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Underwater acoustic recognition system for detection of low-altitude moving source

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ABSTRACT

Air targets detection underwater is an important part of marine safety management. For the difference in the physical property of the water and air, there are many difficulties in the water to air sound detection. In this paper, we present a recognition system using both time and frequency domain characteristics for target detection. In the detection phase, a short-to-long-term energy ratio (SLR) was first obtained using the coupling acoustic data. This initial SLR indicates the possibility of target appearing. For signals exceeding SLR threshold, the cepstral coefficients are extracted by a 4-Gammatone filter with cochlea membrane ability. The validity of the algorithm is proved by a test adopting BP network with both synthetic and real data. The results indicating that joint detection algorithm can detect the low-altitude helicopter real-time and has a good anti-noise performance.

Keywords: Target Detection, Air-to-water Coupling Signals, Dynamic Energy

1. INTRODUCTION

In the air and sea combat, the air platform has an asymmetry advantage to the underwater force. Usually, air targets in the execution of missions have the characteristics of low flight altitude, slow flight speed and occasional hovering. One area of interest is the detection of air targets using acoustic signals coupled from air to water. In response to this problem, early research mainly focused on the modeling of underwater acoustic filed, including computational models based on ray acoustics, wave theory and normal-mode theory (1-3). Some recent studies conducted by domestic scholars include: acoustic filed propagation of airborne source in shallow sea, technology of helicopter detection underwater and so on (4-7).

The estimation of target flight distance is usually difficult when the target model is different and no enough stable environmental parameters. These disadvantages limit the experimental and engineering applications of water-to-air positioning algorithms. In this paper, we propose a detection algorithm based on signal energy and spectral characteristics that is weakly correlated with the calculation models, and generates a trigger signal to start the next accurate localization.

Since the acoustic impedance of air and water differs by more than 4000 times, the sound intensity loss is about 20~30dB when sound propagates through the air-water interface. In addition, total reflection occurs when the incident angle to the water surface exceeds 12.7°, and the acoustic energy coupled into the water is mainly concentrated within a cone angle of about 25.4° (7, 8). Based on this feature of sound propagation, our research is mainly set as a shallow sea area. The rest of this paper is organized as follows: Section 2 presents the system composition of the detection system. A time-frequency joint detection algorithm is given in Section 3. With the extraction features of known air targets, simulation and measurement results are analyzed in Section 4. Then conclusion is given in Section 5.

2. DESCRIPTION OF THE PROPOSED SYSTEM

To achieve the underwater detection of flying targets, the main task of underwater acoustic signal processing is to identify the target signal under low SNR conditions. The paper considers the application of the detector in shallow sea when the altitude of the air target is 100 meters or less, the flight speed is lower than 60km/h and hovering sometimes. The detection system is composed with a

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signal acquisition unit and a signal processing unit. The whole detector is illustrated in Figure.1. The acquisition unit mainly includes two hydrophones (GRAS 10CT) and signal conditioning modules. The hydrophone records the acoustic signal coupled through the air-water interface. After filtering, noise reduction and framing, the signal processing unit runs the detection algorithm and gives a detection result every 0.5s.

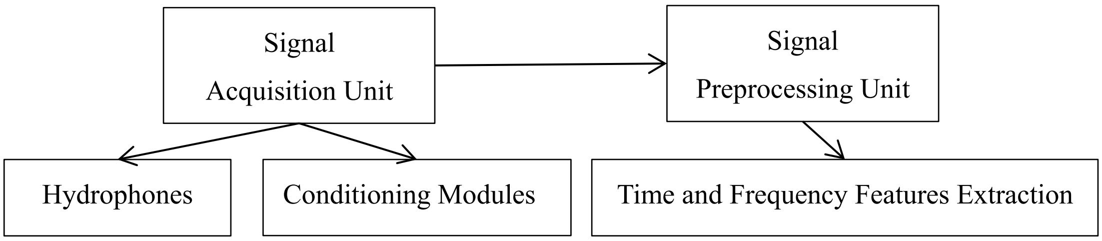


Figure 1 – System composition structure figure

Assuming that the background noise is statistically stable, and the target signal energy is always larger than the background noise. Firstly, calculating an energy ratio of the short and long frame signals, which called a short-to-long-term energy ratio (SLR). If the SLR values of consecutive K frames exceed the set threshold, it is determined that a suspicious target appears. Next, the cepstral coefficients of the current frame signal are extracted using a 4-order Gammatone filter with eardrum filtering characteristics. With these learned features input to a BP neural network, the final judgment result is given as 1 or 0 w means target appears or not. The whole detection process is shown in Figure 2.

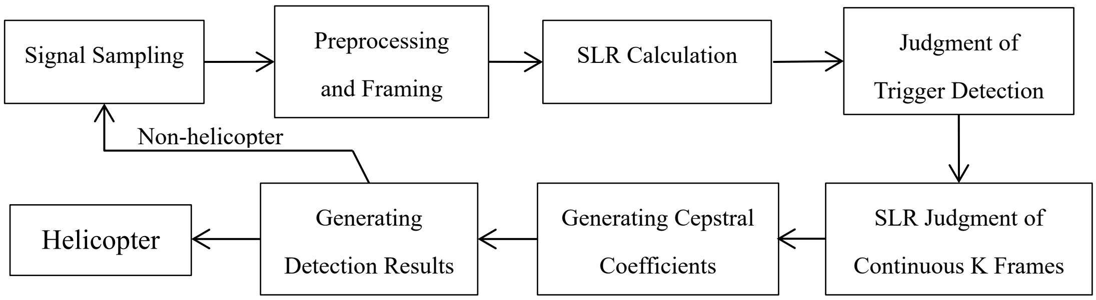


Figure 2 – System detection flow chart

3. TIME AND FREQUENCY JOINT DETECTION ALGORITHM

3.1 Energy Trigger in Time Domain

In the real-time signal processing, the short-term energy is calculated for each frame of data. These values form an energy sequence that called $STA_{En}(i)$(i is the frame number). In addition, the signal long-term energy called LTA_{En} which is the successive K frames before the current frame. All parameters are calculated according to the following expression.

$$STA_{En}(i) = \sum_{m-(i-1)*N+1}^{(i-1)*N+N} x(m)^2 \tag{1}$$

$$LTA_{En} = \sum_{i-(K-1)}^{i} STA_{En}(i) \tag{2}$$

$$SLR_{En} = STA_{En}(K)/LTA_{En} \tag{3}$$

$$\delta y = \frac{1}{K} LTA_{En} + \frac{2.2}{K-1}\sum_{i=1}^{n}(STA_{En}(i) - \frac{LTA_{En}}{K})^2 \tag{4}$$

$$bgthrd(i) = w * bgthrd(i-1) + (1-w) * \delta y \tag{5}$$

Where STA_{En} denotes the short-time energy of the current signal frame, LTA_{En} is the sum of the previous K frame energies, $bgthrd$ is the current trigger threshold with an initial valve set to 0.1, and δy is the adjustment value of the detection threshold. The threshold is dynamically updated according to the above formula (4, 5). The algorithm used two sets of parameters as the conditions for trigger detection, which are STA compared with *bgthrd* while SLR compared with A_0. It is determined that the suspicious target is found when both sets of values exceed the set threshold. The spectrum features are then analyzed to eliminate interference signals.

3.2 Feature Matching in Frequency Domain

Aerial targets, such as helicopters, can be seen as a strong continuous sound source in flight. The signal frequency spectrum is a discrete spectrum of harmonic relationship superimposed on the broadband continuum, as shown in the Figure 3. In general, the fundamental frequency of the main propeller excitation signal is between 10Hz to 25Hz, and the fundamental frequency of the tail propeller excitation signal is between 50Hz to 100Hz.

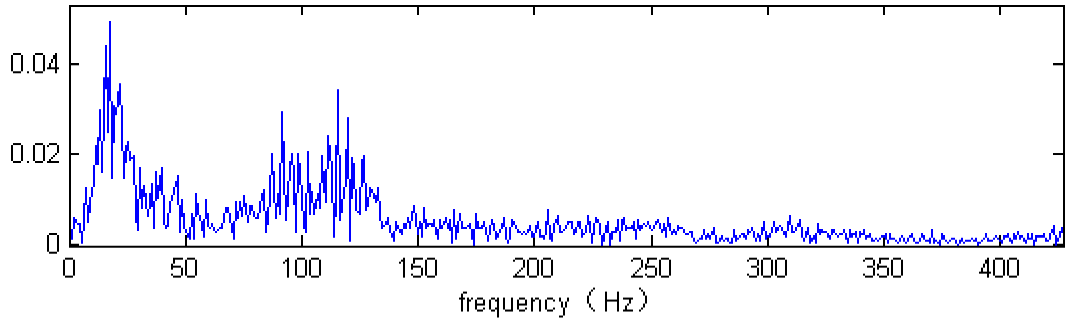
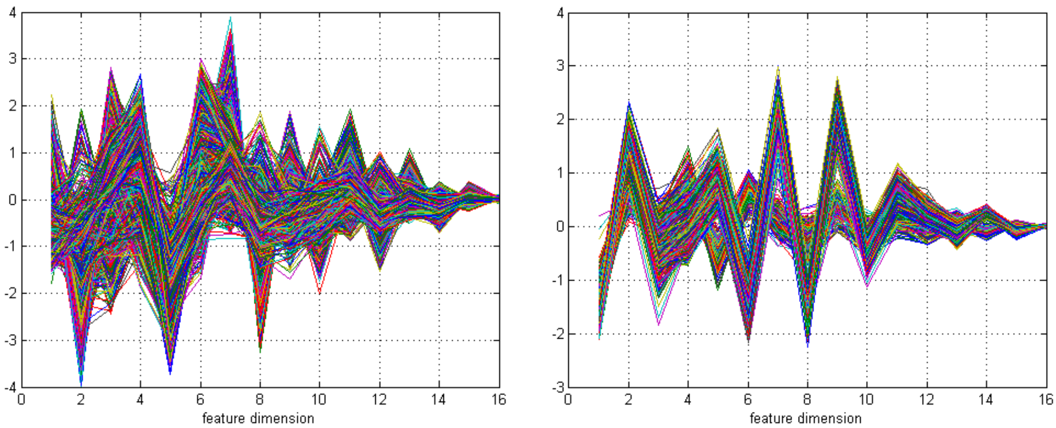


Figure 3 – Typical helicopter signal FFT spectrum

The detection algorithm using the fundamental frequency and harmonic set of helicopter has higher requirements on the SNR of the real-time signal. Without using the sound field propagation calculation models, the filtering cepstrum coefficient extraction based on human auditory feature recognition is studied. Referring to the author's previous airborne feature extraction algorithm (9), the signal features are extracted from current frame are called Gammatone Filter Cepstrum Coefficients (GFCC). The extraction features of two targets are shown in Figure 4.



(a)Helicopter GFCC (b) Background Noise GFCC

Figure 4 – Extraction GFCC of Different Targets

Next, the BP neural network is trained by extracting features to achieve the recognition of specific targets.

4. EXPERIMENTAL RESULTS

4.1 Simulation Experiment in the Pool

First, an experiment was done in a circular pool (6 meters in diameter) to verify the design algorithm. A high-powered speaker was hoisted directly above the center of the pool to play helicopter flight audio files. The above design system was used to collect the coupled water signal (the hydrophone was located at 2m depth), and the signal sampling rate was 8000Hz. The frequency domain features were extracted by acquisition signals from the audio, and the neural network was trained using a training set to prepare for the real experiment of the signal. The network recognition result is shown in Figure 5.

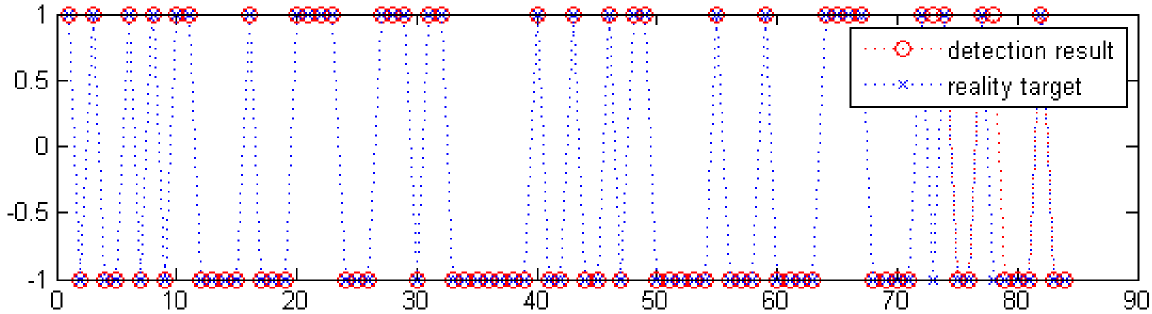


Figure 5 – Detection and recognition results of helicopter and noise

It can be seen that the network identification result error rate is 5.95% for the selected 84 test signals. At the same time, the cepstral coefficient method still has good anti-noise performance in the characteristic expression of underwater coupled signals.

4.2 Physical Flight Experiment in the Lake

The experiment was carried out in X-Lake, and the main test shell of the underwater sound detection system was sunk into different depths (5m, 10m, 15m) in the lake. A French-made small squirrel helicopter was at different heights on the water surface (30m, 50m, 100m) flight or hover, the main results of the experiment and analysis are as follows. The system operation output is 1 and 0, respectively representing to found target and no target.

4.2.1 Detection Performance at Different Flight Altitude

According to the airborne sound propagation characteristics, the system mainly collects the direct refracted water signal. As the flight altitude changes, the duration time of detection does not change much, but the farthest detection distance increases. The results are shown in Table 1.

Table 1 – Detection performance of the detector at 5m depth underwater

Altitude, m	Circling flight		Hovering flight	
	Duration, s	Distance, m	Duration, s	Distance, m
10	8.5(7)	134(-)	157	67-171
20	7	127	171	63-229
50	-	-	93	69-148
100	7	188	125	70-119

From the above results, it can be found that the target in hovering state has a strong energy and can be detected sustainably.

4.2.2 Detection Performance at Different Depth

As the depth of the detector increases, the signal is successfully detected within a water depth of 50m. The results are shown in Table 2.

Table 2 – Detection performance of the helicopter at 20m flight altitude

Depth, m	Circling flight		Hovering flight	
	Duration, s	Distance, m	Duration, s	Distance, m
5	7	127	171	63~229
10	4	125	179	65~69
15	5.5	168	62	44~162

The experimental results show that under the condition of relaxing the number of experiments and the quality of data acquisition, the attenuation of the coupled water signal in the shallow water layer is not obvious to the target source in the same state.

5. CONCLUSIONS

The acoustic detection system for low-altitude target is designed and realized in the shallow water environment. It is proved effectiveness that the signal detection algorithm based on energy threshold judgement and frequency feature recognition. The results show that the algorithm is highly transplantable and insensitive to specific targets. Sequential modeling and analysis of detected threat in the real sea environment is the plan for the future work.

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