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Active Sonar Target Classification Using Multi-aspect Sensing and Deep Belief Networks

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ABSTRACT

Underwater target detection and classification problems have been studied by many researchers for both military purposes and non-military ones. Due to the complicated characteristics of underwater acoustic signal reflecting multipath environments and spatio-temporal varying characteristics, active sonar target classification technique has been considered as a difficult one. And it has a difficulty in collecting real sea-trial data. In this paper, we synthesized active target echoes based on ray tracing algorithm using target model having 3-dimensional highlight distribution. Then, Fractional Fourier transform was applied to synthesized target echoes to extract feature vector. Classification experiment was performed using deep belief networks based on multi-aspect based sensing. As a result, proposed feature extraction method showed a better performance than conventional backpropagation neural network classifier. And, we also obtained a better classification result using multi-aspect based sensing method.

Keywords: Active sonar, classification, fractional Fourier transform, deep belief network, backpropagation neural network.

I. INTRODUCTION

The problem of underwater target detection and classification has been attracted a substantial amount of attention and studied from many researchers for both military and non-military purposes. The difficulty is complicate due to various environmental conditions. Until now, a range of pattern recognition approaches with the active sonar signals are under study, but there are many problems to be considered. Most of previous researches focused on feature extraction method from returned sonar signal in time and frequency domain to increase classification performance based on various classifiers such as HMM(Hidden Markov Model), SVM (Support Vector Machine) and neural networks.

In acoustic sensing scenarios, the target can observed from single or multiple target-sensor orientations (or aspects). Normally, a single sensor is used to detect and classify the objects based upon observations taken from the environment. Recently, the utilization of multi-aspect sensing in underwater target classification problems has widely studied as a general trend[1], [2]. The use of multi-aspect sensing is motivated by the difficulty in detection and classification among different targets from a single aspect. It occurs frequently that echo returns from two different objects at certain orientations are so similar that they may easily be confused. Consequently, a more reliable decision about the presence and type of an object can be made based upon observations of the received signals or patterns at multiple aspect angles. Paul Runkle [1] introduced the HMM to multi-aspect target recognition. Each state of the HMM is characterized by the aspect of the target and a state transition occurs when the target aspect changed by the received sonar signals from different directions. In [2], target classification method with synthesized active sonar signals using matching pursuit and multi-aspect hidden Markov model was introduced.

In addition, since it is difficult to collect real data for research, most studies focused on the experimentally generated data such as sonar returns from submerged elastic cylindrical shaped targets in the water tank or lake [3], [4]. As an alternative approach to this, synthesized sonar signals on the certain target condition can be used. In that case conventional echo highlight model [5] could be used because of its simplicity.

In this paper, we study multi-aspect-based sensing scheme for active sonar target classification to improve the classification performance. Active sonar returns from targets are synthesized based on the ray tracing algorithm for 3-dimensional highlight models. To extract the features, a FrFT(Fractional Fourier Transform) is applied to sonar returns[6]. With the FrFT-based features, four different targets are classified using deep belief network [7], [8]. To prove the effectiveness of proposed scheme, we compare the performance of the proposed method with conventional BPNN(Backpropagation Neural Network) using same feature extraction method.

The paper is organized as follows: Section II describes the synthesis of active sonar returns using 3-dimensional highlight models. Feature extraction method using FrFT with some mathematical overview presented in Section III; Section IV summarizes the experimental results of the proposed method and the comparisons to single sensing scheme and conventional BPNN method, and finally some conclusions are discussed in Section V.

II. SYNTHESIS OF ACTIVE SONAR RETURNS

The target used in the experiment is shown in Fig 1 as four types of models that are highlighted in three-dimensional space. The positional relationship between the target and the sensor is shown in Fig 2. The depth of water was set to 300 m, and the distance between the target and the sensor is 5000 meters. The transmitter and receiver were located at the same position in the water, i.e. monostatic mode, and an unknown target was at 50m below sea level. We adopted the sound velocity profile to calculate the sound velocity at a certain depth of water. Direct echo returns from the target and indirect reflections from sea level and sea bottom were included for the synthesis of active sonar returns [5].

We can obtain the synthesized signal by summing traced signals from each highlight at the receiver position. In this work, we generated active sonar returns for each target by varying its aspect from 0 to 360 degrees by 1 degree increment.

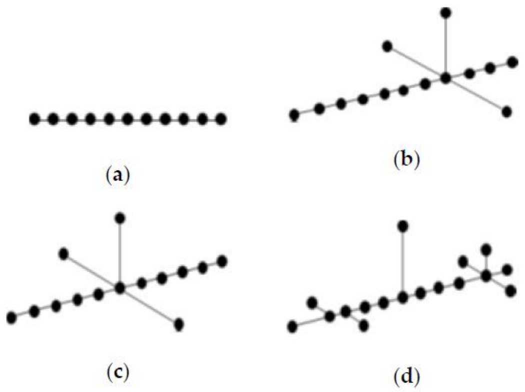

Fig. 1 Target models with 3-dimensional highlights used to synthesize sonar signals (a) Type 1 (b) Type 2 (c) Type 3 (d) Type 4.

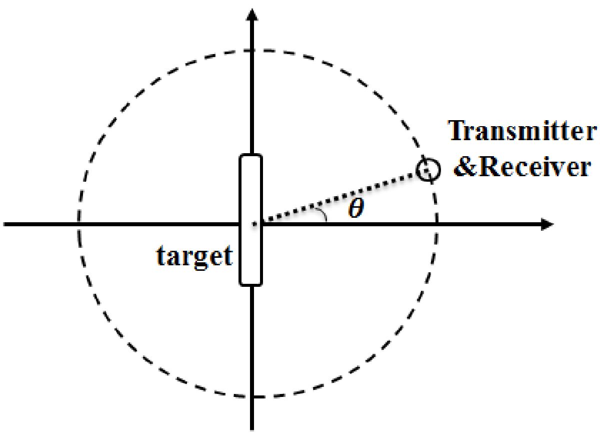

Fig. 2 Environment for target synthesis.

FrFT BASED FEATURE EXTRACTION

FrFT is one of the time-frequency representation methods and is known to have advantages in the analysis of the LFM (Linear Frequency Modulated) signals. It provides an energy compacted peak spectrum for an LFM in the FrFT domain.

Definition formula of the FrFT with transform parameter α is shown in Equation (1)-(4) [6].

$$F^{\alpha}\{s(t)\} = S_{\alpha}(u) = \int K_{\phi}(u,t)s(t)dt \tag{1}$$

$$K_{\phi}(u,t) = A_{\phi}\exp\left[i\pi\left(u^2\cot\phi - 2ut\csc\phi + t^2\cot\phi\right)\right] \tag{2}$$

$$A_{\phi} = \frac{1}{\sqrt{|\sin\phi|}}e^{-j\left(\frac{\pi}{4}\operatorname{sgn}(\phi)-\frac{1}{2}\phi\right)} \tag{3}$$

$$\phi = \frac{\pi}{2}\alpha \tag{4}$$

The main idea to classify the target is reflecting the shape variation of the peak positions depending on the highlight points of the target. The best way to achieve accurate shape variation is the use of entire FrFT coefficients as a feature vector. However, the entire FrFT coefficients contain too much redundant and irrelevant information, this can lead to decrease of discrimination capability. Therefore, to reflect shape variation properly, the feature vector is obtained by dividing the FrFT domain into p equal bands and calculating the energy for each band. This process produces pth-order FrFT based features which reflect the characteristics of shape change adequately and possess discrimination capability. Fig 3 illustrates the feature extraction process.

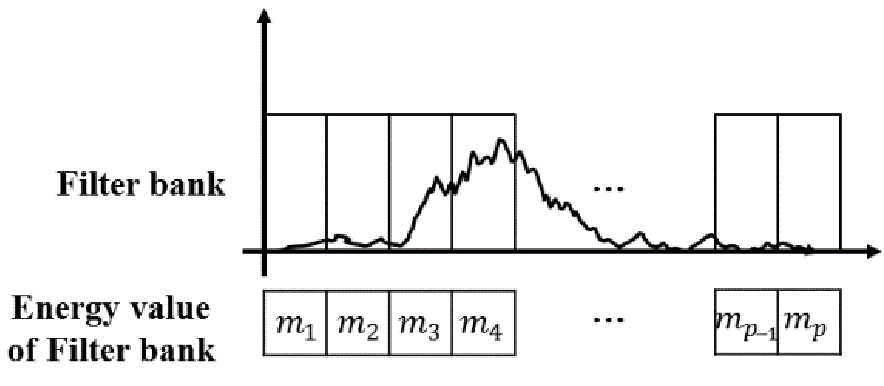

Fig. 3 Process of the feature extraction in FrFT domain.

III. DEEP BELIEF NETWORKS

Deep learning is a method of training deeply structured neural networks with two or more hidden layers. Deep structure neural networks has a vanishing gradient problem in training process. After several algorithms have been developed to solve this problem, deep learning has shown good performance in various fields such as image recognition, speech recognition, and natural language processing [7].

DBN STRUCTURE

Pre-training using DBN is one of the algorithms for deep learning. Pre-trained networks are trained without vanishing gradient problem using a back-propagation algorithm even with deep structures. DBN is a directed acyclic graph composed of random variables. It has been used for the training of deep learning since Hinton announced the greedy learning algorithm [8]. Fig 4 shows the structure of DBN with three hidden layers. According to the greedy algorithm, each layer is trained with RBM.

The pre-training process aims at finding an initial weight matrix in which the network can be well trained through unsupervised training, and in doing so it is able to train the deep neural network well. To use the DBN as a classifier, output layer and fine-tuning processes are required. Fine-tuning is the process of supervised training over the entire network using the initial weight matrix found in the pre-training process. In the pre-training, the training of the DBN composed of the input layer and the hidden layer only is first performed except the output layer. In the fine tuning, then, the training is carried out with the discriminant classifier including the output layer.

IV. EXPERIMENTS AND DISCUSSION

In the synthesis of active sonar signals, the sampling frequency and LFM pulse duration was set to 31.25 kHz and 50ms, respectively. The center frequency and bandwidth of the LFM signal were 7 kHz, and 400 Hz, respectively. The signals synthesized by summing the signals traced from each highlight model depending on aspect angle of the target were then obtained. In this experiment, 1440 active sonar returns were generated from four highlight models by varying its aspect from 0 to 359° with 1° increments.

The α parameter of FrFT was set to 0.9919. The LFM signal used in the experiment has the maximum peak spectrum after FrFT conversion with this parameter value. The feature vector was obtained by dividing the FrFT domain into 100 equal bands and calculating the energy for each band. This feature extraction process led to 100th-order FrFT based features which reflect the characteristics of shape changes adequately and possess discrimination capability.

Fig. 5 shows the features extracted from four different targets at aspect angle of 45° in the FrFT through the feature extraction process of Fig. 4. Features extracted from four different targets have different shapes in FrFT domain depending on target type.

SINGLE-ASPECT BASED CLASSIFICATION

For the performance evaluation, the proposed method and the previous experimental results using BPNN[5] were compared. In case of BPNN, we used 100-24-4 structure, with 100 input neurons, 24 hidden-layer neurons, and four outputs. The stopping criterion used is as follows: the training is stopped either when the average error is reduced to 0.001 or if a maximum of 10,000 epochs is reached. Fig 6 shows the architecture of the DBN used in the experiments. The number of input nodes is 100, two hidden layers of 300 nodes are used, and the number of output nodes is 4. The fine-tuning learning rate was set to 0.25, and the mini-batch size was set to 18. The pre-training learning rate of the DBN was 0.01.

In the single aspect-based classification, only one signal received at a specific aspect is used as an input to the classifier. Table 1 shows the actual classification results using the BPNN[5] and DBN classifiers. As shown in Table 1, it is confirmed that the classification result using DBN is improved by about 3.83% compared with the conventional BPNN classifier.

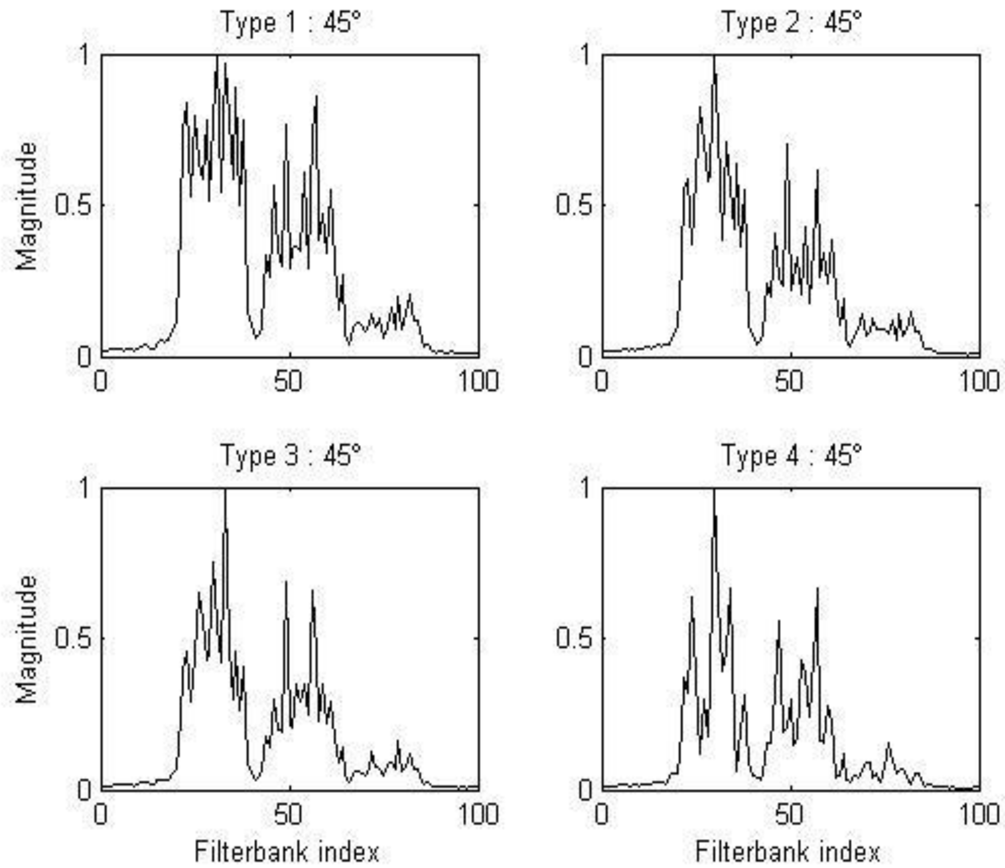

Fig. 5 Features extracted from four different targets at aspect angle of 45° in the FrFT domain

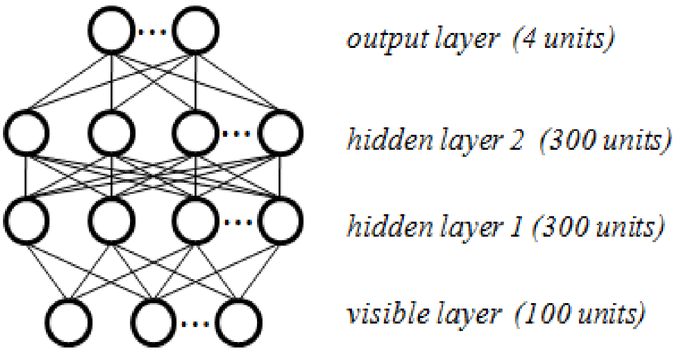

Fig. 6 Deep belief network architecture in the experiments.

Table 1. Result of classification

Class	BPNN	DBN
Type 1	89.17%	91.27%
Type 2	86.67%	88.12%
Type 3	87.78%	89.91%
Type 4	86.67%	96.31%
Total	87.57%	91.40%

MULTI-ASPECT BASED CLASSIFICATION

Recently, the utilization of multi-aspect-based sensing in underwater target classification problems has widely studied. Experiments were carried out by using a multi-aspect based technique that simultaneously uses feature vectors extracted from multiple aspect received from multiple sensors, rather than using only feature vectors extracted from a single received signal observed at a specific aspect. Figure 7 shows an example of multi-aspect receiver structure in 2-dimensional x-y coordinate system which the receiver receives observation signals at specific angular intervals by applying the multi-aspect based sensing.

In the experiment, we used several observation signals received at 1 degree intervals in the range of 0 to 359 degrees along the azimuth angle in the highlight model. We used only odd number of observation signals among 1 - 31 received, and we confirmed the results of classification rate varying according to the number of observation signals. Classification rate was measured by majority voting method. That is, if the result of recognition as a specific class is more than half, it is regarded as successful. For example, when nine observation signals were used, five or more of the nine results were regarded as successful if they were classified as the same target.

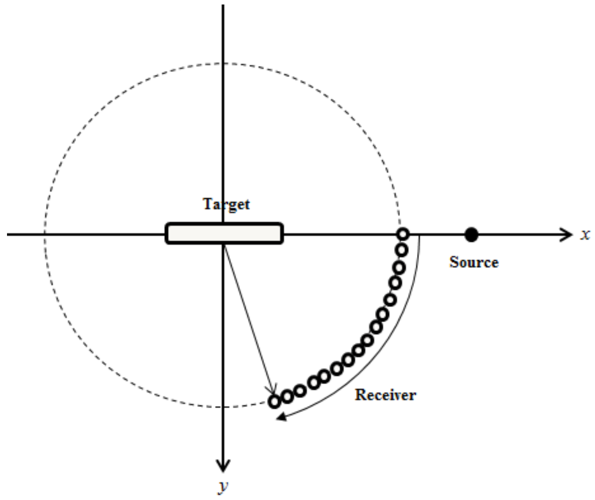

Fig. 7. An example of multi-aspect receiver structure in 2-dimensional x-y coordinate system

Fig. 8 shows the classification rate results according to the number of observation signals. As can be seen from Fig. 8, the classification rate also increases as the number of observation signals increases. Using the DBN classifier, the performance more than 95% is shown when the number of observation signals exceeds 3, and the classification rate of 100% is obtained when the number of observation signals exceeds 13.

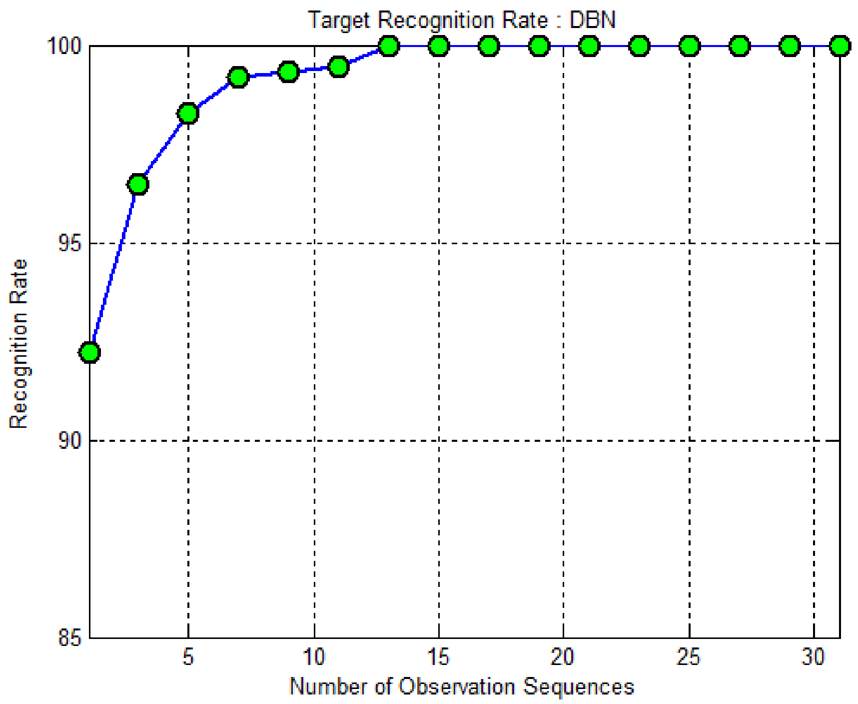

Fig. 8. Classification rate depending on the number of observations and majority voting

V. CONCLUSION

In this paper, we presented multi-aspect based sensing scheme for active sonar target classification to improve the classification performance. Active sonar returns from targets are synthesized based on the ray tracing algorithm for 3-dimensional highlight models. To extract the features, FrFT is applied to sonar returns. With the FrFT-based features, four different targets are classified using deep belief network. To prove the effectiveness of proposed scheme, we compared the performance of the proposed method with conventional BPNN using same feature extraction method.

In case of single aspect experiment, classification result using DBN was improved by about 4.65% compared with the conventional BPNN classifier. Moreover, further performance improvement can be obtained by adopting multi-aspect based scheme with majority voting. Using the DBN classifier with multi-aspect based scheme, the performance more than 95% was obtained when the number of observation signals exceeds 3, and the classification rate of 100% was obtained when the number of observation signals exceeds 13. In future studies, we have plan to conduct additional experiments using real sea-trial data to verify the proposed scheme

Acknowledgements

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