An Approach to Seafloor Classification with GA-Based Neural Network

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Keywords: Neural Networks; Genetic Algorithm (GA); Multibeam Echo Sounder; Seafloor Classification.

SUMMARY

The Learning Vector Quantization (LVQ) Neural Network approach has been widely used in acoustic seafloor classification. However, one of its major weak points is the sensitivity to the initialization, affecting the seafloor classification accuracy. In this paper, Genetic Algorithm (GA) is used to optimize the initial values of LVQ. The GA-based LVQ can rapidly provide the optimum initial reference vectors and accurately identify various types of seafloor sediments. The proposed approach was applied to seafloor classification using Multibeam Echo Sounder (MBES) backscatter strength data in Jiaozhou Bay near Qingdao City of China. Compared with the standard LVQ, the experiment results indicate that the approach of GA-based LVQ can improve the seafloor classification speed and accuracy.

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1. INTRODUCTION

Seabed sediment classification has been an important research topic in marine science and engineering. In ocean resource exploration, marine engineering, port construction and seafloor pipeline investigation, quicker and more accurate seafloor classification methods should be applied for distinguishing the different seafloor types in order to obtain a complete and systematic sediment distribution map. The traditional seafloor classification method depends on grab samples in the site and identifies a variety of sediment types by analyzing sample data in laboratory. However, the method is time consuming and labor intensive, especially in the deep water area, where it is very difficult to grab seabed sediments. Furthermore, traditional grab work is carried out according to planned grid points and its classification results hardly represent the true seabed sediment distribution because the data at a limited number of sampling sites are used to generate sediment distribution map using interpolation methods. In 1970s, marine geologists firstly utilized the echo sounder signal in seabed characteristic mapping (King et al., 1970). Echo sounder measures seabed sediments acoustic parameters (reflection coefficient, sound speed, sound attenuation and backscatter strength), which are used to study sediments geologic properties (grain size, density, composition). This is a remote and rapid classification method and can provide the complete and accurate seafloor characteristics data and maps. From 1960s, multibeam echo sounder (MBES) has been a newly and high-resolution seabed exploring system. It can provide rapid, high-resolution, and complete coverage that include both bathymetry and sidescan backscatter data. Using the seafloor backscatter strength (BS) data from each beam and automatic classification technology, we can directly obtain the seabed sediments distribution maps. Seafloor classification using MBES data plays an important role in the ocean science research and marine engineering construction.

Seafloor classification from MBES backscatter strength data has been an active research area over the past decades. Many methods have been proposed, such as power spectrum analysis (Reut et al., 1985; Pace et al., 1988; Milvang et al., 1993), texture analysis (Subramaniam et al., 1993; Pican et al., 1998), classical statistical classification (Huseby et al., 1993; Pican et al., 1998) and neural networks (Alexandrou et al., 1990; Kavli et al., 1993; Michalopoulou et al., 1995). Especially, Kohonen's competitive-learning neural network such as Learning Vector Quantization (LVQ) neural network is widely applied in the acoustic seafloor classification (Zerr et al., 1994; Chakraborty et al., 2003, 2004; Zhou et al., 2005). However, one of the major weak points of LVQ is its sensitivity to the initialization (Chung et al., 1993; Pal et al., 1993), affecting the seafloor classification accuracy. In this study, Genetic Algorithm (GA) is used to optimize the initial values of LVQ. The GA-based LVQ can rapidly provide the optimum initial reference vectors and accurately classify and identify various types of seafloor sediments, such as rock, gravel, sand, fine sand and mud.

This paper briefly introduces the process for backscatter data pre-processing, followed by the theory of LVQ neural network. Then the approach of GA-LVQ neural network in seafloor classification is discussed, including the theory of GA and it is used to optimize the initial values of LVQ. A set of real data is analyzed and the results discussed. Some concluding remarks are finally made.

2. DATA PRE-PROCESSING FOR SEEFLOOR CLASSIFICATION

A MBES system records both depth data and seafloor backscatter strength information. The backscatter strength is understood as echoes from the seafloor, and it is dependent on the incidence angle, seafloor roughness, sediment properties and the sound through the water column (Simrad, 1998). The different backscatter strength then represents the seafloor's ability to reflect sound energy. This makes it possible to differentiate between different types of sediments. In general, rock reflects more energy than sand, and sand reflects more energy than mud, etc. *BS* is defined as (Lurton et al., 1994; Zietz et al., 1996; Simrad, 1998):

$$BS = BS_B + 10\lg A \qquad (1)$$

where, *A* is the seafloor insonified area (Figure 1). Around normal incidence (θ = 0°),

$$A = \theta_T \theta_R R^2 \qquad (2)$$

and elsewhere,

$$A = \frac{1}{2\sin\theta} c\tau\theta_T R \qquad (3)$$

θ_T and θ_R are respectively the transmitter and receiver beam width, *R* is the range, θ is the beam departure angle, *c* is the sound velocity and τ is the pulse length. BS_B is the bottom backscatter coefficient which is the property that determines the reflectivity of the seafloor. It is dependent on the incidence angle θ. When θ = 0°, BS_B is the constant.

$$BS_B = BS_N \qquad (\theta = 0°) \qquad (4)$$

When θ ≠ 0°, BS_B is not only dependent on the incidence angle, but also on the seafloor roughness. Its variety complies with the Lambert's law (Lurton et al., 1994)

$$BS_B = BS_O + 10\lg\cos^2\theta \qquad (\theta \neq 0°) \qquad (5)$$

According to equation (1), (2), (3), (4) and (5), around normal incidence,

$$BS = BS_N + 10\lg(\theta_T \theta_R R^2) \quad (6)$$

and elsewhere,

$$BS = BS_O + 10\lg\cos^2\theta + 10\lg(c\tau\theta_T R/2\sin\theta) \quad (7)$$

where, BS_N is the normal backscatter strength, BS_O is the oblique backscatter strength. They only reflect the seafloor's characteristics. The incidence angle θ can be calculated through the Snell's law. In order to get BS_N and BS_O, the raw backscatter strength data must be corrected for the transmission loss, ray bending, Lambert's correction, seafloor local slope, insonified area correction, and near nadir reflection correction (Figure 2). Finally, the backscatter strength data which only reflect the seafloor's characteristics can be obtained through data pre-processing (Tang et al., 2005). The corrected data can now be used for the further seafloor classification research.

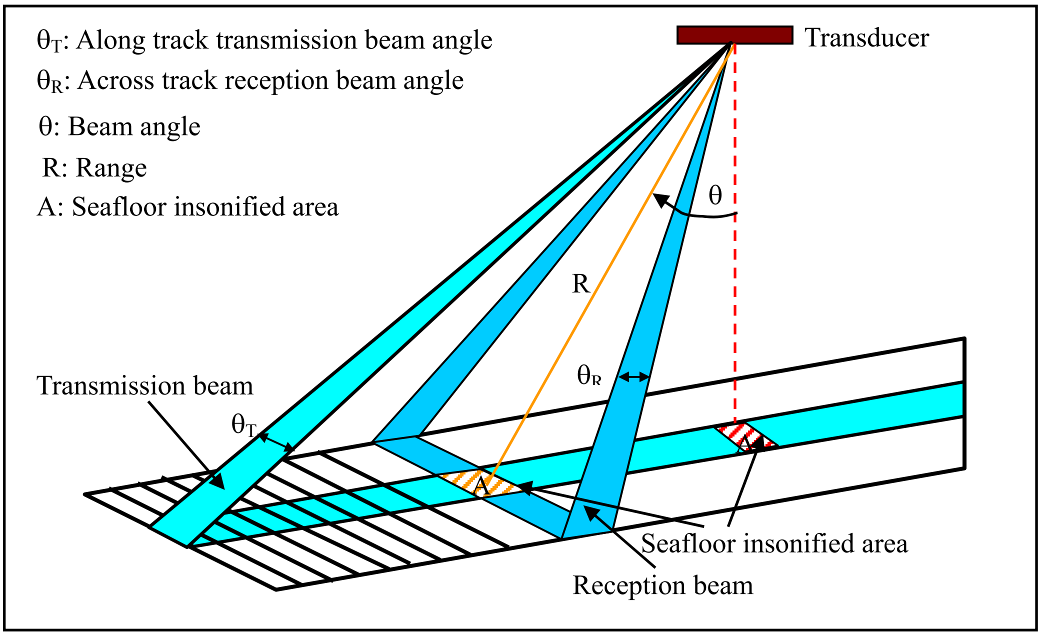

Figure 1. Beam geometrical configuration of multibeam echo sounder

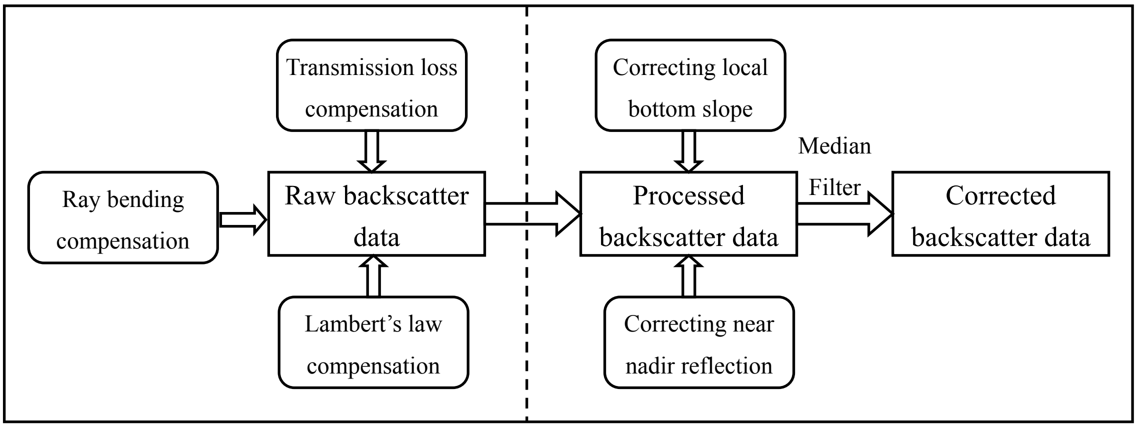

Figure 2 Process flow for backscatter data pre-processing

3. LVQ NEURAL NETWORK

Neural network is the data-driven, nonlinear and nonparametric model. It has been an important tool in the complex signal processing and classification in the last decades. Classification has been one of the most active application fields in neural network researches. There are usually two kinds of neural network models in seafloor classification. One is the supervised learning neural network which needs geologic grab samples; the other is the unsupervised learning neural network which does not need any grab samples. LVQ neural network is the integrated network structure of supervised and unsupervised learning and its learning rate is much faster than Back Propagation (BP) neural network. LVQ neural network is composed of input layer, competitive layer (hidden layer) and output layer (Figure 3). The first layer and second layer constitute a competitive-learning neural network. As a traditional competitive-learning neural network, such as Kohonen's Self-Organizing Map (SOM) neural network, it can automatically learn the classification of input vectors according to the nearest-neighbor method by calculating the Euclidean distance. However, the LVQ algorithm is a competitive approach under the supervised learning. By means of the supervised and unsupervised learning, LVQ neural network can distinguish the target vectors from the input vectors, and then divide targets into different types. The third output layer of LVQ neural network can change the transferred information from competitive layer into the defined target classes which we need.

The core of LVQ neural network is based on the nearest-neighbor method by calculating the Euclidean distance. Distances between each input vectors and competitive layer neural nodes can be calculated, and the output node which is of minimum distance is designated as a winning node (Kohonen, 2001).

$$d(X, W_c) = \min\{d(X, W_i)\} \qquad (i=1,2,\ldots,n) \qquad (8)$$

where X is the input vector, W_i is the reference vector, $d(X, W_i)$ is the distance between X and

W_i, and W_c is the winner subclass.

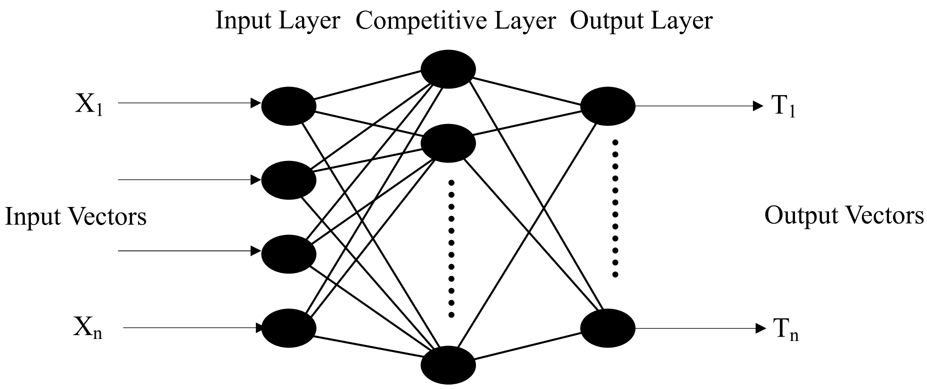

Figure 3 Schematic depiction of LVQ neural network

The following equations define the basic LVQ algorithm process:
when $i = c$,
if X and W_c belong to the same class,

$$W_c(t+1) = W_c(t) + \alpha(t)[X(t) - W_c(t)] \tag{9}$$

if X and W_c belong to the different classes,

$$W_c(t+1) = W_c(t) - \alpha(t)[X(t) - W_c(t)] \tag{10}$$

when $i \neq c$,

$$W_i(t+1) = W_i(t) \tag{11}$$

where $0 < \alpha(t) > 1$, and learning rate $\alpha(t)$ is usually made to decrease monotonicity with time. It plays a very important role for network convergence. By the iterative learning, the input vector X will be assigned to the class which the reference vector W belongs to. The class of each input vectors can be obtained through the competitive learning process.

4. SEEFLOOR CLASSIFICATION USING GA-LVQ NEURAL NETWORKS

LVQ neural network has a good identification property and any input vectors can be used in the network whether it is linear or nonlinear. Furthermore, LVQ neural network has much better tolerance and robustness than BP neural network. When the LVQ neural network is established and set right parameters, it will get satisfactory classification results. Hence, LVQ neural network has been widely used in seafloor classification. However, the traditional LVQ is sensitive to the reference vectors and it does not work efficiently if the initial reference vectors are not set properly. As a special optimization algorithm, GA can search all over the operation space and get the optimum initial reference vectors.

4.1 Genetic Algorithm

GA provides a universal frame of optimization solutions to the problem of nonlinear, multi-modeling and multi-object complex system (Holland, 1975). It has been used in the areas of function optimization, combination optimization, auto-control, machine learning, image processing, artificial intelligence and genetic code, etc. GA has much better robustness and universal optimization ability. It searches the most optimum value from the point of space until the global optimization results can be obtained. Combined with GA's global optimization ability, LVQ neural network can rapidly select appropriate reference vectors.

(1) Coding method
The coding method is a key issue in GA. GA has many different coding methods, such as binary bit string, Gray code and float coding. In order to improve the local search ability of GA, the proposed approach has been implemented using Gray code because it is easy to process crossover and mutation operations.

(2) Fitness function
The GA's fitness function is used to estimate the individual optimization degree by optimizing computation. Those individuals who have much higher fitness will have more opportunities to be duplicated to next generation. Different problems have different definition methods of fitness function.

(3) Selection, crossover and mutation
GA includes three basic operations: selection, crossover, and mutation. Selection operation chooses the best individual from the initial group and makes it as father generation who produces the new offspring to the next generation. This process simulates natural selection of biology evolution. Crossover is an extremely important operation in GA. It is a recombination operation that combines subparts of parent individuals to produce offspring who contain some part of both parents' genetic material. Crossover operation behaves the thoughts of information exchange between mating individuals. Mutation provides an opportunity for producing offspring and introduces variation into the individuals. That variation would be global or local. Mutation operation occurs occasionally but randomly changes the value of a string position.

4.2 GA-LVQ Neural Network

The most optimum reference vectors W firstly can be obtained by the above genetic algorithm. The calculated optimum reference vectors can be applied to LVQ neural network and it will improve the seafloor classification speed and precision. LVQ neural network combined with GA can rapidly and accurately classify and identify different seafloor types. The calculation steps of GA-LVQ neural network are following (Figure 4).

(1) Establishment of LVQ

LVQ neural network must be primarily established. X is chosen as input sampling vectors and T is the relative output target vectors. The nerve cell number of LVQ is set S. The input vector X should be normalized, and its value is between 0 and 1.

(2) Definition of GA Parameters

The N initial strings are produced randomly and each string structure is named as an individual. N individuals constitute a population. Let set number of generation t be 0 and the initial population $P(0)$ be formed. Suppose crossover and mutation probability is P_c and P_m. The error ε represents the end of iteration in GA.

(3) Calculating Fitness Function

In the first instance, the mean square error distance between random individuals and input data is calculated as follows:

$$D(t)=\left[\frac{1}{M}\sum_i (X_i(t)-P_i(t))^2\right]^{1/2} \tag{12}$$

where $D(t)$ is the mean square error distance, M is the population number, $X_i(t)$ is input sampling vectors and $P_i(t)$ is the individual. Then, the fitness function $f(t)$ can be defined as:

$$f(t)=\frac{1}{1+D(t)} \tag{13}$$

where $f(t)$ is within [0,1]. Lastly, calculating:

$$d=D(t)-D(t-1) \tag{14}$$

If $|d| < \varepsilon$, then go to step 5, and the iteration of GA is end.

(4) Iterative calculation

According to calculated fitness, the individual crossover operation and mutation operation with probability P_c and P_m is carried out. Let $t = t + 1$, form t'th generation, then go to step 3.

(5) Obtaining initial reference vector

Through the iterative calculation, when $|d| < \varepsilon$, the GA stops. The initial reference vector W can be obtained.

(6) Network training

Let set learning rate α, maximum training epoch n and mean square error ω. After many iterative training, the distribution of reference vector will be changed in the competitive layer of LVQ neural network. This distribution is fit for classification of input data.

(7) Network testing and application
While the network has been trained, the reference vector is stable and the network is tested by simulative function and sampling data. LVQ neural network will provide each input data with corresponding classification results.

Finally, when all of backscatter data are imported into the trained and tested network, it will classify and identify different seafloor types and the sediment distribution map can be obtained by GA-LVQ neural network ultimately.

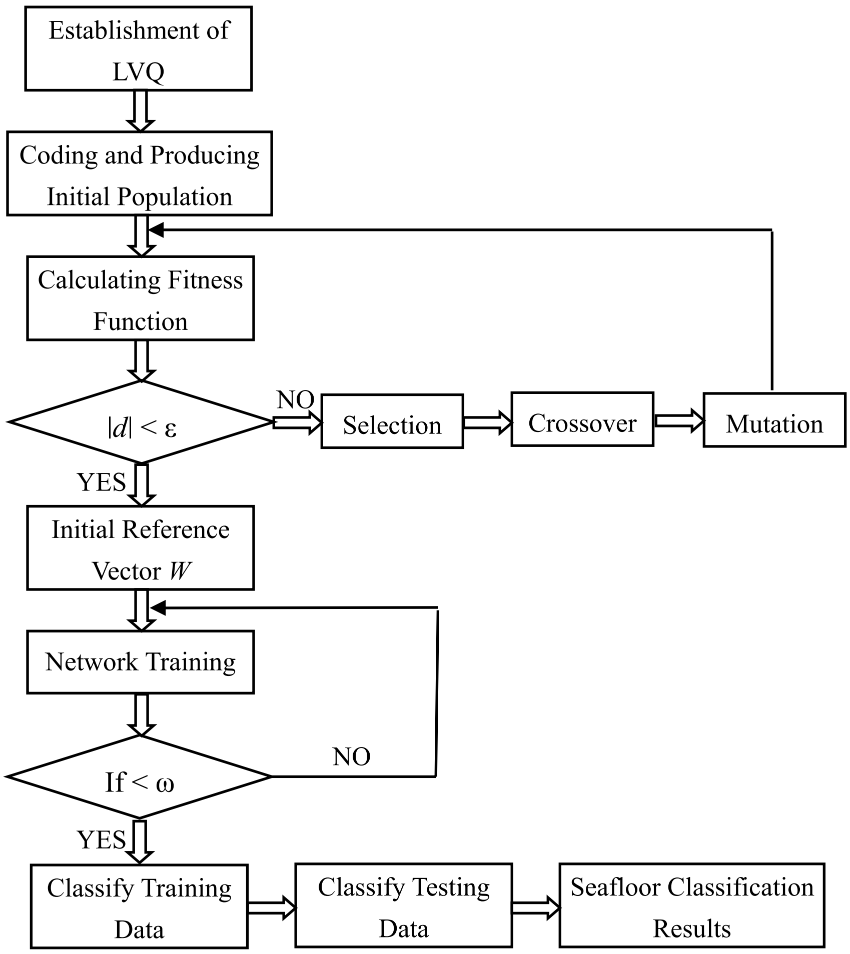

Figure 4 Process flow for classification of GA-LVQ neural network.

5 EXPERIMENTAL RESULTS

5.1 Study Area Data

The MBES backscatter strength data were collected using a hull-mounted Simrad EM3000 (300kHz) system in a study area located in Jiaozhou Bay near Qingdao City of China (Figure 5). Analyzing from the earlier sediment distribution map and recent 42 ground-truth grab samples, the study area can be divided into five homogeneous regions in terms of seabed sediment types, which are rock outcrop (class A), gravel (class B), sand (class C), fine sand (class D), and mud (class E) (Figure 5).

EM3000 system records not only longitude, latitude, depth data but also co-registered backscatter strength information. Due to many factors, such as ocean environmental noise, sound scattering and reverberation, sound transmission loss, sound absorbing, local bottom slope and near nadir reflection, the recorded raw backscatter strength can not directly reflect true seafloor characteristics. The raw backscatter strength data must be corrected for a series of corrections (Figure 2), and the backscatter strength data which only reflect seafloor characteristics can be obtained through data pre-processing (Tang et al., 2005). Through analyzing the geologic grab samples in site, the corresponding 3828 processed backscatter strength data are used in this experimental study (Including 782 rock, 550 sand, 450 sand, 990 fine sand and 1056 mud backscatter strength data). The total of 3828 backscatter samples are divided into 2552 training samples, about two thirds of the total backscatter samples, and 1276 testing samples.

5.2 Results and Analysis

Establish LVQ neural network, then 2552 training sample data are inputted into network and the output target vectors represent 5 different seafloor types. Let set nerve cell numbers S = 30, learning rate $\alpha = 0.01$, mean square error $\omega = 0.003$. During the process of GA, using genetic individual numbers $N = 30$, 24 bit gray code, crossover probability $P_c = 0.9$, mutation probability $P_m = 0.1$, $\varepsilon = 0.001$, and the end of GA is $|d| < \varepsilon$ (Figure 4).

Figure 6 shows a comparison between the results with the standard LVQ and GA-LVQ neural network. One can see that GA-LVQ neural network has great improvements in the convergence speed and ability compared with the standard LVQ neural network. When GA-LVQ neural network runs 1575 steps, its $\omega < 0.003$ and the convergence condition achieved. While the standard LVQ neural network runs 3000 steps, its mean square error is still 0.1 and bigger than its convergence value 0.003. The network is still oscillated and it is difficult to converge quickly.

2552 training data and 1276 testing data were respectively inputted into the trained GA-LVQ and the standard LVQ neural network. The classification results are shown in Table 1 and Figure 7. In Table 1, the total data percentage of classification precision is not simply data average precision, but calculated by total sample data (including training samples and testing samples) and obtained 5 different seafloor types precision. From Table 1 and Figure 7, the classification precision for rock, gravel, sand, fine sand and mud is 95.4%, 85.3%, 91.7%, 88.2% and 90.2% by GA-LVQ neural network, which is much higher than the classification precision with the standard LVQ neural network that is 89.7%, 72.0%, 80.3%, 75.2% and 82.1%, respectively.

From the above experimental results, the proposed GA-LVQ neural network has great improvement in classification speed and precision over the standard LVQ neural network.

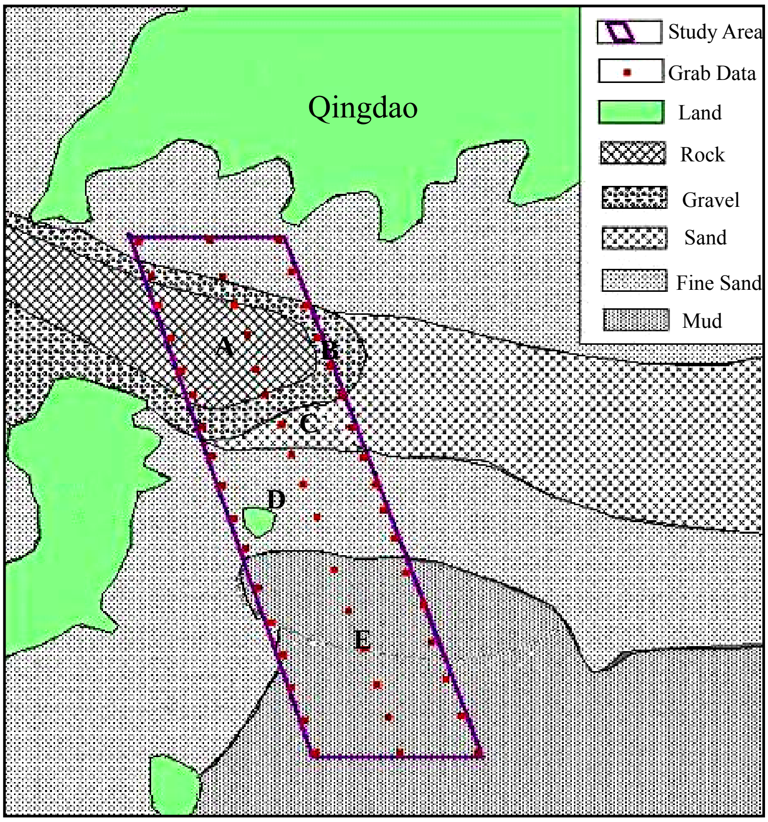

Figure 5 Schematic depiction of sediment distribution on the study area near Qingdao.

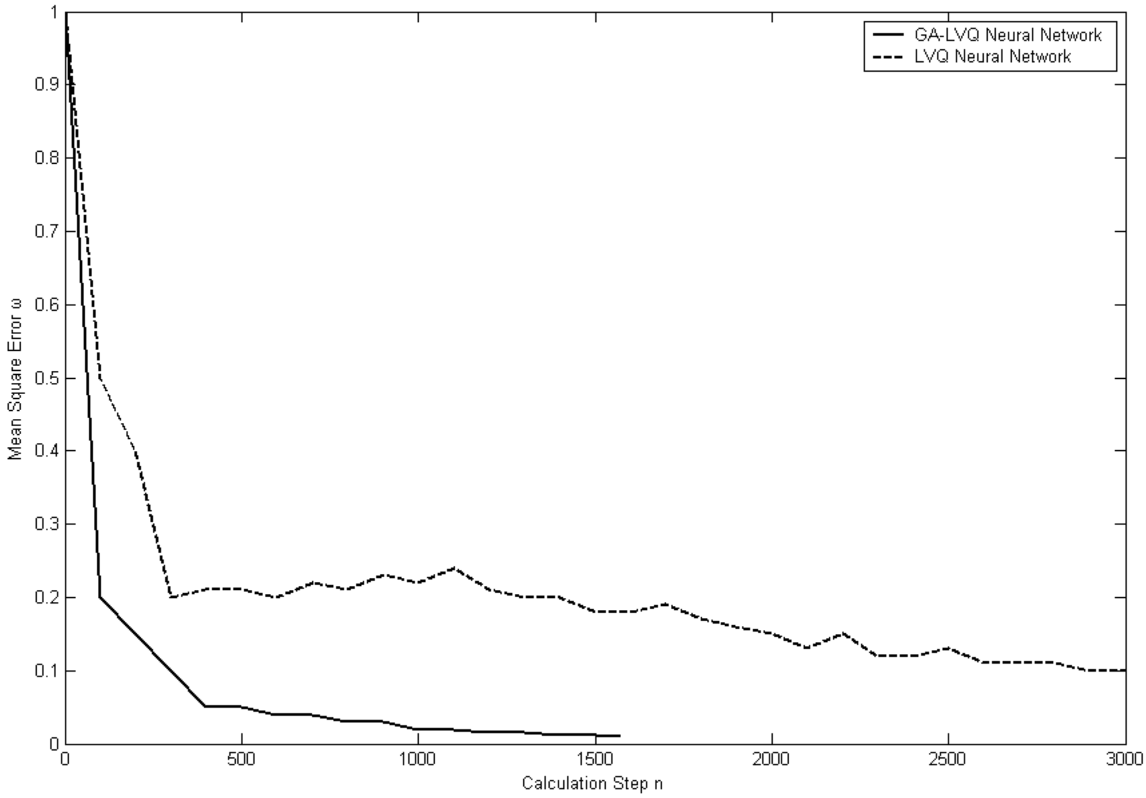

Figure 6 Mean square errors of GA-LVQ and standard LVQ neural network.

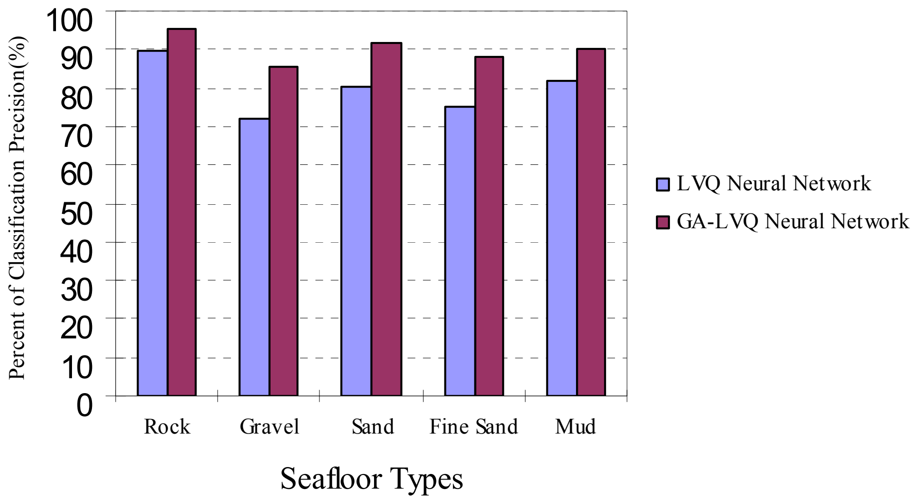

Figure 7 Classification precision with two approaches

Table 1 Results of seafloor classification using GA-LVQ and LVQ neural network

Seafloor Types	Training Samples	Testing Samples	Training Precision		Testing Precision		Total Precision	
			LVQ	GA-LVQ	LVQ	GA-LVQ	LVQ	GA-LVQ
Rock	521	261	90.2%	95.6%	89.3%	95.2%	89.7%	95.4%
Gravel	367	183	72.4%	85.7%	71.5%	84.7%	72.0%	85.3%
Sand	300	150	81.1%	92.0%	79.6%	91.5%	80.3%	91.7%
Fine Sand	660	330	75.4%	88.6%	75.0%	87.8%	75.2%	88.2%
Mud	704	352	82.3%	90.8%	81.7%	89.7%	82.1%	90.2%

6 CONCLUDING REMARKS

In this paper, GA is used to optimize the initial reference vector of LVQ neural network. The GA-LVQ neural network can rapidly obtain the optimum initial reference vector and it speeds up the convergence of network and improves the classification precision over the standard LVQ. Comparing the GA-LVQ with the standard LVQ, the experiment results indicate that the proposed GA-LVQ approach rapidly and accurately classify and identify various different types of seafloor, such as rock, gravel, sand, fine sand, and mud in the study area.

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BIOGRAPHICAL NOTES

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