An intelligent computation of adaptive neuro-fuzzy inference system (ANFIS) to quantify and classify fish species and seafloor types

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Abstract. Underwater acoustics is the study of the sound propagation in water and the interaction of the acoustical waves with boundaries and targets. The underwater acoustic technology had been developed for various instruments such as single beam echosounder, multibeam echosounder, acoustic doppler current profiler, side scan sonar etc. This research used a quantitative echosounder that is able to detect water column objects such as fish and the seabed. Acoustic identification of fish and seafloor is necessary for reducing uncertainty in target interpretation. A crucial novel approach towards better species and seafloor identification would be to combine the echo signal analysis and computation of artificial intelligence such as machine learning and deep learning. This paper is concerned with the problem of detecting and identifying of underwater objects such as fish and seafloor, based on acoustic echoes. The computing method for fish identification and seafloor type discrimination employs combined artificial neural networks and fuzzy logic. The neuro-fuzzy classifiers were built, integrated and tested using the program. The systems were validated on fish and seafloor echoes obtained by digital echo sounder. The results are promising with reference to the fish and seafloor classifiers performance.
Key Words: intelligent system, neuro-fuzzy, fish species classification, seafloor type.

Introduction. Underwater acoustic technologies for fish and seafloor detection are non-invasive, fast and more cost effective (Manik et al 2006; Manik 2015). This method becomes well-recognized and indispensable in fish stock assessment and bottom sediment mapping. Designing automatic methods of fish identification and seafloor typing is a challenge. In recent years, the advanced acoustic technologies that use split beam echosounder, side scan sonar and multibeam echosounder have been successfully applied for quantifying and classifying fish, suspended sediment, and seafloor (Manik & Firdaus 2021). However, the application of single beam echosounder for fish detection and mapping seabed are still in use due to its versatility and simplicity (MacLennan & Simmonds 1992; Horne & Clay 1998; Manik et al 2017; Xie 2000).

Soft computing methods had been used in many areas including ocean acoustic modelling and marine resource engineering (Simpson 1990). Modelling complex nonlinear systems is one of the successful applications of artificial intelligence (AI) techniques such as fuzzy inference systems (FIS), artificial neural networks (ANNs), machine learning and deep learning. Several authors studied various AI techniques in underwater acoustics modelling, fish monitoring and assessment, predicting the concentrations of suspended sediment concentration (Simpson 1992).

The performance of AI methods such as machine and deep learning methods and their generalization ability increases with the number of input parameters. Characteristic of class of AI using neural network and discriminant analysis were successfully adapted to classify and cluster object (Simpson 1993; Jang 1993; Simmonds et al 1996; Maravelias et al 2003). The objective of the paper was to investigate the possibility of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) for fish species identification and seafloor classification. The objective of this research was to exploit the advantages of

ANFIS, an approach that combines the rule based fuzzy inference system and artificial neural networks for classification of fish and seafloor.

Material and Method

Adaptive Neuro-Fuzzy Inference System (ANFIS). Adaptive neuro-fuzzy inference system (ANFIS) is a method for using in many applications. ANFIS use a fuzzy set "if-then rules" and has a learning capability with a neuro-fuzzy-type structure (Jang et al 1997). ANFIS has some hybrid learning algorithm such as Sugeno-type fuzzy inference systems for identifying parameters (Marc 1992). The least-squares method was used for Sugeno-type fuzzy algorithms, in combination with a membership training function. This Sugeno system emulates a given training data set. ANFIS model of Sugeno type has five layers for generating inference system. There are several nodes in each layer. These layers work as follows: the input signals in the present layer are the output signals obtained from nodes in the previous layers. First-order Sugeno-type model is based on the rules (Marc 1992):

1: if (x is A_1), (y is B_1), then (f_1 = $p_1x+q_1y+r_1$)
2: if (x is A_2), (y is B_2), then (f_2 = $p_2x+q_2y+r_2$)

Where:
$x_{1,2}$ - inputs;
A_i and B_i - fuzzy sets;
f_i - outputs within the fuzzy region identified by the rules;
(pi, qi and ri) - determined during the training process.

The ANFIS architecture is given in Figure 1.

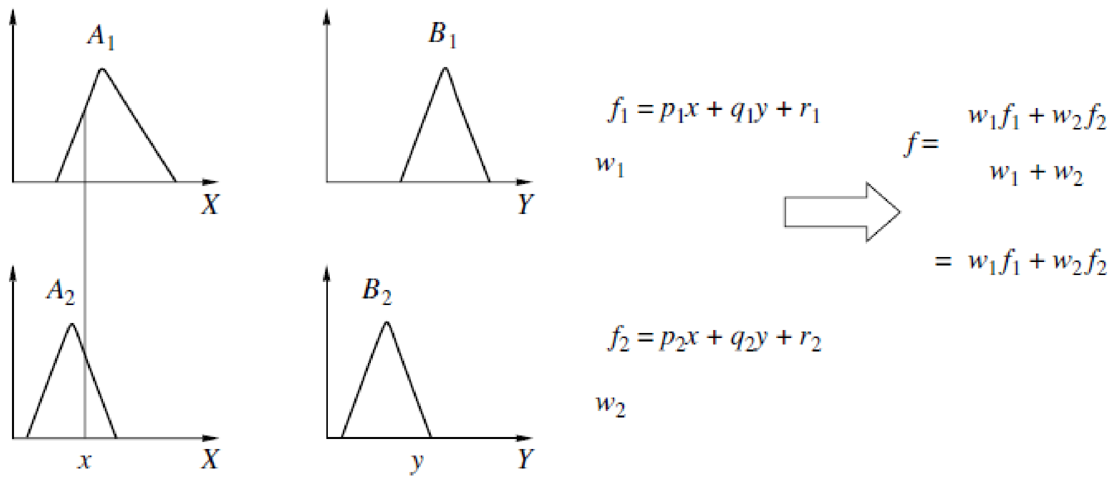

Figure 1. ANFIS membership function and the rules of the model of the Sugeno fuzzy method.

The logical rules of premises and conclusions obtained by fuzzy methods cannot be analyzed with traditional probability theories. Development of fuzzy "if then" rules is the starting point in constructing a fuzzy system. An effective tool for this purpose is a method that can convert data to the required fuzzy rules. Alternatively, artificial neural networks are capable of generating appropriate relations between input and output variables through learning capabilities based on different training patterns. a combination of artificial neural networks and fuzzy inferences, accomplished by using numerical data to compute outputs, can generate an powerful tool: the ANFIS.

Integration of neural networks with fuzzy systems deal with important aspects of computing, representation, inferencing and learning process. Takagi-Sugeno type fuzzy inference system was used in ANFIS where every rule's output can be a constant (Tagaki & Sugeno 1985). The basic architecture of ANFIS, which has two inputs (x, y) and one output (z), is presented in Figure 2. Architecture of fuzzy classifier for bottom typing is shown in Figure 3.

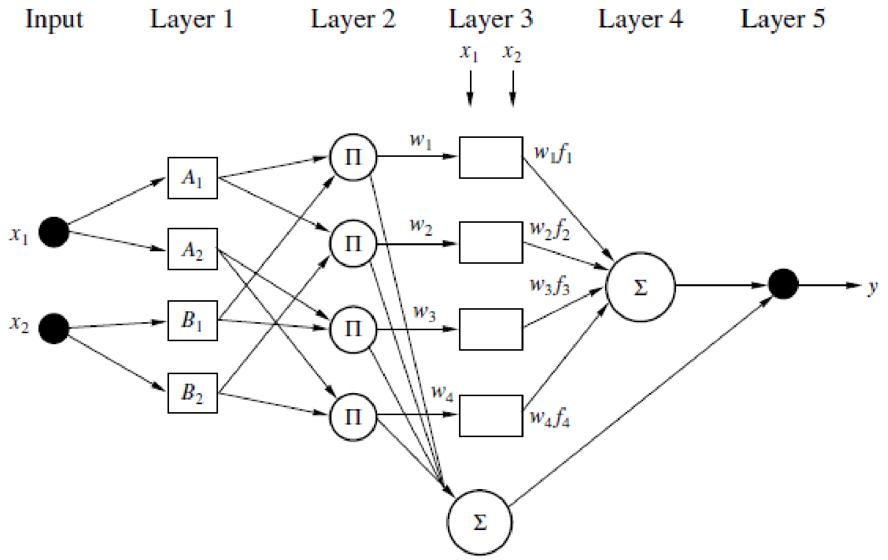

Figure 2. ANFIS architecture for a two-input first-order Sugeno fuzzy model.

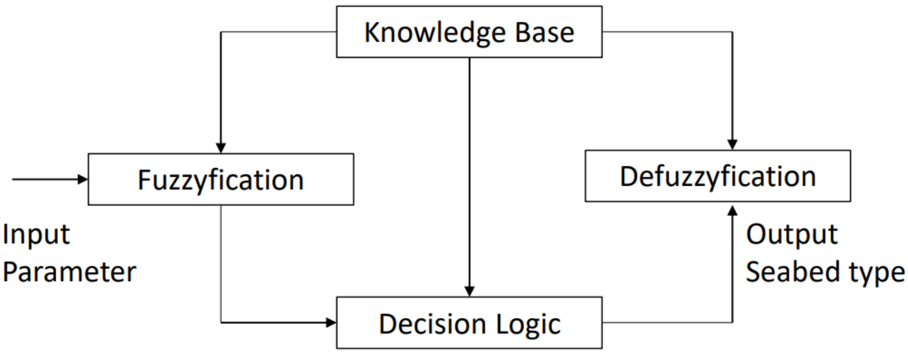

Figure 3. Architecture of fuzzy classifier for bottom typing.

In the Sugeno ANFIS architecture, consecutive layers are applied to different tasks. Layers 1 and 2 contain rules, layer 3 contains inferences, layer 4 and layer 5 are used for refining the outcome.

An Artificial Neural Network (ANN) is a mathematical model analogous to the human brain. It is a system comprising many basic elements (neurons), arranged in highly interconnected layers. For the learning process, ANN has several inputs and outputs and can be trained. According to their internal architecture, the types of ANN consist of self-organizing mapping (SOM), back-propagation algorithms, radial basis network (RBN), learning vector quantification and neocognitrons. In the present study, we examined the ANN for fish school data. The scheme of generic ANN is shown in Figure 4.

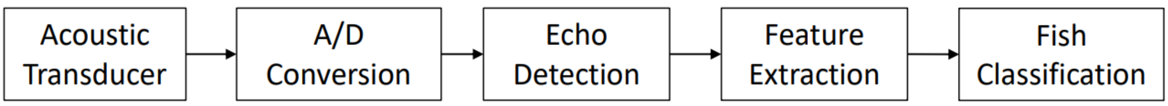

Figure 4. Artificial intelligence concept for fish species classification.

Results and Discussion

Seafloor classification. The experimental data were collected from the acoustic survey conducted in Seribu Island using a single beam digital echosounder EK15. The echosounder was operating at a frequency of 200 kHz with a pulse duration of 0.4 ms.

The acquisition sampling rate for this echosounder was 42 kHz, which was equivalent to acquiring around 58 samples m^{-1}. The beam width of transducer was 29°. This echosounder was equipped with Time Varied Gain (TVG) with 20 log R and 40 log R, where R is range from the transducer to the target. Bottom samples were taken simultaneously with bottom echo recorded by the echosounder. Four type of sediment were analyzed in the laboratory, consisting of rock, sand, silt and clay bottoms. The percentages of correctly classified echoes achieved after computing of 300 bottom echoes were 85.25% (Figure 5 and Table 1). After the second stage of ANFIS computation, the percentage of bottom echoes correctly classified in total was 80.75% (Figure 6 and Table 2). This result shows the potential of the ANFIS method for underwater target recognition and classification.

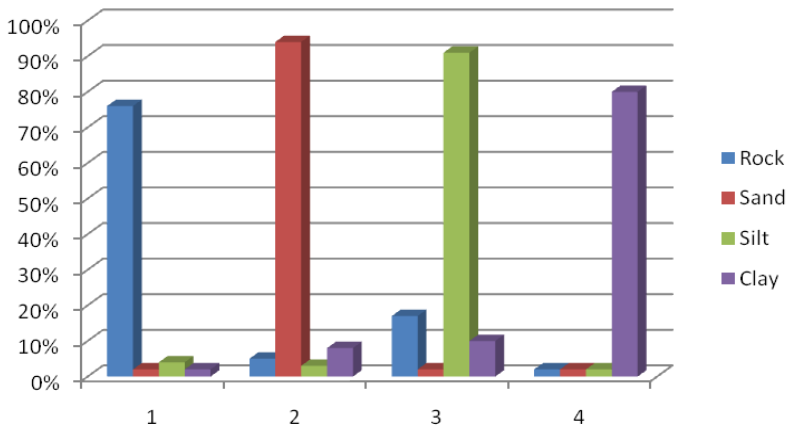

Figure 5. Box diagram of the testing results.

Table 1

Confusion matrix of the percentage of bottom echoes

True class	*Rock*	*Sand*	*Silt*	*Clay*	*Not known*
Rock	76%*	5%	17%	2%	0%
Sand	2%	94%*	2%	2%	0%
Silt	4%	3%	91%*	2%	0%
Clay	2%	8%	10%	80%*	0%

* the percentage of successful recognition.

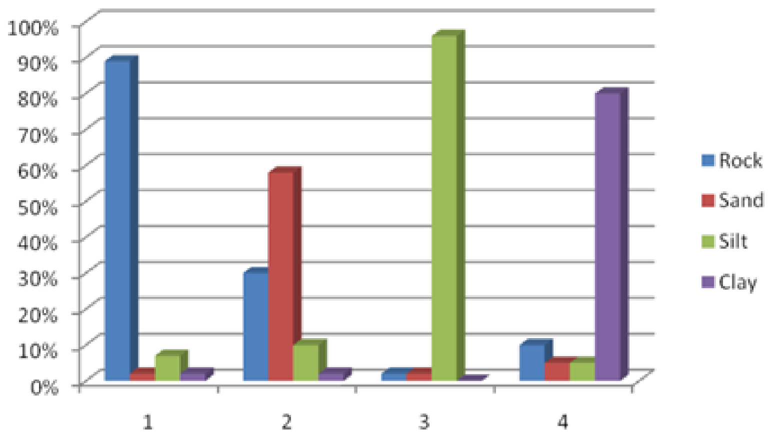

Figure 6. Box diagram of the testing results after the 2nd stage.

Table 2

Confusion matrix of the percentage of bottom echoes after 2nd stage

True class	*Rock*	*Sand*	*Silt*	*Clay*	*Not known*
Rock	89%*	2%	7%	2%	0%
Sand	3%	92%*	3%	2%	0%
Silt	2%	2%	96%*	0%	0%
Clay	2%	3%	10%	85%*	0%

* the percentage of successful recognition.

Fish species classification. The collection of acoustic data was carried out for 3 days and testing was performed using a neural network classifier. A total of 5 fish species were obtained and 5 different types of coral from the reef to train the data (Table 3, Table 4). Then, 50 unknown targets were used to collect data sets for blind tests and the identification of results was carried out. A total of 13,619 pings were used to train the neural networks, of which 7,743 samples were fish pings and 5,876 were pings for coral reefs.

Table 3

Confusion matrix of artificial neural network

Multi layer network	*Species*	*Recognized category (%)*					
		Butterfly fish	*Red tail fish*	*Baronang fish*	*Mackerel*	*Unrecognized*	*Number of cases*
True category (%)	Butterfly fish	95.8	2.3	1.5	0.4	0	986
	Red tail fish	1.5	96.3	0.2	1.8	0.2	89
	Baronang fish	1.1	0.5	98.2	0.2	0	549
	Mackerel	2.8	1.5	1.2	94.5	0	345
Total							1,969

Table 4

Confusion matrix of artificial neural network after 2nd stage

Multi layer network	*Species*	*Recognized category (%)*					
		Butterfly fish	*Red tail fish*	*Baronang fish*	*Mackerel*	*Unrecognized*	*Number of cases*
True category (%)	Butterfly fish	89.9	5.2	2.6	2.3	0	889
	Red tail fish	2.9	93.5	2.5	1.1	0.1	78
	Baronang fish	2.5	1.6	94.5	1.4	0	580
	Mackerel	0.3	1.2	0.3	98.2	0	422
Total							1,969

The classification makes a probabilistic decision with a degree of similarity between 0 and 1.0. If the value is close to 0, the sample is fish and if it is close to 1, it corresponds to a coral reef. Blind test identification was carried out on 50 data points during the second and third days, of which 5 data points (ID 10025, 10060, 10235, 10250, 10310) were used to train the neural network classifier. These five data sets are not considered real blind tests and are not counted as tested data. Because blind tests are collected in a controlled environment and for different weather conditions, the addition of treatments will result in data sets simulating real environmental variations. Thus, a total of 45 unknown data and 5 known data were tested to evaluate the performance of the neural network classifier. Table 5 is the result of the blind test.

Table 5

Fish classification using artificial neural network

Order	*Target ID*	*Pings*	*Neural network classification*					*Reality (ground truth)*		*Result of classifier neural network*
			Fish		*Coral reef*		*Decision*	*Actual*	*Aspect*	
			Count	*%*	*Count*	*%*				
1	10011	201	250	95.8	10	4.2	Fish	Fish	Dorsal	True
2	10015	220	215	91.2	20	8.8	Fish	Fish	Dorsal	True
3	10018	210	107	47.8	120	52.2	Coral reef	Fish	Dorsal	False
4	10020	223	265	94.5	18	5.5	Fish	Fish	Ventral	True
5	10025	228	280	96.5	10	3.5	Fish	Fish	Dorsal	True
6	10028	225	268	95.7	12	4.3	Fish	Fish	Dorsal	True
7	10030	230	188	89.5	22	10.4	Fish	Fish	Dorsal	True
8	10040	216	168	83.8	34	16.8	Fish	Fish	Dorsal	True
9	10045	245	190	82.6	40	17.3	Fish	Fish	Ventral	True
10	10056	265	23	10.1	203	89.8	Coral reef	Coral reef	Photo	True
11	10058	220	215	95.5	10	4.4	Fish	Fish	Dorsal	True
12	10060	225	280	94.2	17	5.7	Fish	Fish	Dorsal	True
13	10080	287	198	92.5	16	7.4	Fish	Fish	Dorsal	True
14	10100	213	145	92.3	12	7.6	Fish	Fish	Ventral	True
15	10110	214	167	89.7	19	10.2	Fish	Fish	Dorsal	True
16	10115	218	189	90	21	10	Fish	Fish	Dorsal	True
17	10118	225	192	94.1	12	5.8	Fish	Fish	Dorsal	True
18	10215	227	187	91.2	18	8.7	Fish	Fish	Dorsal	True
19	10218	234	219	94.3	13	5.6	Fish	Fish	Dorsal	True
20	10220	243	245	93.1	18	6.8	Fish	Fish	Dorsal	True
21	10230	283	176	92.1	15	7.8	Fish	Fish	Dorsal	True
22	10240	276	157	92.8	12	7.1	Fish	Fish	Dorsal	True
23	10235	289	134	89.9	15	10.0	Fish	Fish	Dorsal	True
24	10245	293	117	90.6	12	9.3	Fish	Fish	Ventral	True
25	10250	171	115	83.3	23	16.6	Fish	Fish	Dorsal	True
26	10267	189	132	88.5	17	11.4	Fish	Fish	Dorsal	True
27	10287	120	189	88.7	24	11.2	Fish	Fish	Dorsal	True
28	10290	140	201	94.3	12	5.6	Fish	Fish	Dorsal	True
29	10300	211	245	93.1	18	6.8	Fish	Fish	Dorsal	True
30	10310	290	132	87.4	19	12.5	Fish	Fish	Dorsal	True
31	10340	302	134	92.4	11	7.5	Fish	Fish	Ventral	True
32	10346	390	137	93.8	9	6.1	Fish	Fish	Dorsal	True
33	10400	347	104	81.8	23	18.1	Fish	Fish	Dorsal	True
34	10402	359	125	88.0	17	11.9	Fish	Fish	Dorsal	True
35	10405	349	132	91.6	12	8.3	Fish	Fish	Dorsal	True
36	10410	355	189	93.1	14	6.8	Fish	Fish	Dorsal	True
37	10410	358	141	83.9	27	16.0	Fish	Coral reef	Photo	False
38	10412	360	181	94.2	11	5.7	Fish	Fish	Dorsal	True
39	10415	315	15	7.3	190	92.6	Coral reef	Coral reef	Photo	True
40	10419	319	178	94.1	11	5.8	Fish	Fish	Dorsal	True
41	10425	330	186	93	14	7	Fish	Fish	Dorsal	True
42	10430	340	179	90.8	18	9.1	Fish	Fish	Dorsal	True
43	10436	404	167	92.7	13	7.2	Fish	Fish	Dorsal	True
44	10445	430	231	87.1	34	12.8	Fish	Fish	Dorsal	True

Order	Target ID	Pings	Neural network classification				Decision	Reality (ground truth)		Result of classifier neural network
			Fish		Coral reef			Actual	Aspect	
			Count	%	Count	%				
45	10455	450	213	93.4	15	6.5	Fish	Fish	Dorsal	True
46	10480	312	219	94.8	12	5.1	Fish	Fish	Dorsal	True
47	10490	360	245	96.0	10	3.9	Fish	Fish	Ventral	True
48	10510	314	14	4.6	287	95.3	Coral reef	Coral reef	Photo	True
49	10550	321	301	94.6	17	5.3	Fish	Fish	Dorsal	True
50	10567	431	189	90.8	19	9.1	Fish	Fish	Dorsal	True

According to the previous research, such as the study of Cabreira et al (2009), the ANN used in this study performed successfully to classify fish species from echosounder data. A discrimination technique for the identification of several fish, using several parameters extracted from detected schools, had been used by Ramani & Patrick (1992) and by Haralabous & Georgakarakos (1995).

Categorization methods were described in this paper, methods to improve data quality, techniques for efficient processing of single-frequency acoustic data and automatic identification of biologically generated acoustic backscatter. An ANN was used in our study, in order to classify fish species from echo-recording data, which performed satisfactorily, similarly to the results presented in earlier studies (Ramani & Patrick 1992; Simmonds et al 1996; Hui 2009). Other researchers used multiple neural networks for classifying underwater targets (Tong 2000; Xingyue & Kunde 2020).

Underwater acoustic technologies are very popular in fisheries research because these methods are fishery-independent, quantitative, noninvasive, remote, rapid and synoptic (MacLennan & Simmonds 1992). Acoustic instruments are capable of sensing multiple scales, from centimeters to thousands of kilometers, in sailed distance. These technologies can sense both organisms and their habitat, including water column, bottom and sub-bottom.

Conclusions. In this study, the adaptive network based on fuzzy inference system (ANFIS) has been a very useful method to classify the sea bottom type. This result shows the potential applications of fuzzy logic to the problem of target classifying by underwater acoustics. The application of the neuro-fuzzy classifier method for identification of seabed types has an accuracy of 87.8%. Classification of fish species based on fish group (fish school) data using Artificial Neural Network (ANN) has been produced with an accuracy level of 95.1%. Further studies using this procedure should be undertaken in order to evaluate its applicability to commercial fish.

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Conflict of interest. The author declares no conflict of interest.

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