A New Algorithm for Clustering of Seabed Types

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Abstract  By using sonar imaging, this paper presents a new algorithm for the clustering of seabed types based on the self-organizing feature maps (SOFM) neural network. The theory as well as data processing is studied in detail. Some valuable conclusions and suggestions are given.

Keywords  sonar image; self-organizing feature maps (SOFM); clustering of seabed types

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Introduction

Both side scan sonar (SSS) system and multibeam bathymetric system (MBS) can provide sonar images for reflecting seabed relief. A sonar image is produced by the interaction between the sonar beam and seabed types. We can fulfill the clustering of seabed types with the sonar image. There are several methods for the clustering of seabed types, such as spectral analysis, texture analysis and traditional Bayesian classification\(^1\)\(^-\)\(^6\). In actual applications, spectral analysis is easily influenced by abnormal echo signal. Texture analysis recognizes seabed types by extracting the texture characters of the sonar image, but may decrease the clustering accuracy when using these low-quality sonar images\(^3\). In order to get accurate clustering of seabed types, the paper presents a new algorithm for the clustering of seabed types, on the basis of self-organizing future maps (SOFM) neural network.

1 Sonar image and image processing

For sonar systems such as SSS and MBS, the sound intensity of a beam change from source energy level to final energy level in an emitting and receiving procedure is expressed as

\[
E_I = S_L - 2T_L + B_S - N_L + D_{Dx}
\]

\[
N_L = N_0 + 10\log(W)
\]

\[
T_L = 20\log R + \alpha R
\]

\[
D_{Dx} = 10\log\left(\frac{4\pi S}{\lambda^2}\right)
\]

where \(S_L\) is source energy; \(E_I\) is echo-to-noise level; \(T_L\) is transmission loss; \(N_L\) is noise level; \(D_{Dx}\) is directivity index; \(B_S\) is backscatter strength; \(R\) is the beam spreading range; \(\lambda\) is the wave length of sound; \(\alpha\) is absorption coefficient of sea water; \(W\) is the bandwidth of receiver; \(S\) is the area of transducer’s active face.

According to Eq.(1), \(B_S\) is

\[
B_S = E_I - S_L + 2T_L + N_L - D_{Dx}
\]

In order to get a pure sound intensity, \(B_{SS}\), which is independent of the incident angle \(\theta\) of the beam, the area \(AE\) of the beam footprint on the seabed, the hardness and roughness of the seabed as well as the gradient of seafloor topography and only reflects the interaction between sound beam and sediment type,
we also need to implement the correction of Lambert law \((B_L)\) and the correction of the area of the beam footprint \((B_{AE})\).

\[
B_S = B_L - (B_L + B_{AE}) \\
B_L = 10 \lg \cos^2 \theta \\
B_{AE} = 10 \lg AE
\]

Generally, \(B_S\) is expressed in the form of gray image. If \(B_S\) lies in \(-128\) dB–\(126\) dB, gray level \((G_L)\) in gray image can be transformed from \(B_S\) by

\[
G_L = B_S + 128
\]

Through the above transformation, image mosaic, image rectification and image registration, we can obtain a gray image, namely the image of seabed relief.

The quality control of the sonar image can be done by wavelet analysis. Besides we also need to implement image equalization. Image equalization is fulfilled by histogram modification.

## 2 Clustering of seabed types

The seabed type with high density and hard bottom produces a sharp bottom echo with high amplitude while that with low density and soft bottom produces an elongated echo with lower amplitude, which is reflected by the color of the gray image on the echogram of the echo sounder\(^1\). The phenomena implies that there exists a relationship between seafloor type and corresponding \(B_S\)\(^5,6\). Now, the problems are how to build the mapping relation and which method will be chosen for the construction of the mapping relation.

Self-organizing feature maps (SOFM) can learn to classify input vectors according to how they are grouped in the input space\(^3\). SOFM includes an \(|\text{indist}|\) box, which accepts the input vector \(p\) and the input weight matrix \(IW_{1,1}\), and produces a vector with \(s_i\) elements. The elements are the negative of the distances between the input vector and vectors \(IW_{1,1}\) formed from the rows of the input weight matrix. The net input \(n_i\) of a competitive layer is computed by finding the negative distance between input vector \(p\) and the weight vectors. Another component in SOFM is the competitive transfer function, which accepts a net input vector for a layer and returns neuron outputs of 0 for all neurons except for the winner, the neuron associated with the most positive element of net input \(n_i\). The winner’s output is 1. The neurons in the layer of a SOFM are arranged originally in physical positions according to a topology function. The distances between the neurons are calculated according to their positions with a distance function. SOFM network identifies a winning neuron \(i^*\) by a competitive layer, all neurons within a certain neighborhood \(N_{i^*}(d)\) of the winning neuron are updated by using the Kohonen rule.

If a vector \(p\) is presented, the weights \(w\) of the winning neuron \(i^*\) and its close neighbors move towards \(p\). Consequently, after many presentations, neighboring neurons will have learned vectors similar to each other and fulfill the classification of input vectors. If we know approximately the bottom types in a water area, a SOFM network can be built by defining the number of neurons, output class, ordering-phase learning rate, tuning-phase learning rate, ordering-phase steps and the function of tuning-phase neighborhood distance and the topology function. Through encoding the gray level of each pixel in an image, dividing the original image into small image units and forming input vector, SOFM can train automatically and establish a perfect network for seabed classification.

## 3 Applications and analysis

Five parameters, which are topology function (TFCN), distance function (DFCN), ordering phase learning rate (OLR), ordering phase steps (OSTEPS) and tuning phase learning rate (TLR), decide the performance of SOFM in the construction of the clustering network. Through a lot of experiments, we think it is appropriate to set TFCN, DFCN, OLR, OSTEPS and TLR as grid topography function, link distance function, 0.9, 1 000 and 0.1 in the network training.

The original sonar image is shown in Fig.1(a). We use the SOFM network after 1 000-time training and that after 100 training to fulfill the clustering of seabed

![Fig.1 Effect of training times for SOFM network](image)
types. The clustering results are shown in Fig.1(b) and Fig.1(c). Comparing the two results, we know that the network achieved by 1 000-time training can fulfill accurate classification of seabed types with respect to that achieved by 100-time training. The reason is that more training time can ensure the stability of the SOFM network. In the processes of constructing the SOFM network, we also need to provide output classes, namely seabed types. Generally, seabed types are known by actual underwater sampling.

Input vectors, namely image samples, can be directly extracted from the relationship database established previously. An image sample represents the overall characters of the corresponding bottom type. Thus, we should choose an appropriate size for these image samples. A large-size sample may include some miscellaneous characters and thus decrease the classifying accuracy, while a small-size sample can enhance the classifying accuracy and increase training time. Therefore, to delimit the size of an image sample we should consider the resolution of the original image and the accuracy of the seabed classification. The higher the resolution of the original image is, the smaller the size of an image sample should be.

In Fig.2, we choose a sonar image from MBS as studying target for the clustering of seabed types (Fig.2 (a)). We define 5 output classes and use 10 samples. In order to analyze the influence of the size of sample for the clustering of seabed types, we define the samples’ sizes by $3 \times 3$ pixels and $10 \times 10$ pixels, respectively. The different seabed clusters are marked with the mean gray level (MGL) of clustering result of sonar image samples. The corresponding clustering results are shown in Fig.2 (b) and Fig.2 (c). The clustering result in Fig.2 (b) is obviously better than that in Fig.2 (c) in the accurate degree of clustering seabed types.

In Fig.3, we implement another experiment for analyzing the influence of samples’ number for the clustering of seabed types. In the experiment, we define the size of the sample to be $3 \times 3$ pixels, and output class to be 5. We provide 20 samples and 10 samples for the clustering of seabed types, respectively. The clustering results are shown in Fig.3 (b) and Fig.3 (c). Comparing Fig.3 (b) with Fig.3 (c), we find that the former is better than the latter which shows that more samples are beneficial for building an accurate SOFM network and improving the clustering quality.

An integrated procedure of seabed clustering is implemented with multibeam backscatter strength data. First, we implement a calibration for backscatter strength. Then, the calibrated data is transformed to the gray image shown in Fig.4 (a). There exist 5 bottom types in the raw image. Thus, we define the output class in SOFM network as 5. These image samples concerning these output classes, which are extracted from the raw image and shown in Table 1, will be used as input samples for the network training. In order to improve the clustering result, we set the size of each image sample as $3 \times 3$ pixels, and provide 5 image samples for each corresponding output class. After 1 000-time training, the SOFM network for seabed clustering is formed. Input samples are classified well by the network. The clustering result achieves high consistency with the actual underwater samplings, which shows that the network has high accuracy in interior check.
Table 1  Output classes and the corresponding gray levels

| Bottom Type       | Output class | Gray level | Mean gray | Area /m² | R %  |
|-------------------|--------------|------------|-----------|----------|------|
| Bedrock           | 1            | 24~64      | 44        | 4 807 800| 7.7 765|
| Sand & Gravel     | 2            | 64~162     | 98        | 7 665 300| 12.3 985|
| Clean Sand        | 3            | 97~177     | 143       | 15 874 200| 25.6 762|
| Sandy & Mud       | 4            | 164~205    | 189       | 14 499 900| 23.4 533|
| Mud               | 5            | 205~208    | 208       | 18 977 400| 30.6 955|

Comparing the original image and the clustering result, we find a high similarity between them, which shows that the clustering method has higher accuracy. We also compare the clustering result with actual underwater sampling result. The statistic shows that the exterior accuracy of the classification lies within the scope from 90% to 95%.

Because the whole image is divided into many small image blocks as input samples and we get their types by the well-trained SOFM network, we can calculate the areas of different bottom types in the corresponding seabed according to the relation between image scale and geographic coordinate. For an image block with special seabed type, we can compute the actual area $A$ of the image block according to the resolution $P$ of the original image. Adding up the areas of same-type image blocks, we can also determine the total area $S_k$ of the $k^{th}$ bottom type by

$$ S_k = n_k P^2 $$

where $n_k$ is the number of $k^{th}$ class samples with size of $I \times I$ pixels.

We can also calculate the area of the whole image $S_{all}$ and the ratio $R_k$ which reflects the proportion of the $k^{th}$ type area with respective to that of the whole original image by

$$ R_k = \frac{S_k}{S_{all}} $$

for $k = 1, \ldots, 5$.

$$ S_{all} = \sum_{i=1}^{class} S_i $$

here, $S_{all}$ is the area of the whole original image.

4 Conclusion

Using the sonar image from the multibeam bathymetric system or side scan sonar system, we can fulfill the clustering of seabed types. In the clustering, the first thing to do is to construct the relation between actual underwater sampling and the corresponding sonar image. In virtue of the relationship database, we can implement the clustering processing. In the construction of the SOFM network, the size and the number of input samples are very important. Small size sample and more samples can improve efficiently the performance of the SOFM network.

References

[1] Hughes Clarke J E (1993) The potential for seabed classification using backscatter from shallow water multibeam sonar [C]. The Institute of Acoustics Conference on Acoustic Classification and Mapping of the Seabed, Bath, UK

[2] Hughes Clarke, J E (1994) Towed remote seafloor using the angular response of acoustic backscattering: a case study from multiple overlapping GLORIA data [J]. IEEE Journal of Ocean Engineering, 19(1): 364-374

[3] Pican N, Trucco E, Ross M, et al. (1998) Texture analysis for seabed classification: co-occurrence matrices vs. self-organizing maps[C]. IEEE/OES OCEANS’98 Conference, Nice, France

[4] Tamsett D (1993) Sea-bed characterization and classification from the power spectra of side-scan sonar data[J]. Marine Geophysical Researches, 15: 43-64

[5] Yang Fanlin, Liu Jingnan (2003) Seabed classification using BP neural network based on GA[J]. Acta Oceanologica Sinica, 22(4): 523-531

[6] Zhou Xinghua, Chen Yongqi (2004) Seafloor sediment classification based on multibeam sonar Data [J]. Geo-spatial Information Science, 7(4): 290-296