], and a spectrum-sensing algorithm based on a support vector machine (SVM) was proposed in [20]. An SVM is a powerful machine-learning tool that employs quadratic programming to solve diverse problems in pattern recognition, regression analysis, and probability. It is based on the principles of minimizing structural risk and limiting sample data, which are highly applicable to real situations of solving spectrum perception problems at a low SNR. To complement previous studies of spectrum sensing, in the present study, we focused on efficient scheduling of sensing in a timely and cost-effective manner with the aim of improving the selection of detection variables and threshold values.

The aim of this paper is to introduce a more effective spectrum-sensing method for the electromagnetic environment in the terminal control zone. The signal is first sampled according to the sub-Nyquist sampling theorem. The measurement y is obtained by using a DCT matrix. The normalized variance (NV) of measurement y defined as the ratio between its second-order and fourth-order estimates is used as the new testing variable and compared with the testing variable for the energy composition of nonreconstruction measurements for detection. In addition, to break the shortcoming that the threshold value and detection probability obtained by the traditional detection algorithm are based on the approximate values of the limit theorem, this paper presents a proposed an SVM-based spectrum-sensing model. SVM uses these detection results as historical data to train and establish the classification model, which can give the actual threshold value and detection probability. Then, the test data are preprocessed and implemented into the classifier to achieve detection. The simulation results show that the proposed methods exhibit an improvement on sensing performance. A comparison between the proposed nonreconstruction compression-sensing normalized variance (NRCSNV) with the nonreconstruction compression sensing using energy detection (NRCSED) demonstrates the higher performance in terms of probability of detection and processing time by testing different numbers of samples.

The remainder of this work is organized as follows. Section 2 presents the signal model and Section 3 describes the ED method for the case of nonreconstruction CS. Section 4 describes the novel proposed scheme, and simulation results and discussions are drawn in Section 5. The final conclusions are drawn in Section 6.

2. Signal Model

The spectrum-sensing process involves detecting the existence of the primary user, which can be regarded as a simple binary hypothesis-testing model expressed as follows:

$$\begin{cases} r(t) = n(t), & H_0, \\ r(t) = s(t) + n(t), & H_1, \end{cases} \tag{1}$$

where $s(t)$ is the primary user signal and $n(t) \sim N(0, \sigma_n^2)$ indicates Gaussian white noise. H_1 states that, in the presence of the signal of interest, the received signal is $r(t) = s(t) + n(t)$; otherwise, H_0 states that, in the absence of the signal, the received signal is $r(t) = n(t)$. By setting the decision variable to be compared with a fixed threshold, a decision can be made as to whether the primary user exists in a certain frequency band.

The CS algorithm is introduced in order to shorten the mean detection time. The subsample vector obtained by CS as

$$\mathbf{y} = \mathbf{\Phi} \mathbf{r}, \tag{2}$$

where $\mathbf{r}$ is the $N \times 1$ vector of Nyquist sampling denoting signal $r(t)$, $\mathbf{y}$ is the $M \times 1$ measurement vector, and $\mathbf{\Phi} \in \mathbf{C}^{M \times N}$ $(M \ll N)$ is the sensing matrix. A DCT matrix is selected as the sensing matrix in the absence of prior information about the signal. Most of the energy information of the time-domain signal can compressed into a small number of DCT domains, as represented by

$$\phi(k, i) = c(k) \cos\left(\frac{\pi (2i+1) k}{2N}\right), \tag{3}$$

where $k \in (0, M-1)$, $i \in (0, N-1)$, and $c(k)$ is the matrix coefficient. Hence, we arrive at the measurement signal notation of

$$\mathbf{y} = [y_1, y_2, \ldots, y_M]^{\mathrm{T}} = [s_1 + n_1, s_2 + n_2, \ldots, s_M + n_M]^{\mathrm{T}}. \tag{4}$$

3. Energy-Detection Algorithm of Nonreconstruction Compression Sensing

An NRCSED algorithm is firstly applied. According to Figure 1, the spectrum-sensing problem is stated as follows. The compressed signal energy needs to be calculated from the measured signals, comparing it to the predetermined threshold value λ. Corresponding to the abovementioned detection problem, the detection result is given.

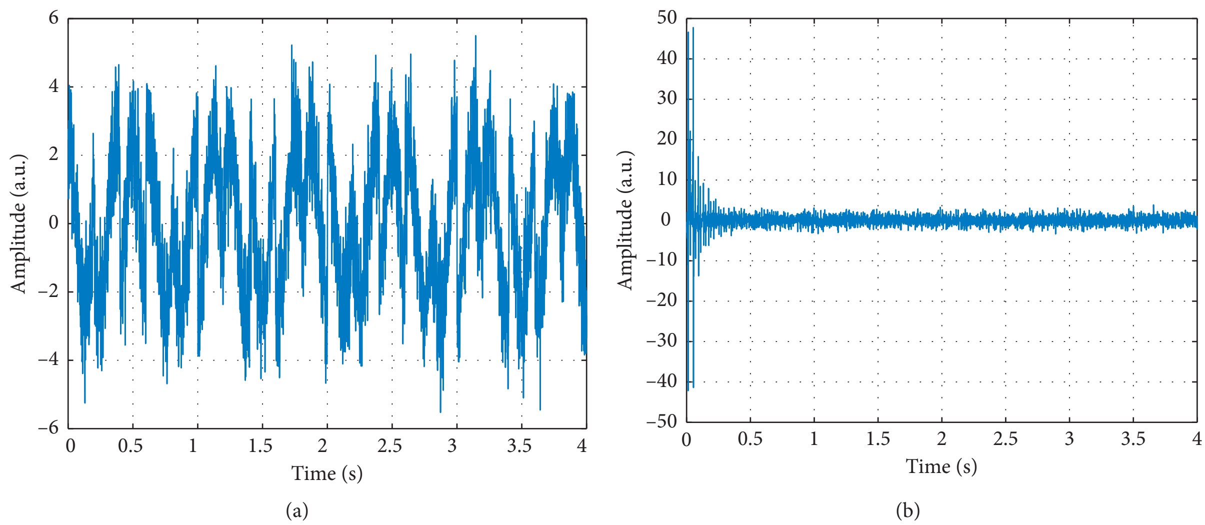

FIGURE 1: Time-domain waveform (a) and waveform after applying the DCT (b).

The energy of the estimated measurement, which is used as a decision variable, is formulated as

$$\xi_1 = \frac{1}{M}\sum_{k=0}^{M-1}\left(\frac{y_k}{\sqrt{\sigma_\omega^2}}\right)^2, \quad (5)$$

where σ_ω^2 is the variance of nonreconstruction CS of the received signal. If the testing variable is larger than the threshold, the algorithm decides for hypothesis H_1; otherwise, the choice is for hypothesis H_0.

Under hypothesis H_1, there is only additive white Gaussian noise, and so (5) obeys the central χ^2 distribution with M degrees of freedom and obeys the noncentral χ^2 distribution with M degrees of freedom under hypothesis H_0. Thus, we can obtain the probability density function:

$$f(y) = \begin{cases} \dfrac{1}{2^{M/2}\Gamma(M/2)} y^{(M/2)-1} e^{-(y/2)}, & H_0, \\ \dfrac{1}{2}\left(\dfrac{y}{u}\right)^{(M-2/4)} e^{-((y+\gamma)/2)} I^{(M/2-1)}(\sqrt{uy}), & H_1, \end{cases} \quad (6)$$

where $\Gamma(\cdot,\cdot)$ is the incomplete gamma function and $u = \sum_{k=0}^{M-1}(s_k/\sqrt{\sigma_\omega})^2$ is a noncentrality parameter. Let $u_E = \sum_{k=0}^{N-1} s_k^2$ be the total energy of the primary user signal before it is compressed. It is easy to conclude that the two are proportional, and so it is derived as $u = \eta\gamma$, where η is the proportionality coefficient and γ is the SNR. The probability of a false alarm is calculated as

$$P_f = P(H_1 \mid H_0) = P(y > \lambda_1 \mid H_0) = \frac{\Gamma(M/2, \lambda_1/2)}{\Gamma(M/2)}. \quad (7)$$

The constant false-alarm rate (CFAR) procedure, which is often employed to perform effective tests, is adopted to determine the threshold value:

$$\lambda_1 = Q^{-1}(P_f)\sqrt{\frac{4\sigma_w^4}{M}} + 2\sigma_w^2. \quad (8)$$

The probabilities of detection and missed detection, respectively, become

$$P_d = P(H_1 \mid H_1) = P(y > \lambda_1 \mid H_1) = Q_{M/2}(\sqrt{u}, \sqrt{\lambda_1}),$$
$$P_m = P(H_1 \mid H_1) = 1 - P_d = 1 - Q_{M/2}(\sqrt{u}, \sqrt{\lambda_1}). \quad (9)$$

Accurate prior information about the signal is impossible to obtain in most cases. The central limit theorem can be used to approximate the mean and variance of the signal data $2\sigma_w^2$ and $4\sigma_w^4/M$, respectively. In the range of variance $[(1/\rho)\cdot\sigma_w^2, \rho\cdot\sigma_w^2]$, the noise uncertainty can be $\rho = 1$ dB.

4. Normalized Variance of Nonreconstruction Compression Sensing

Section 3 summarizes how the NRCSED algorithm—and particularly the CS algorithm—is applied to the spectrum-sensing problem. Unfortunately, the detection performance is not optimal in the case of a low SNR, and so this section derives the nonreconstructed-signal NV algorithm to further improve the detection probability for a low SNR. The NRCSNV is a detection variable defined as the ratio between the fourth- and the second-order estimated values of the nonreconstructed compressed received signal. Section 4.1 explains the detection algorithm and Section 4.2 explains the design of the signal-discrimination algorithm.

4.1. Spectrum-Detection NRCSNV Algorithm. Assuming that the signal and the noise are both zero mean, mutually independent complex random processes, the fourth- and second-order estimated values of the nonreconstructed compressed measured received signals are as follows:

$$\widehat{M}_2 = E\left[|\mathbf{y}|^2\right] = \frac{1}{M}\sum_{k=0}^{M-1}\left(\frac{y_k}{\sqrt{\sigma_\omega^2}}\right)^2,$$

$$\widehat{M}_4 = E\left[|\mathbf{y}|^4\right] = \frac{1}{M}\sum_{k=0}^{M-1}\left(\left(\frac{y_k}{\sqrt{\sigma_\omega^2}}\right)^2\right) = \frac{1}{M}\sum_{k=0}^{M-1}\left(\frac{y_k}{\sqrt{\sigma_\omega^2}}\right)^4. \tag{10}$$

The variance can be written as

$$\operatorname{var}\left[|y|^2\right] = E\left[|y|^4\right] - E\left[|y|^2\right]^2 = \frac{1}{M}\sum_{k=0}^{M-1}\left(\frac{y_k}{\sqrt{\sigma_\omega^2}}\right)^4 - \left(\frac{1}{M}\sum_{k=0}^{M-1}\left(\frac{y_k}{\sqrt{\sigma_\omega^2}}\right)^2\right)^2. \tag{11}$$

Then, the NRCSNV can be formulated as

$$\widehat{\xi}_2 = \frac{(1/M)\sum_{k=0}^{M-1}\left(y_k/\sqrt{\sigma_\omega^2}\right)^4 - \left((1/M)\sum_{k=0}^{M-1}\left(y_k/\sqrt{\sigma_\omega^2}\right)^2\right)^2}{\left((1/M)\sum_{k=0}^{M-1}\left(y_k/\sqrt{\sigma_\omega^2}\right)^2\right)^2}. \tag{12}$$

Let (12) be the new test variable, which is asymptotically Gaussian as a direct consequence of the central limit theorem. On the basis of the constant false alarm rate (CFAR) procedure, under hypothesis H_0, the mean of $\widehat{\xi}_2$ is $E[\widehat{\xi}_2 \mid H_0] = 0$. Since $P_f = P(\widehat{\xi}_2 > \lambda_2 \mid H_0) = \int_{\lambda_2}^{\infty} 1/\sqrt{2\pi \operatorname{var}[\widehat{\xi}_2 \mid H_0]}\exp(-\widehat{\xi}_2^2/2\operatorname{var}[\widehat{\xi}_2 \mid H_0])d\widehat{\xi}_2$, solving for the algebra of P_f, the new threshold value is calculated as

$$\lambda_2 = E\left[\widehat{\xi}_2 \mid H_0\right] + \sqrt{2\operatorname{var}\left[\widehat{\xi}_2 \mid H_0\right]}\cdot \operatorname{erfc}\left(1 - 2P_f\right), \tag{13}$$

where $\operatorname{erfc}(\cdot)$ is the inverse of the well-known error function. In the same way, if the detection variable is greater than the threshold, the algorithm decides for H_1; otherwise, the choice is for H_0. The detection probability can then be defined as

$$P_d = \frac{1}{2} + \frac{1}{2}\operatorname{erf}\left(\frac{-\lambda_2 + E\left[\widehat{\xi}_2 \mid H_1\right]}{\sqrt{2\operatorname{var}\left[\widehat{\xi}_2 \mid H_1\right]}}\right). \tag{14}$$

The mean probabilities of missed detection and the error are, respectively, obtained as

$$\begin{cases} P_m = \dfrac{1}{2} - \dfrac{1}{2}\operatorname{erf}\left(\dfrac{-\lambda_2 + E\left[\widehat{\xi}_2 \mid H_1\right]}{\sqrt{2\operatorname{var}\left[\widehat{\xi}_2 \mid H_1\right]}}\right), \\ P_e = P_f + P_m. \end{cases} \tag{15}$$

4.2. Signal-Discrimination NRCSNV SVM Algorithm. An NRCSNV SVM algorithm is proposed for solving the problem that the threshold and detection probabilities are approximate. This SVM algorithm transforms the low-dimensional data into nonlinear high-dimensional data, bypassing the situation where the main user signal and the noise signal are mixed in a low-SNR condition by separating the noise and the signal space through the use of a hyperplane.

The detection results of the NRCSNV algorithm with better performance are selected as historical data, and the classification model is established using an SVM. The detection results are classified using the detection function $y = \operatorname{sgn}(\sum_{x_i \in S} y_i \alpha_i k(x, x_i) + b)$. If the results are consistent with hypothesis H_1, $y = 1$; otherwise, $y = -1$. Let the training data be $S = \{(x_1, y_1), \ldots, (x_l, y_l)\}, x_i \in R^n,\ \ y_i \in \{+1, -1\}$, and $y_i \in \{+1, -1\}$, $\alpha_i \geq 0, i = 1, 2, \ldots, l$, where n is the ample dimension, l is the number of samples, x_i denotes the training data vector, y_i represents the class of x_i, and sgn is the signum function, where $\operatorname{sgn}(\alpha) = \begin{cases} 1 & \alpha \geq 0 \\ -1 & \alpha < 0 \end{cases}$. Instead of all training examples, only l examples need to be stored, thereby reducing computation and memory costs. The learning performance of SVM is strongly dependent on selection of a suitable feature S. The training set is put into the SVM to construct the optimal separating hyperplane, which is used to obtain the actual threshold and detection probabilities. The optimal separating hyperplane obtained in the training process is utilized to detect the testing data and get the judgment result about whether the primary user exists or only noise is present. The general procedure is described in Algorithm 1.

The computational complexity of the training steps in the proposed NRCSNV method can be roughly expressed as Table 1. Since $M \ll N$, the number of computations significantly decreases with compressive sensing.

5. Simulations and Discussion

This section presents the results of numerical simulations used to analyse the performance of ED, NV, NRCSED, NRCSNV, NRCSED-SVM, and NRCSNV-SVM. The obtained simulation results indicate that our proposed algorithm performs well.

5.1. Simulation Setting. In this section, a variety of Monte Carlo simulations are presented to illustrate the performance of the algorithm. The number of Monte Carlo simulations was set as 10^5, assuming $P_f = 10^{-2}$ and a noise uncertainty of $\rho = 1$ dB as required for the IEEE 802.22 draft standard. This study chose an actual communication environment that involved signals with a bandwidth of 2.4 GHz and sub-Nyquist sampling using 16QAM and QPSK modulation types including AWGN, which were simulated using MATLAB. The SNR was varied between −15 dB and 5 dB, and N was 500. A Gaussian kernel function was selected for training in the SVM-based algorithm, and the input two-dimensional data were the NV of the nonreconstruction measurements and the decimal SNR. All the simulation results are generated on a Windows 10 personal computer equipped with a 64 bit Intel Core i5-8265U CPU running at 1.6 GHz and 4 GB of RAM. The proposed algorithm and the competing methods are implemented with MATLAB R2016a (64 bit).

Proposed NRCSNV SVM algorithm
A. Training Procedure (30% of total samples)
Input: $\mathbf{r}$, $\mathbf{\Phi}$, SNR,
Step1: $\mathbf{y} = \mathbf{\Phi r}$ is the sensing sample.
Step2: Compute feature value vector NV using (12).
Step3: Result of Step2 is used as training data to train and save the training model.
Step4: Calculate the threshold using (13), if the detection function is 1, the primary user is detected; if the detection function is −1, the primary user is not exist. Generate historical data with obtained values.
Step5: Put the simulated data into the training classifier.
Output: generate parameters that adapt to the environment.
B. Testing Procedure (70% of total samples)
Step1: As in Step1 of the training process.
Step2: As in Step2 of the training process.
Step3: Put the training set into the classifier constructed to obtain the judgment result.
Step4: Generate detection results: An output of 1 indicates that the spectrum is occupied and that the primary user exists; otherwise, it does not exist.

Algorithm 1: Proposed NRCSNV SVM algorithm.

Table 1: Computational complexity of NRCSNV.

Training steps	Computational complexity
1 Input signal $\mathbf{r}$	O (N)
2 Measurement signal $\mathbf{y}$	O (N^2M)
3 NRCSNV	O (KM)
4 Threshold value calculation	O (M)
5 Detection calculation	O (M)

5.2. Results and Discussion. PSK modulation is used in the SATCOM air-ground communication system. In this work, the QPSK-modulated signal was verified first.

Figure 1 illustrates the DCT matrix compression method, in which the time-domain signal for a specific frequency used in civil aviation is received and the DCT is applied. The figure shows that, after applying the DCT, the energy of a spectrally sparse signal is concentrated within a small area in front, and the redundant part of the signal can be discarded to achieve signal compression.

The compression ratio is defined as the size of the compressed signal as a percentage of the original signal:

$$r = \frac{\text{compressed signal}}{\text{original signal}} \times 100\%. \quad (16)$$

The task is to find the optimal compression ratio.

Figure 2 presents the signal energy preservation for different compression ratios. The simulation results show that, for compression ratios of 10%–20%, up to 90% of signal energy was saved, which indicates that most of the energy is concentrated in this region, as shown in Figure 1. It is therefore feasible to apply the DCT matrix as the sensing matrix.

In our previous work, we have selected three kinds of low SNR (−8 dB, −10 dB, and −15 dB) to verify detection probabilities under different false alarm probabilities.

Figure 3 shows the ROC performance in the three kinds of low SNR. It is easy to see the detection probability is higher when the SNR is higher. When false alarm probability is between 0 and 0.1, detection probabilities can be higher. In

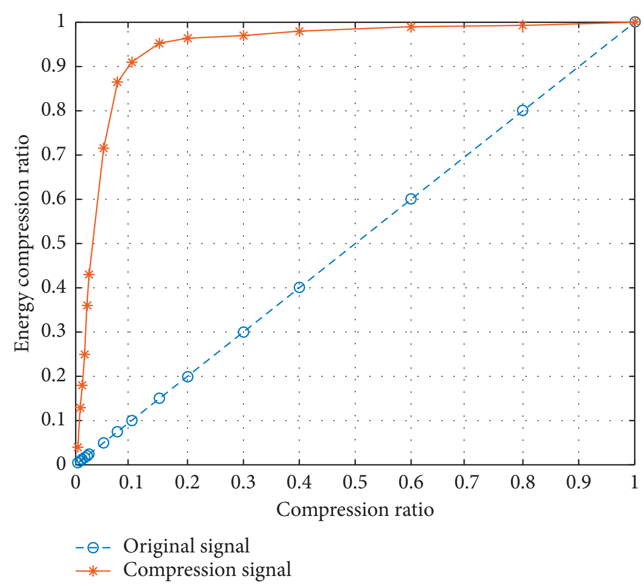

Figure 2: Energy compression ratio of the original and compressed signals.

order to get the appropriate threshold value, we did simulations by setting different false alarm probabilities from 0.001 to 0.1. Then, according to the simulation results, our method is most effective when false alarm probability is 0.01. Therefore, this work only discusses the simulations under the condition of false alarm probability 0.01.

Figure 4 shows the detection probabilities of NRCSED for compression ratios of 10%, 15%, 20%, and 1, according to the results of Figures 1 and 2. The detection performance of the NRCSED algorithm was optimal for a compression ratio of 15%. At SNR = −10 dB, the detection probability improved by 0.28 compared with that, without compression, which indicates that the introduction of nonreconstruction CS does not destroy the feasibility of the algorithm, while it improves the detection efficiency.

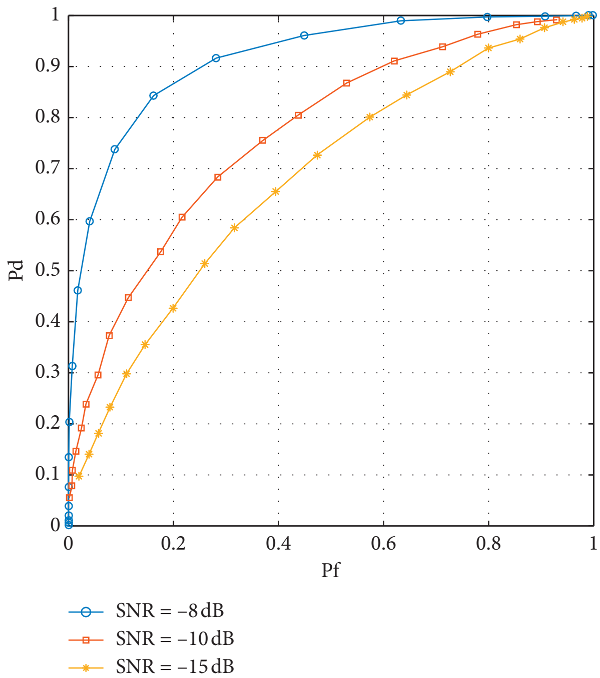

Figure 3: Different SNR for simulation.

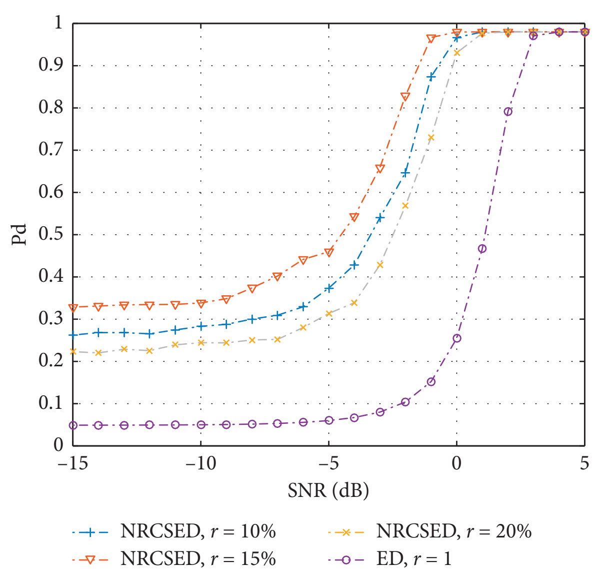

Figure 4: Detection probabilities for different compression ratios.

The proposed NRCSNV and NRCSED algorithms are compared in Figure 5, which illustrates that the NRCSNV algorithm still had good detection performance. When the SNR is −10 dB, the detection probability of NRCED is 34% and the detection probability of NRCSNV is 47%, which increased by 14% for a compression ratio of 15%. At SNR = −5 dB, the compression ratio is 15% and the detection probability of NRCSNV can be reached 60% higher 13% than NRCSED under the same condition. The green curve with the triangle and the red curve with the triangle both show high level of performance under nonreconstruction

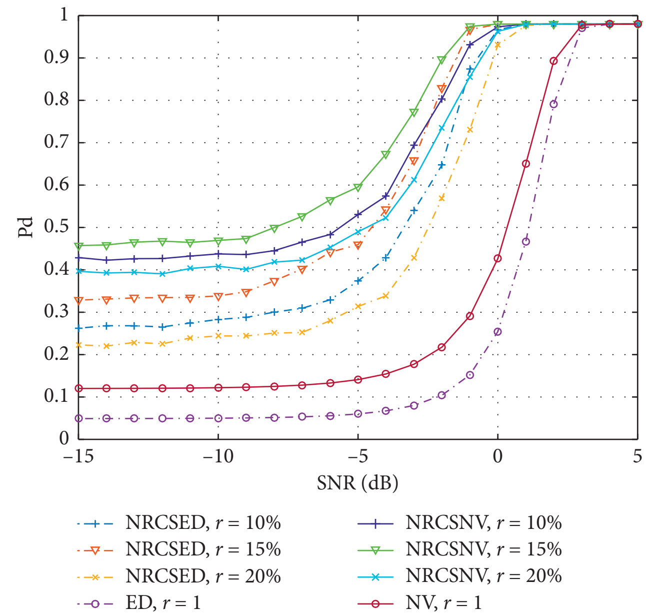

Figure 5: Performance of NRCSED and the NRCSNV for different compression ratios.

framework. The proposed method could fully detect the signal when the SNR was −3 dB, while ED could only be used when the SNR was 2 dB, indicating that the proposed algorithm is still highly applicable in a low-SNR environment.

For spectrum-sensing processing, the mean detection time reflects the algorithm performance. The mean detection time is defined as the time needed on an average before a correct detection is declared.

Figure 6 indicates that the mean detection time was much longer (by up to 41 s) for ED than for the other three detection algorithms and for the NV it was up to 16 s longer, but this is still one-third lower than that of ED. The detection times for the two nonreconstruction detection algorithms utilizing CS were very short, at less than 10 s (6 s for the NRCSNV), which is much faster than that, for ED. This corresponds to Figure 2 indicating that when the compression ratio was about 15%, most of the energy of the original signal had been obtained so that the mean detection time could be further reduced without wasting time on processing the redundant signal.

16QAM is another modulation method that is commonly used in communication systems. The frequency-band utilization ratio of a 16QAM-modulated signal is higher than that of a QPSK-modulated signal, while the anti-interference performance is worse. We verified the usefulness of the proposed algorithm with a 16QAM-modulated signal. According to the results of Figures 2 and 3, compression ratios of 10% and 15% have been used for simulations.

Figure 7 shows that the performances of NRCSED and NRCSNV for compression ratios of 15% and 10%. Thanks to the high information rate and spectrum utilization of 16QAM, most of the energy was compressed when the compression ratio was 10%, and so the performance was only slightly better than for a compression ratio of 15%. The

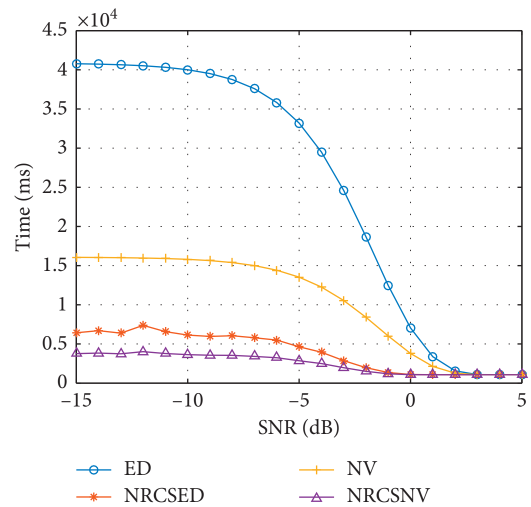

Figure 6: Comparison of mean detection times for a compression ratio of 15%.

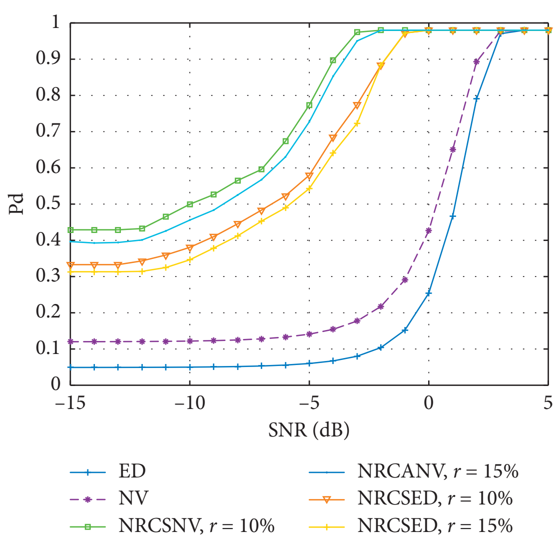

Figure 7: Performances of NRCSED and NRCSNV for different compression ratios.

overall detection probability decreased slightly under the same conditions due to the poor anti-interference performance of 16QAM relative to QPSK, while the bit error rate was relatively high. However, the performance of the proposed method was still better than for the other algorithms, and when the SNR is −5 dB, the detection probability of NRCSNV can be achieved to 78%, while NRCSED detection probability is 57%. The top green curve shows the superiority of the proposed algorithm in detection. All of the detection processes could be completed at an SNR of −2 dB, which shows that the proposed algorithm is still applicable in this situation.

Figure 8 presents the 16QAM-modulated signal detected when the compression ratio was 10%. Reducing the compression ratio significantly shortened the mean detection time compared with the QPSK-modulated signal which had a compression ratio of 15%. When the SNR was −15 dB, the

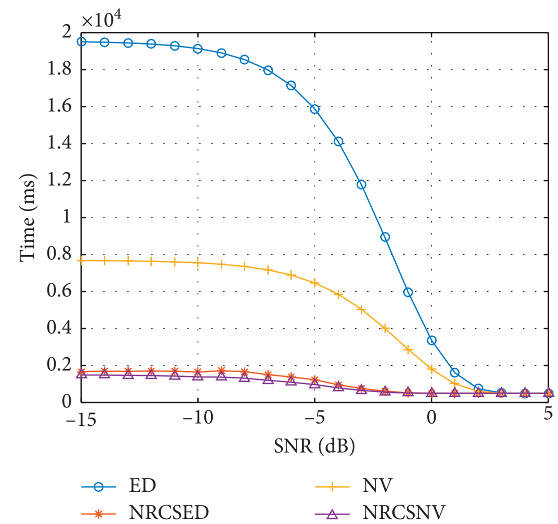

Figure 8: Comparison of mean detection times for a compression ratio of 10%.

mean detection time of ED was still the longest in this case (up to 20 s), while it was the shortest for the NRCSNV at 1.7 s and 1.9 s for NRCSED. Combined with the detection probability, the proposed method performance is still optimal.

The NRCSNV algorithm detection result was used as historical data, with the QPSK-modulated signal that has better anti-interference performance being selected, a compression ratio of 15%, and 5000 data points to verify the performance of the NRCSNV-SVM detection method.

The test data preprocessed such as the historical data were put into classification model to perform the detection, and the accuracies of the four algorithms were compared.

Figure 9 shows that the detection probabilities of the two SVM-based detection algorithms were higher than those of the nonreconstruction measurement algorithms, as expected, when the compression ratio was 15% and SNR was −15 dB. The accuracy of the input data used for the training historical data is particularly important, for the considered scenarios, both the NRCSED-SVM and NRCSNV-SVM could achieve optimal detection at an SNR of −5 dB, while the other two methods achieved optimal detection results; when SNR was close to 0 dB, NRCSNV just can be get 60%. The top purple curve with a star shows that NRCSNV-SVM is validated by its accuracy.

Figure 10 presents the performance of the NRCSNV-SVM for different SNRs and numbers of samples for a fixed compression ratio. It can be seen that the algorithm performance was significantly improved for 10,000 samples, with no obvious changes when this was increased to 20,000 or 40,000. Consequently, the NRCSNV-SVM provided no obvious performance advantage when there were more than 40,000 samples. This also indicates that an SVM is suitable for processing a small amount of sample data, while too much data will adversely affect its performance. The detection probability was significantly higher for NRCSED and the NRCSNV. Our results also show that the threshold value obtained by using historical data was more suitable for the real detection situation.

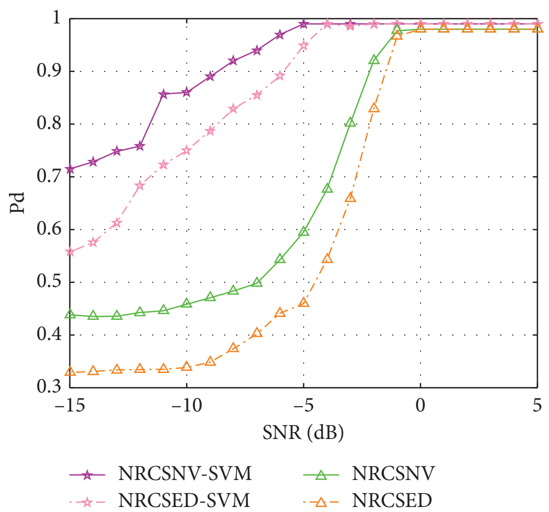

Figure 9: Performance of the NRCSED-SVM and NRCSNV-SVM for a compression ratio of 15%.

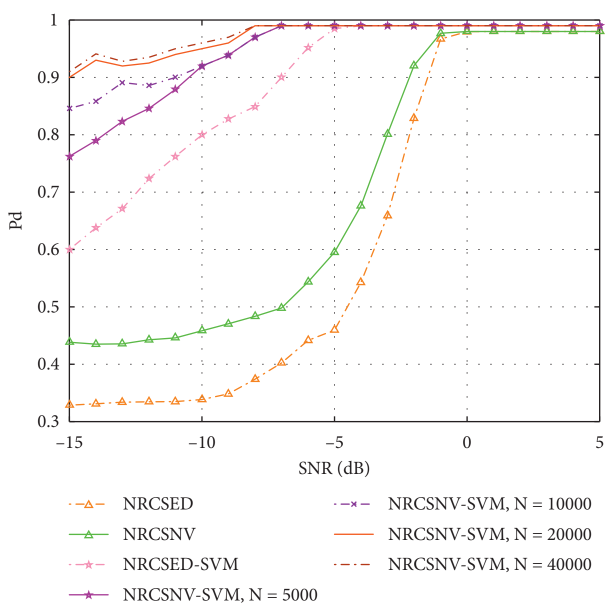

Figure 10: Performance of the NRCSNV-SVM for different sample sizes.

6. Conclusion

In this work, a novel and effective spectrum sensing method has been presented for the electromagnetic environment in the terminal control zone. The signal was firstly sampled according to the sub-Nyquist sampling theorem by using a DCT matrix. The normalized variance (NV) of measurement defined as the ratio between its second-order and fourth-order estimates is used as the new testing variable for the primary user. Furthermore, a SVM-based spectrum-sensing model using detection results as historical data to train the classification model was proposed, which gives the actual threshold value and detection probability. And the test data were preprocessed and implemented into the classifier to achieve final detection. The simulation results have demonstrated that the proposed method exhibits significant improvement on detection performance with a less mean detection time competing with other state-of-the-art spectrum-sensing methods. In the future, the adaptive threshold values need further research. Moreover, it is also worth investigating the impact of false alarm possibility when exploiting deep neural network on big data.

Abbreviations

CS:	Compression sensing
CFAR:	Constant false alarm rate
DCT:	Discrete cosine transform
ED:	Conventional energy detection
NV:	Normalized variance
NRCSED:	Nonreconstruction compression sensing for energy detection
NRCSNV:	Nonreconstruction compression-sensing normalized variance
SNR:	Signal-to-noise ratio
SVM:	Support vector machine.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

ZS developed and implemented the core concepts of the algorithm presented within this manuscript, QW provided refinements and performed data acquisition and generation as well as further supplemental programming. All authors had a significant contribution to the development of early ideas and design of the final methods. All authors read and approved the final manuscript.

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