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Research Article

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The application of weak passive acoustic endpoint detection based on sparse decomposition feature technology

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ABSTRACT

To detect and recognize passive fish acoustic signal from marine noisy environment, sparse decomposition is present to realize the endpoint detection by coherent ratio feature. During training，the algorithm extracts feature of fish and wave acoustic as test object under different signal-to-noise(SNR), feature from noisy signal segment is extracted in the testing to classify with test object, finally it is realized by threshold endpoint detection method. Experiment shows that effective signal segments can be detected more accurate by this algorithm than by the power spectrum feature algorithm under low SNR.

Key words: Acoustic signal; coherent ratio; endpoint detection; sparse decomposition

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INTRODUCTION

With the increasing demand for marine resources, marine biological resources development has been paid more and more attention, China has successfully applied the technology of exploring the sound of fish actively to investigate fish resources in Yellow Sea and East China Sea. Besides, the technology is also applied to investigate the North Pacific Pollock resources. The acoustics of fisheries has become an important way to evaluate fishery resources and monitor marine ecosystem[1].

Compared to the active fish scattered acoustic technology, passive fish radiation acoustic target technology is different from the traditional optical and active acoustic detection method. Passive acoustic technology is not harmful、destructive to object, besides it can achieve long-term observation、monitor the marine environment pollution and the damage of marine organism from human activities[2-4]. Because the passive acoustic data collected include ocean ambient noise and fish sound segment which is the main research object, endpoint detection technology is the basis of subsequent recognition and survey.

Endpoint detection technology is the extension of voice activity detection. The essential of the endpoint detection is differentiate fish sound and noise by the different characteristics of the same parameters. The distinction usually adopts the end-point judgment which is the decision criterion(such as threshold decision or mode classification) to distinguish fish sound and noise signal. Voice activity detection technology depends on new characteristic parameters(time-frequency parameters, Mel frequency cepstrum coefficient, self-related distance, information entropy and combined characteristic parameters) mainly to improve the anti-noise performance of the algorithm[5].

Sparse decomposition algorithm proposed by Mallat and Zhang has become a hot topic recently, it has been widely used in image, video, medical signal processing[6-14]. Sparse decomposition algorithm can adapt to select the proper basis functions to complete decomposition under the condition of lack of the statistical characteristics of noise. It also can use the redundant features of the dictionary to capture the natural characteristics of the original signal. The coherent ratio in the sparse decomposition algorithm can characterize the degree of residual signal reduction and reflect the features of the original signal from the signal reconstruction and de-noising.

For noisy and passive fish sound segment, the coherent ratio of passive fish sound and wave noise after sparse decomposition under different noise-signal ratio are extracted as test acoustic target in the training. Besides, feature of moving noisy signal segment and the test are classified and divided. Finally, threshold decision method is adapted to endpoint detection.

COHERENT RATIO OF SPARSE DECOMPOSITION

1. System-level auto-zero

Sparse matching pursuit algorithm is a kind of adaptive signal decomposition algorithm which selecting the best matching atom to approximate the local time-frequency structure in a complete high degree redundancy dictionary during iteration. From the perspective of passive fish acoustic signals, the main low frequency acoustic vibration signals delegate the sparse component of fish acoustic signals. The signals have a certain structure whose structure is coincide with that of atom. However, high frequency vibration is uncorrelated randomly. If meaningful atoms can be extracted from the signals, the extracted part will be the distribution of main passive fish sound. Or else meaningful signal cannot be extracted and the iteration will be ceased. During the process of signal sparse decomposition and iteration, atoms which have biggest inner product with signal or residual will be selected. Sparse decomposition is a process of constantly tracking and extracting atomic vectors which are best match to the original and residual signal. These extracted atomic vectors are distribution of main passive fish sound. We adopt coherent ratio as iteration terminal condition. The Gabor atom in the dictionary structure can be represented as[15]:

$$g_r(t) = \frac{1}{\sqrt{s}} g(\frac{t-u}{s}) \cos(vt+w) \ . \qquad (1)$$

where, $g(t) = e^{-\pi t^2}$ is a Gaussian window function. $\gamma = (s,u,v,w)$ is time-frequency parameter which delegates atomic expansion, displacement, frequency and phase position respectively,. Figure 1 is a program flow chart based on MP sparse de-noising.

The steps of concrete realization are as follows:

Define over-complete dictionary $D = \{g_{r_m}\}(m = 0,1,\cdots,M-1)$ in Hilbert space, where $\|g_{r_m}\| = 1$.

Clean passive fish acoustic signal can be represented as: $x(n)$, $n = 1,2,\cdots N$, N is the length of the signal. $x(n) = R^0 x$, $n = 1,2,\cdots N$, $R^0 x$ is the initial residual signal.

Select the optimal atom $g_{r_o} \in D$ as the MP algorithm and let $\left|\left\langle R^0 x, g_{r_0}\right\rangle\right|$ reach largest. The obtained residual is $R^1 x = R^0 x - \left\langle R^0 x, g_{r_0}\right\rangle g_{r_0}$ .Select the optimal atom $g_{r_1} \in D$ as the MP algorithm again and let $\left|\left\langle R^1 x, g_{r_1}\right\rangle\right|$ reach largest. The obtained residual is $R^2 x = R^1 x - \left\langle R^1 x, g_{r_1}\right\rangle g_{r_1}$, $\cdots\cdots$,, $R^m x = R^{m-1} x - \left\langle R^{m-1} x, g_{r_{m-1}}\right\rangle g_{r_{m-1}}$

The steps are iterated constantly, coherent ratio is defined as $\lambda(R^m x) = \sup_{g_{r_m} \in D} \left|\left\langle R^m x, g_{r_m}\right\rangle\right| / \|R^m x\|$.Value will reduce gradually with the increase of the iterations. If set to a convergence value, iterate value is M. Get the M+1st residual: $R^{M+1} x = R^M x - \left\langle R^M x, g_{r_M}\right\rangle g_{r_M}$.

Get $y(n) = \sum_{m=0}^{M} \left\langle R^m x, g_{r_m}^l\right\rangle g_{r_m}^l + R^{M+1} x$, $n = 1,2,\cdots N$.

Finally, select coherent ratio to parameters of acoustic signals.

Figure.2 shows sparse decomposition flow chart of passive acoustic signal(Campylomormyrus elephas). The wave of original fish acoustic signal covers the periodic high amplitude pulse and trailing signal.

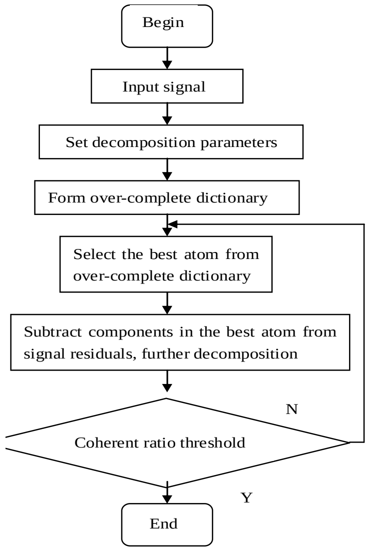


Fig1. Flow chart of the MP algorithm

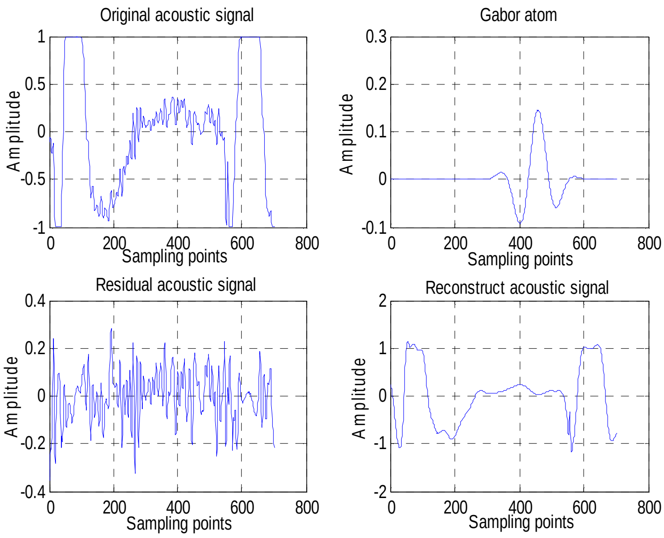
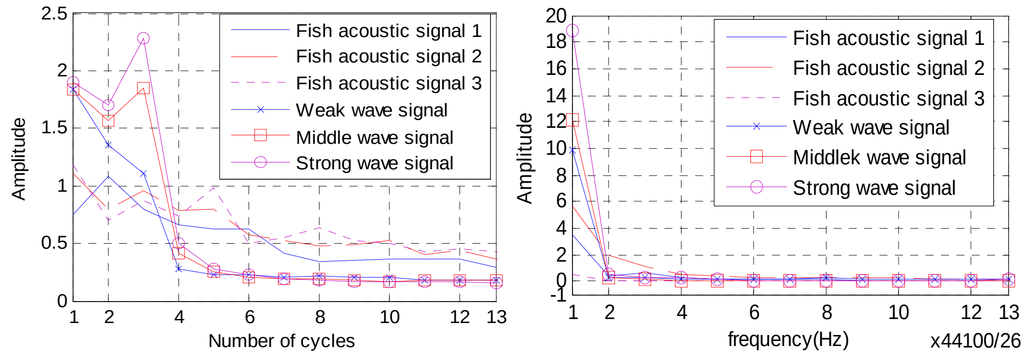


Fig.2 Passive acoustic signal (*Campylomormyrus elephas*) sparse decomposition

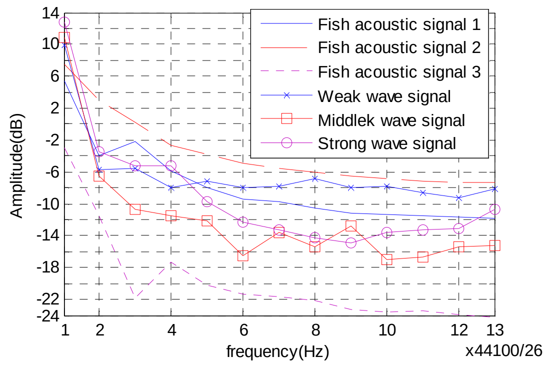
2. The comparison from coherent ratio between fish and ocean acoustic

Select three groups of clean passive acoustic signal(Campylomormyrus elephas) and three groups of wave passive acoustic signals. Sampling frequency of fish acoustic signal is 44.1 kHz. Distribution figure is shown by sparse decomposition, power amplitude and power spectrum method (order 26). Add the strong wave noise to clean campylomormyrus elephas passive fish sound. Distribution figure is shown in Figure 4 under different noise-signal ratio (Defined as the maximum energy ratio between signal and noise).

The amplitude and tendency of fish acoustic signals are similar in Figure 3(a) and different from wave sound signal obviously. Passive fish acoustic signal shows strong non-stationary and remarkable low-frequency characteristics. But wave noise has good stability and unobvious low-frequency with high frequency. During sparse decomposition iterative early, atomic signal is easy to match the low frequency signal of passive fish acoustic but difficulty to match the wave noise of high frequency. Hence the residual signal of fish acoustic signal is lower than wave sound signal. It is almost lower one time in the figure. In addition, the non-stationary of fish sound signal makes wave volatility greater than the sound of the wave. There are some individual differences between fish sound signal and wave sound signal in the low frequency in the Figure3(b). But most frequency is almost coincide. There are less significant differences compared to coherent ratio characteristic value. Compared to Figure3(b), the distribution of individual show obvious from Figure3(c). But there are no significant discriminations in the low or high frequency between wave sound signal and fish acoustic signal. The power spectrum is present to compare later.

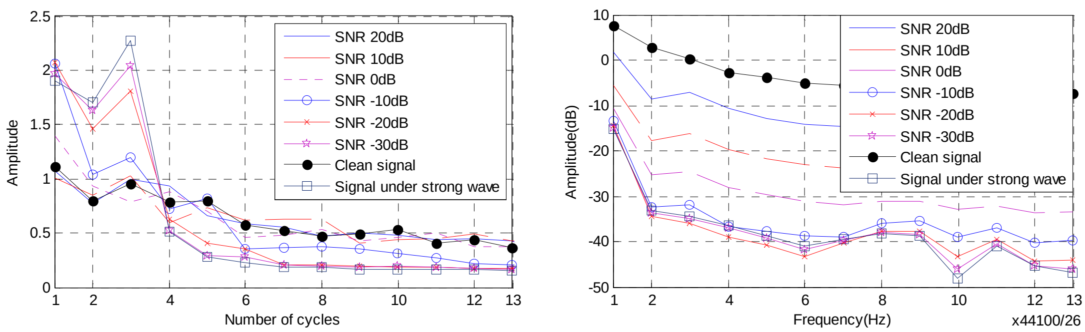


(a) Coherent ratio **(b) Power distribution**



(c) Power spectrum distribution

Fig.3 Contrast between clean acoustic signal (Campylomormyrus elephas) and wave noise



(a) Coherent ratio **(b) Power spectrum distribution**

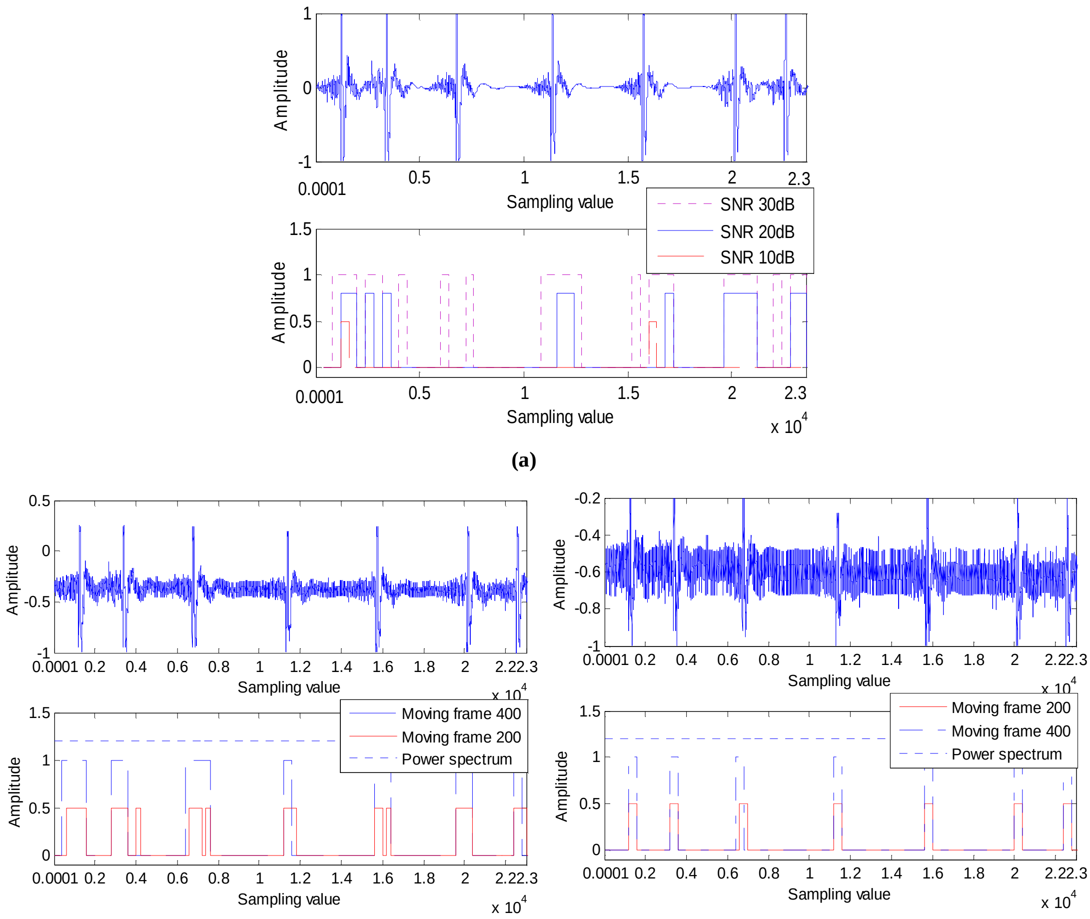
Fig.4 Contrast of passive acoustic (Campylomormyrus elephas) under different SNR (strong wave noise)

Figure4(a) shows that the distribution of the coherent ratio is close to the fish sound signal when SNR is more than 0dB. The distribution of characteristics is still close to clean fish acoustic signals when -10dB SNR. The distribution of characteristics is close to the sea noise gradually when SNR reduced from -20dB. The distribution of noisy fish acoustic signal characteristics isn't approaching to fish acoustic signal or strong wave noise obviously. With the SNR decreased gradually, the distribution of characteristics is tend to strong wave noise.

In conclusion, even if fish acoustic signals detected are hidden in wave, discrimination can be realized under -10Db SNR. Therefore, the coherent ratio can be represented as characteristics of different acoustic signals. The difference between the characteristics is easy to realize the passive fish acoustic signals' endpoint testing later.

EXPERIMENTAL SIMULATION BY ENDPOINT DETECTION

Figure5 shows that time domain waveform and endpoint detection results under different low SNR(Gnathonemus petersii)



(a)

(b) **(c)**

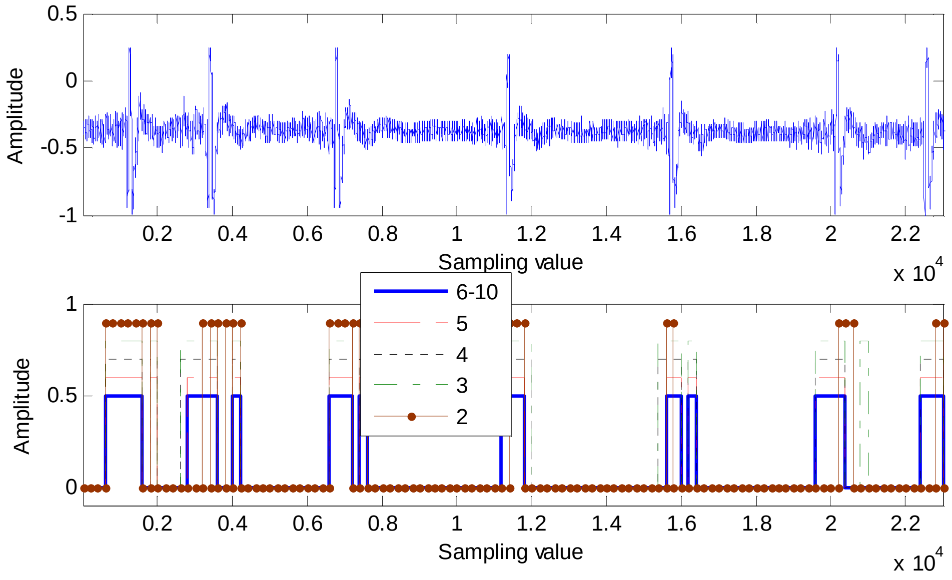
(a) Clean acoustic signals and detection results based on the power spectrum under 10,20,30dB SNR (frame shift 400 points).(b)Time domain waveform and endpoint detection results under 0dB SNR.(c)Time domain waveform and endpoint detection results under -10dB SNR.

Fig.5 Time domain waveform and endpoint detection results under different low SNR (Gnathonemus petersii)

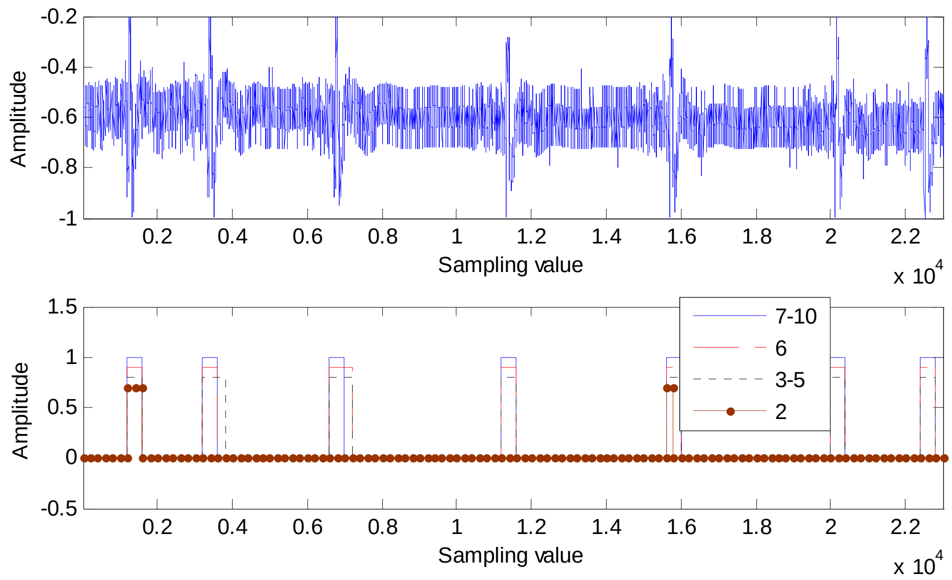
From Figure5, the accuracy of endpoint detection improves with the SNR from 10dB to 30dB based on characteristics of the power spectrum. Fish acoustic signal can't be detected effectively when SNR is less than 20dB. Signal and noise will be distinguished by the coherent ratio characteristics when frames reach 400 and 200 samples. Sparse decomposition algorithm can distinguish the endpoints of acoustic signal and wave noise accurately when SNR reaches -10dB, and the accuracy of 200 frames is higher than 400 frames. In fact, Figure3(c) and Figure 4(b) show the differenc between fish sound and wave noise power spectrum noise is tiny. The noise power spectrum characteristic is close to the distribution of wave noise power spectrum when SNR is less than 0dB. Fish acoustic signal cannot be detected in Figure5 by the power spectrum method. Better discrimination degree determines the better accuracy of detection under 0dB and -10dB SNR.

Figure 2 and Figure 6(a) show that the amplitude of the tail and noise time domain are similar when SNR is 0dB, but the frequency of tail part is lower than that of noise. Sparse decomposition algorithm will judge the tail signal as fish acoustic signal. Besides, with the frame reducing, the accuracy of the detection will increase. When SNR is -10dB, it can't be detected because the tail is submerged in noise totally when SNR is low. However, with the shift of frame reducing, the accuracy of the detection will increase. The accuracy of detection is higher when the frame shift is 200 rather than 400.

From Figure6, detection results are better on the condition of six features when 0dB SNR and seven features when -10 dB SNR. We can improve the efficiency of the algorithm by reducing the value of characteristics.



(a) 0dB



(b) -10dB

Fig.6 Comparison of different endpoints of sparse (Gnathonemus petersii)

CONCLUSION

Passive fish radiation acoustic target technology is the method different from the traditional optical technology and the active acoustic detection. Passive acoustic data collected include ocean ambient noise segment and fish sound signal segment and the fish acoustic signal is the main research object. In order to realize fish acoustic endpoint detection technology, this paper adopts the sparse decomposition algorithm to extract coherent ratio characteristic value. The algorithm extract the characteristic value of clean passive fish sound and wave noise under different SNR in the training stage as acoustic testing target characteristics. Then, moving noise segment and the testing characteristics are extracted to classify in the detection stage. Finally, threshold decision method is adapted to detect the endpoint. The experimental results show that sparse decomposition algorithm can realize the detection of the effective signal accurately compared with power spectrum algorithm under the condition of low SNR.

Acknowledgements
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