Detect Black Box Signals with Enhanced Spectrum and Support Vector Classifier

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Abstract. When the plane crash into the sea and the search and rescue team search the location black box, we need to detect a specific acoustic signal in the ocean. The underwater acoustic channel has several distinct features: multipath propagation, high attenuation, and sound velocity varying as a function of depth and temperature, which make the detection of underwater signals very difficult. This paper proposes a new method in the marine signal detection and discrimination based on adaptive line enhancer and support vector machine classifier, which can provide a new idea for marine black box search. The adaptive line enhancer of the least mean square algorithm can detect narrowband signals hidden in wideband noise, while the support vector machine classifier maps signals to high-dimensional space and screens out hyperplanes separating different signals from machine data through previous data. Experimental data show that this method can bring a very high recognition rate.

1. Introduction

Underwater acoustic channels are generally recognized as one of the most difficult communication media in use today.[1] So searching for specific signals in the ocean has always been a big challenge, especially for high-frequency sonar signals, because high-frequency signals attenuated greatly in the ocean. However, in the scene where the plane crashed into the ocean, the search and detection domain of the underwater black box target in deep-sea conditions became a crucial matter. Since the sound source emission level of the black box is low (only 160.5dB), the working frequency is high (37.5kHz), the absorption loss is large (10.9dB/km), and the underwater acoustic signal environment is complex, it is necessary to solve the problem of extracting and discriminating the beacon signal under the condition of extremely low signal-to-noise ratio (SNR).

After beamforming performed on a line array and pre-filter, the weak signal is enhanced and a reliable classifier needs to be utilized to discriminate the signal of interest. Since the frequency of the commonly used black box signal is extremely high, which is 37.5 kHz and is very rare in natural sound, we use the spectrum as the recognition feature. An adaptive line enhancer (ALE) of least mean square (LMS) is used to enhance the performance of this feature. ALE is widely used to mine narrowband signals buried in broadband noise, whose main advantage is that it does not require any reference signal to eliminate the noise signal.[2] After the feature of signal has been extracted, support vector machine (SVM) classifier is used for finally making the judgement if there is signal of interest. Figure1 is the block diagram of the whole processing.

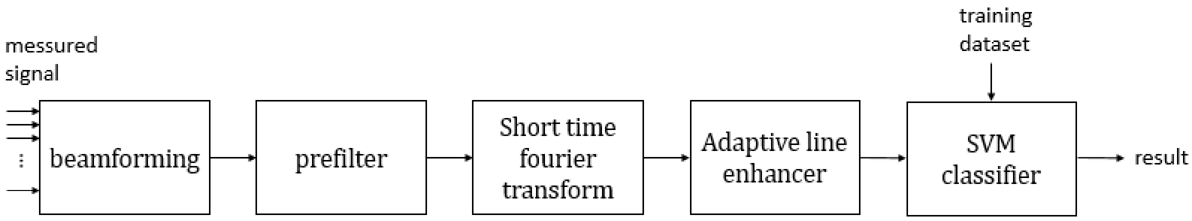


Figure 1. block diagram of the whole detection processing

In this paper, we use the short-time Fourier transform to obtain the time-frequency characteristics of the messured signal, and use ALE to spectrally enhance it and sum in time, taking the spectral value of the 35kHz~40kHz frequency as the feature input into the SVM classifier. Section II briefly introduces the basic theory of ALE of LMS algorithmn and SVM. Section III shows the experimental results. Section IV summarizes the paper.

2. Theory and method

2.1. Adaptive line enhancer

The ALE structure for detecting periodic pulse signals is shown in Figure 2. [3] $x(k)$ is the primary input signal and is composed of signal of interest $s(k)$, which is a periodic pulse signal, and broadband noise $n(k)$ with a bandwidth of B. The reference input $z(k)$ is $x(k)$ delayed by some time, that is, $z(k) = x(k - \Delta)$. $e(k)$ is the error signal. The weight $w(k)$ is adjusted using LMS algorithm.

$$e(k) = z(k) - y(k) \tag{1}$$

$$y(k) = \sum_{n=0}^{L-1} w_n z(k - n - \Delta) \tag{2}$$

The main idea of line enhancer is that the autocorrelation function of the narrowband signal is shorter than the time-dependent radius of the autocorrelation function of wide-band noise. In the enhancement of the periodic pulse signal we set

$$1/B << \Delta = T_0, \tag{3}$$

where B is the noise bandwidth, Δ is delay and also the time-dependent radius of signal of interest, and T_0 is the width of each sub-pulse. [3]

Since that the useful signal is sinusoidal, then $x(k) = s(k) + n(k) = a \cdot e^{j(wkt+\varphi)} + n(k)$, where φ is a random variable uniformly distributed in $[0, 2\pi]$, thus we can obtain the response formula to the signal of the system.[4]

$$y(k)_s = \frac{(N+1)\alpha^2}{\sigma_n^2 + (N+1)\alpha^2} s(k) \tag{4}$$

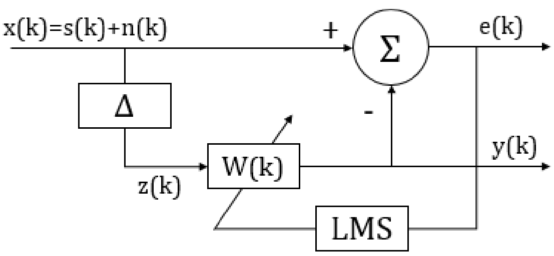


Figure 2. adaptive line enhancer

It can be seen that $x(k)$ and $y(k)$ are in phase. And when N is large enough, the noise output power is reduced to $1/(N+1)$ of the input while the signal power is unchanged, i.e. the SNR is increased by a factor of N after ALE processing.

And we use the LMS algorithm for adaptively iteration, which was first developed by Widrow and Hoff in 1959.[2] Its basic iteration formulas are as follows:

$$\begin{aligned} & y(k) = w^{\mathrm{T}}(k)x(k) \\ & e(k) = z(k) - y(k) \\ & w(k+1) = w(k) + \mu e(k)x(k) \end{aligned} \tag{5}$$

where $w(k)$ and $w(k+1)$ are weight values before and after iteration, respectively, μ is the convergence factor.

Among the three typical characteristics (frequency, pulse period and pulse width) of black box signal, the frequency is the most obvious and the easiest to extract, thus we choose to mainly discriminate signal with its frequency. After ALE processing the difference between the frequency of target signal and noise is widened, then the spectrogram is accumulated in time and the advanced power spectral density values on the target band (35~40kHz) is obtained. Compared with directly obtaining the power spectral density, the ALE processing method can bring a higher recognition rate.

2.2 Support vector machine

SVM is a data mining method widely used in classification problems in various fields. It can successfully deal with many problems such as regression problem and pattern recognition. Here we briefly introduce the working mechanism of SVM, for further details we refer to[6]-[8].

Suppose that there are two categories in the training sample set $\{(\mathbf{x_i}, \mathbf{y_i}), i = 1, 2, ..., l\}$ of size l, and if $x_i \in \mathbb{R}^N$ belongs to the first category, it is marked as positive ($y_i = 1$), Marked as negative if it belongs to second category ($y_i = -1$). We use the following equation to describe a m-dimensional hyperplane.

$$\boldsymbol{\omega} \cdot \mathbf{x} + b = 0, \quad \boldsymbol{\omega} \in \mathbb{R}^N, b \in \mathbb{R} \tag{6}$$

By finding the minimum value of $\|\boldsymbol{\omega}\|^2/2$, the optimal hyperplane with the largest classification interval can be obtained. The constraint here is:

$$\mathbf{y}_i[\boldsymbol{\omega} \cdot \mathbf{x}_i + b] - 1 \geq 0 \quad i = 1, ..., N \tag{7}$$

When the training sample set is linearly inseparable, a non-negative relaxation variable $\xi_i, i = 1, 2, ..., l$ is introduced, and the optimization problem of the classification hyperplane is

$$\begin{aligned} & \min_{\boldsymbol{\omega}, b, \xi} \frac{1}{2} \boldsymbol{\omega}^T \boldsymbol{\omega} + c \sum_{i=1}^{l} \xi_i \\ & s.t. \quad y_i (\boldsymbol{\omega}^T \cdot \mathbf{x}_i + b) \geq 1 - \xi_i \\ & \quad \xi_i \geq 0, \quad i = 1, ..., l \end{aligned} \tag{8}$$

where c is the penalty parameter. The constrained optimization problem is solved through a Lagrangian function:

$$L(\boldsymbol{\omega}, b, a) = \frac{1}{2} \|\boldsymbol{\omega}\| - a_i (\mathbf{y}_i [\boldsymbol{\omega} \cdot \mathbf{x}_i + b] - 1) \tag{9}$$

where $a_i > 0$ is the Lagrangian coefficient. And the solution of the optimization problem satisfies

$$\frac{\partial L}{\partial \boldsymbol{\omega}} = 0, \frac{\partial L}{\partial b} = 0 \tag{10}$$

Translates the original problem into the corresponding dual problem:

$$\max Q(\mathbf{a}) = \sum_{j=1}^{l} \alpha_j - \frac{1}{2}\sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)$$
$$s.t. \quad \sum_{j=1}^{l} \alpha_j y_j = 0, \quad 0 \le \alpha_j \le c \quad j = 1,\dots,l \tag{11}$$

and obtain $\mathbf{a}^* = (a_1^*, a_2^*, \dots, a_l^*)^T$.

In the optimization solution, a_i may be one of the following: ① $a_i = 0$ ② $0 < a_i < c$ ③ $a_i = c$. The x_i corresponding to the latter two occasions is the support vector (SV), and only the support vector contributes to $\boldsymbol{\omega}$. The x_i corresponding to ③ is actually the mismatched training sample point, and the x_i corresponding to ② called Normal Support Vector (NSV), according to which we obtain the wanted solution.

For NSV, we can obtain

$$\boldsymbol{\omega}^* = \sum_{j=1}^{l} a_j^* y_j x_j \tag{12}$$

$$b^* = y_i - \sum_{j=1}^{l} a_j^* y_j (x_j \cdot x_i) \tag{13}$$

Therefore, the optimal classification hyperplane and thus the optimal classification function can be obtained

$$f(\mathbf{x}) = \mathrm{sgn}[(\boldsymbol{\omega}^* \cdot \mathbf{x}) + b^*] = \mathrm{sgn}[(\sum_{j=1}^{l} a_j^* y_j (x_j \cdot x_i)) + b^*], \mathbf{x} \in \mathbb{R}^N \tag{14}$$

For the linear indivisible case, the the input vector is mapped to a high-dimensional eigenvector space, and construct the optimal classification surface in the feature space.

Convert $\mathbf{x}$ from the input space $\mathbb{R}^N$ to the feature space $\mathbb{H}$:

$$\mathbf{x} \to \boldsymbol{\Phi}(\mathbf{x}) = (\Phi_1(\mathbf{x}), \Phi_2(\mathbf{x}), \dots, \Phi_l(\mathbf{x}))^T \tag{15}$$

So the optimal classification function can be obtained as:

$$f(\mathbf{x}) = \mathrm{sgn}[(\boldsymbol{\omega} \cdot \boldsymbol{\Phi}(\mathbf{x})) + b] = \mathrm{sgn}[\sum_{j=1}^{l} a_j y_j \boldsymbol{\Phi}(\mathbf{x}_i) \cdot \boldsymbol{\Phi}(\mathbf{x}) + b^*] \tag{16}$$

In the above problem, it is actually only necessary to calculate the inner product, which can be implemented by the function in the original space without necessity to know the form of the transformation. As long as the kernel function $\psi(x, x_k)$ satisfies the Mercer condition, it corresponds to the inner product in a variable space.

Therefore, the nonlinear case can be realized by using the appropriate kernel function $\psi(x, x_k)$ in the optimal classification plane, but the computational complexity is not increased. Commonly used 4 kernel are as follows:

(1) Linear kernel: $\psi(x, x_k) = x_k^T x$

(2) Polynomial kernel of degree d: $\psi(x, x_k) = (x_k^T x + 1)^d$

(3) RBF kernel: $\psi(x, x_k) = \exp\{-\| x - x_k \|_2^2 / \sigma^2\}$

(4) Two layer neural kernel: $\psi(x, x_k) = \tanh[\kappa x_k^T x + \theta]$

where σ, κ and θ are constants.

3. Experiment result

A marine experiment was conducted in the shallow sea around Zhoushan, and the receiving array is shown in Figure 3 and the experimental arrangement is shown in Figure 4. In the experiment, a hydrophone uniform line array was utilized which keeped stationary, while the transmitting transducer moved slowly at a distance from the receiving array. Three sets of signals of different emission intensities are emitted, and since the transducer moves slowly the SNR of messured signal was varying during receiving. We use the signals received by each channel of the receiving array to construct data sets.

After the line spectrum of the signal is enhanced, we intercept the spectral of 35 kHz~40 kHz as the extracted feature and input it into SVM classifier for training and testing. Figure 5 shows a case of extracted feature vector.

In the training and testing set, each sample is a received signal with a length of 2s, the sampling frequency is 200 kHz, the FFT points of the STFT are 1024, and the window length is 1024. The training set contains 634 sets of positive samples with SNR ranging from -5 to 10 dB. The negative samples are composed of 642 sets of pure noise at sea. The recognition rate of this frame is tested under different SNR. The results are listed in table1. And the receiver operating characteristic (ROC) curve of three test sets are shown in Figure 6.

From the reorganization results it can be seen that, the recognition rate of the high-SNR group is above 95%; in the group of -5~5dB, the recognition rate still maintains as high as 90%; and in the group of SNR less than -5dB (in which case it is difficult to calculate the actual SNR), the recognition rate is about 68.2%.

Figure 3. line array with 16 elements

Figure 4. Experimental arrangement

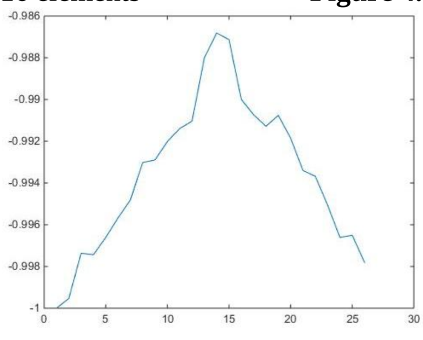
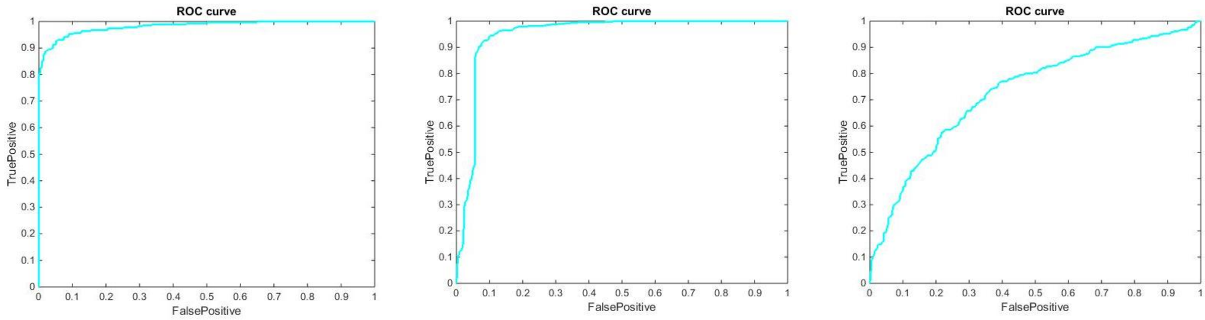


Figure 5. the feature vector of signal extracted (26 points)

Table 1. Test results of the framework.

SNR	Size of test dataset(samples)	Recognition rate
5~10dB	276 positive and 214 negative	95.5714%
-5~5dB	214 positive and 214 negative	90.8879%
Below -5dB	336 positive and 428 negative	68.1937%



(a) (b) (c)

Figure 6. ROC curve of three test sets. (a) ROC curve of high SNR(5~10dB)
(b) ROC curve of middle SNR(-5~5dB) (c) ROC curve of low SNR(below -5dB)

4. Conclusion

In the detection of the black box signal under the sea, the ALE of LMS algorithm is used to enhance the time-frequency diagram of the received signal, according to which the feature of signal is extracted and input into SVM classifier. This framework of signal detection is proved effective by the experiment results, which shows great performance in the identification of acoustic beacon signal at a very low SNR (-5 dB). In the scene of search in ocean, the target signal can be transmitted artificially and collected in the target sea area to train the SVM classifier, which then can be used in the following detection.

Acknowledgments

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