FISH SCHOOL IDENTIFICATION IN THE BALI STRAIT USING ACOUSTIC DESCRIPTOR AND ARTIFICIAL NEURAL NETWORKS TECHNIQUES

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Abstract

Accurate fish school identification is one of the crucial pieces of information for fish stock assessment. The fish stock assessment, in turn, is used as a basis for fisheries management action plan. In this paper, we discuss the development and application of acoustic descriptor (AD) and artificial neural networks (ANN) technique for fish school identification. Data (echogram) was obtained from the acoustic survey conducted in November 2000 in the Bali Strait, using SIMRAD EK500 split-beam acoustic system. In this preliminary study, the usage of AD is confined to the geometrical properties (area, perimeter, height, length, elongation, circularity, rectangular, and fractal dimension) of the echogram or acoustic backscattering images, while the ANN used back-propagation technique and a sigmoid activation function to transform the input to output. The results show that the accuracy of identifying fish school for various ANN learning rate value is about 73.3%. We observed that the school of Lemuru *Sardinella lemuru,* which is dominant in the Strait of Bali during the time of the survey, takes elongated geometrical formation and occupied particular water depth. Future study will incorporate the more complete set of AD, for example by employing the energetic dimension, to improve the accuracy of the school identification.

Keywords: school identification, acoustic descriptor, artificial neural networks

I. Introduction

Responsible and sustainable usage of fisheries resources call for a sound fisheries management. However, development of a sound fisheries management action plan requires a good description of the fish stock. Fish stock assessment is complicated task, especially for multi-species resources. In the presence of large diversity and relatively small school size, such as those found in the tropical waters of Indonesia, the identification process becomes even more complicated.

One of the fish stock assessment technique that has become more intensive and widely used is the hydro-acoustic technique (McLennan and Simmonds, 1992) due to the availability of more sophisticated acoustic instrumentations and their signal processing analysis. However, at present, one of the main obstacles in fish stock estimation using hydroacoustic technique is how to determine the species composition from echogram,

Acoustic technique has been used to identify fish school (Gerlotto, 1973) as well as plankton-like organism (Barange, 1994; Miyashita et al., 1997). Even, several attempts were made to identify fish species, for exampie Simmonds et al. (1996), Zakharia et al. (1996) using wideband sounder. To carry out such studies, it is necessary to employ an acoustic signal processing. For example, special image analysis technique has been used to study and identify fish school (Reid and Simmonds, 1993; Lu and Lee, 1995), and ded-

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icated software was developed to classify fish shoal (Weill etal., 1993).

It is important to mention that the identification of fish school is very much known at the sampling stations, while outside of these stations are not, except special form of procedure established to identify them. For example using statistical modeling and prediction based on the fish school features (Reid, 2000). One of the automatic extractions of the fish school features is artificial neural networks (ANN).

In this paper, the artificial neural network technique is applied to further process the acoustic data. The ANN has been used in fish school identification (Haralabous and Georgakarakos, 1996) and then combined with discriminant analysis (Simmonds et al., 1996). The usage of ANN technique is expected to overcome the difficulty of identifying fish school as mentioned early. Specifically, in this paper, we discuss the development and application of acoustic descriptor (AD) and ANN technique for fish school identification. Data (echogram) was obtained from the acoustic survey conducted in November 2000 in the Bali Strait, using SIMRAD EK500 split-beam acoustic system. In this preliminary study, the usage of AD is confined to the geometrical properties (area, perimeter, height, length, elongation, circularity, rectangular, and fractal dimension) of the echogram or acoustic backscattering images, while the ANN used back-propagation technique and a sigmoid activation function to transform the input to output.

II. Method of Identification

Fish school data to be identified were obtained from hydro-acoustic survey conducted with RV Baruna Jaya in November 2000 in the Bali Strait, using SIMRAD EK500 split-beam acoustic system (at 120 kHz). In the following sections, the method of extraction of acoustic descriptor is first described and then second the ANN.

2.1 Acoustic descriptor of the fish school

In this study, the usage of AD is confined to the geometrical properties (area, perimeter, height, length, elongation, circularity, rectangular, and fractal dimension) of the echogram or acoustic backscattering images.

Prior to the calculation of the acoustic descriptor, the echograms were extracted using SIMRAD EP500 and then stored in the bitmap format. The image analysis technique was carried out and the acoustic descriptors of the fish school were calculated as follow: (1) Each pixel in the echogram were read systematically with a resolution equal to 1 m on the depth (vertical axis) and to 1 ping on the horizontal axis, (2) color filtering of the image were conducted based on the target strength (TS) value of the fish school to be analyzed, (3) the filtered echogram were then further separated into two colors only (the object and the background) (Figure 1). Once the binary image was obtained, and using standard edge detection technique, the acoustic descriptor of the school can be calculated. In the present study the edge detection technique was performed using 8-path method (Figure 2).

2.2 Artificial Neural Networks

The fundamental concept of ANN is based on the premise that some behavioral characteristics of the insonified schools, which are related to the aforementioned descriptors, are species specific (Ripley, 1996; Reid, 2000). In other word, the idea behind the application of ANN is based on the ability of ANN to learn the pattern, in this case these species specific descriptor.

The ANN was constructed using three layers: input layer, hidden layer and output layer (Figure 3). The input layer consist of acoustic descriptor values (given in Table 1), extracted from the "known" fish school. One layer was selected as the hidden layer to be applied in this ANN. In order to detect features in a pattern process, the classical sigmoid function was used as the activation function. The output layer of the network is the result of fish school identification.

To measure the performance of the ANN, the actual output of the network computation was compared to the correct output over a number of trials. The different data set were used for training and testing, as required to know how well the networks learned.

A program to compute ANN was developed under Visual Basic 6.0 platform, using back-propagation algorithm. This algorithm used a general minimization problem and applied so called the generalized delta rule (Hecht-Nielsen, 1991). In this rules, to reduce the difference between the actual output pattern and the target output during training is performed by changing the weights. This correction is back-propagated through the network during training. The model structure of ANN is shown in Figure 3.

The number of data set used for the training set of fish school descriptor were 40 units, and the training process for ANN were conducted up to 200,000 to 250,000 iterations. The ANN was trained using sigmoid logistic constant of 1 and three different learning rate, namely 0.3, 0.5 and 0.9. The main purpose of using different learning rate was to obtain the smallest sigma error. Meanwhile, the determination on the number of iteration was based on the level of accuracy of ANN estimate. When the accuracy level reaches 100% then the iteration will be stopped; otherwise, if the level of accuracy far from 100% then the iteration will be continued. The number of data set used for the validation purpose of the ANN was 30 units. The limitation on the number of data set used both for training and validation merely due to the availability of the total data set.

HI. Result and Discussion

Within the 277 original (raw) echograms obtained from the hydro-acoustic, only 30 echograms contain fish school images or pattern. Based on these 30 echograms, the numbers of descriptor that are successfully extracted are 70 data sets. This data set then split into two, 40 data sets are used for the training of ANN and 30 data sets for validation of ANN.

3.1. Training of ANN

During the training of ANN the 40 data sets are successfully separated into two: 22 units are identified as Lemuru fish school and 18 are not. The statistic of the descriptor for the training purpose is shown in Table 2.

As shown in Table 2 and 3, there are not much different between descriptor of the Le-

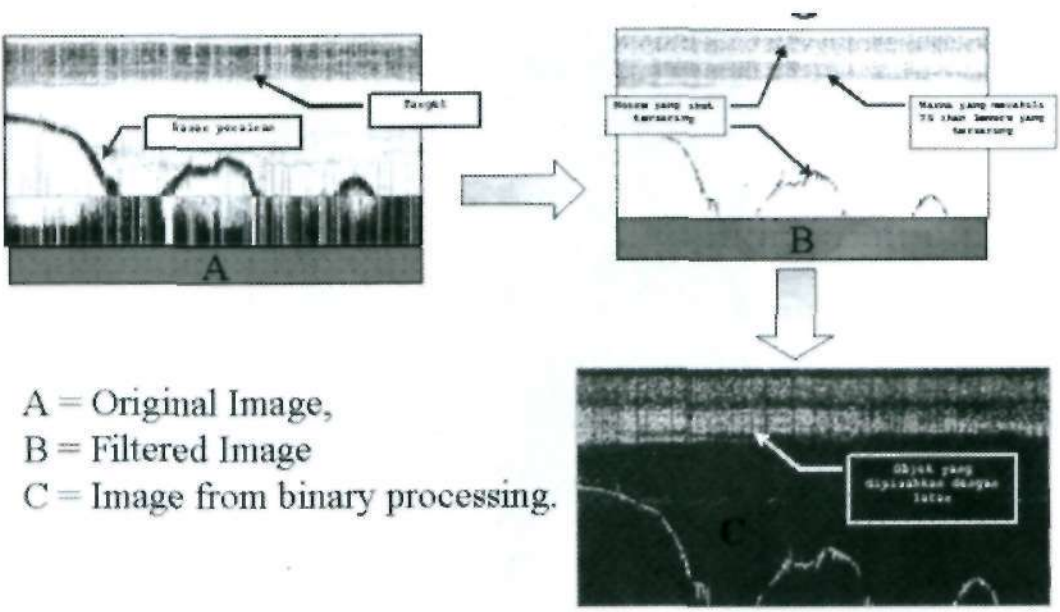

Figure 1. Pre-processing of the echogram to obtain binary image

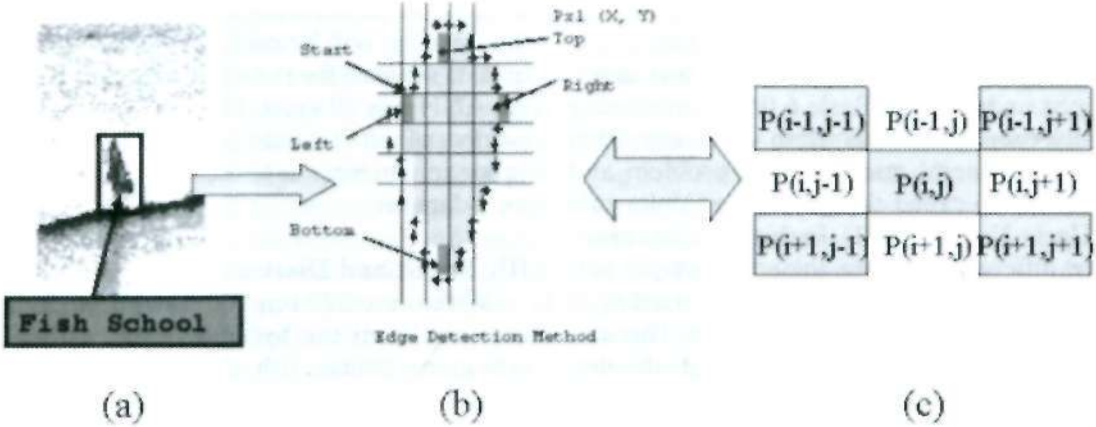

Figure 2. Illustration of edge detection method.

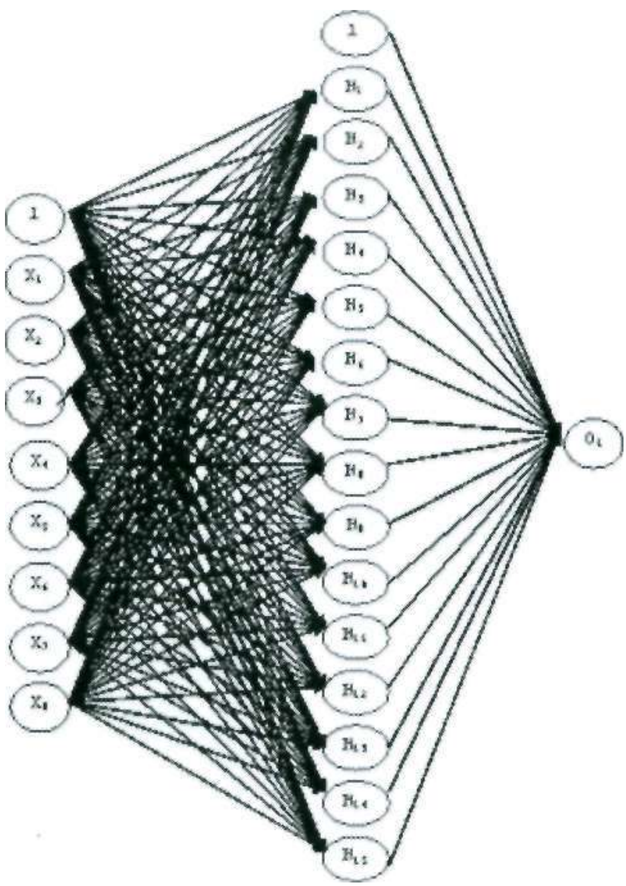

Figure 3. ANN structure used in the computation.

muru and non-Lemuru, except in the elongation (E) parameter. The Lemuru school tends to be more elongated, in which the ratio of length over height is stretch from 0.8 to 7.9. Thus it takes ellipsoidal to layer-like shape.

The process of training of ANN is conducted using 200,000 to 250,000 iterations, as mentioned in the previous section. The result of the training for three different learning rates is given in Table 4. The application of different learning rate clearly shown that the ability of the network varies depend on the given learning rate constant. As expected, the higher the rate, the faster the network

Table 1. Acoustic school descriptor used as an input for the neural networks application

Variable Name	Descriptor and Computation	Units
X_1	Area (A)	M^2
X_2	Perimeter (P)	M
X_3	Height (H)	M
X_4	Length (L)	M
X_5	Elongation $(E = \frac{L}{H})$	
	Circularity $(C = \frac{P^2}{4\pi A})$	
	Rectangularity $(R = \frac{(L.H)}{A})$	
	Fractal Dimension $\left(F = \frac{2\left[\mathrm{Ln}\left(\frac{P}{4}\right)\right]}{\mathrm{Ln}(A)}\right)$	

Table 2. Descriptor statistic, which are identified as Lemuru fish school in the training set

	A	P	H	L	E	C	R	F
Average	68299	60082	271	832	3.53	4222.1	4.35	1.72
St. Dev.	72347	58573	126	413	2.06	3791.4	1.92	0.02
Maximum	314997	251194	525	1957	7.96	15940.5	10.75	1.75
Minimum	3434	3390	119	120	0.80	266.3	2.42	1.67

Table 3. Descriptor statistic, which are identified as other (non-Lemuru fish school) in the training set

	A	P	H	L	E	C	R	F
Average	68144	59305	647	563	0.92	4120.4	5.17	1.72
St. Dev.	41556	36331	254	397	0.61	2555.0	2.30	0.02
Maximum	178220	151200	1034	1454	2.20	10207.9	11.16	1.75
Minimum	13244	12615	232	149	0.27	956.2	2.63	1.68

Table 4. Sigma error for three different learning rates

Learning Rate	Sigma Error	Accuracy
0.3	8.13063E-05	100
0.5	4.97716E-05	100
0.9	2.59634E-05	100

to adapt to a given target.

3.2. Validation of ANN

The number of fish school data set to be used for validation purpose is 30 units and the result of ANN computation for three different learning rates are given in Table 5.

The ANN model that used learning rate constant of 0.3 and 0.5 are found to give a good estimate, with accuracy of 73.3%; meanwhile for the learning rate of 0.9 the accuracy is found to be slightly lower, 70%. The difference in the accuracy may be account for the limited variability of the data set, both in the training as well as in the validation, beside the different learning rate applied. As observed earlier, the fast learning rate caused the networks response is quick to adapt, however, there is a price to pay, namely lower accuracy. This is may be due to the effect of local and global minimum values that occurred during the training. The occurrence of local minimum is a result of the networks to adapt very fast in respect to the changes in error value, where the network found artificial error.

IV. Conclusions

Species identification is a key factor in the hydro-acoustic technique and the first step toward a better and accurate assessment of multi-species fisheries. In the present study we have successfully extracted from echogram the fish school descriptor. Based on the statistic of the descriptor, the school of Lemuru *(Sardinella lemuru),* which is dominant in the Strait of Bali during the time of the survey, takes elongated geometrical formation. We also have developed a technique for fish school identification using ANN and acoustic descriptor as input. The results show that the accuracy of identifying fish school using the developed ANN model for various learning rate value is about 73,3%, which is good and satisfactory. Thus, the ANN model is capable of and successfully achieving its objective.

Future study will incorporate the more data set and more complete set of AD, for example by employing the energetic dimension of fish school images in ANN model, to improve the accuracy of the school identification. In addition, by adding more sub-layers in the hidden layer in order to detect other features in the data, such as using a Gaussian function for the second sub-layers, a better result may be achieved.

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Table 5. Validation of ANN for three different learning rates

Learning Rate Constant		Number of Data Set	Fish School	Non-Fish School	Ratio of the Correct Estimate	Accuracy (%)
0.3	Lcmuru	21	21	0	21/21	100
	Other	9	8	1	1/9	11.1
		Total			22/30	73.3
0.5	Lemuru	21	21	0	21/21	100
	Other	9	8	1	1/9	11.1
		Total			22/30	73.3
0.9	Lemuru	21	21	0	21/21	100
	Other	9	9	0	0	0
		Total			21/30	70.0

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