A New Method of Pipeline Detection in Sonar Imagery Using Self-Organizing Maps

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Abstract

The main purpose of this paper is to detect and follow the pipeline in sonar image. This work is performed by two steps. The first one is to split an transformed line image of pipeline signal into regions of uniform texture using the Gray Level Co-occurrence Matrix Method (GLCM) which is widely used in texture segmentation application. The last one addresses the unsupervised learning method based on the Artificial Neural Networks (Self-Organizing Map or SOM) used for determining the comparative model of pipeline from the image. To increase the performance of SOM, we propose a penalty function based on data histogram visualization for detecting the position of pipeline. After a brief review of both techniques (GLCM and SOM), we present our method and some results from several experiments on the real world data set.

1. Introduction

Besides the human interpretation, the high-resolution Side Scan Sonar seems to be the advanced tool for analyzing the sea floor. Three kinds of regions can be visualized: echo, shadow and sea bottom reverberation. The echo information is caused by the reflection of acoustic wave from the object while the shadow area corresponds to a lack of acoustic reverberation behind the object and the remaining is the sea-bottom reverberation area. The only available type of sonar image is the gray level of the pixels corresponding to the acoustic reflectance. Many studies have done about the performance of various families of computational methods, for instance, the 2-dimensions of FFT, the Gray Level Co-occurrence Matrix (GLCM), Gray Level Run Length and etc. In addition, a comparative study from several methods show that the GLCM is a excellent statistical tool for extracting second-order texture information from image. In our study, we can not use the GLCM for detecting directly the position of pipeline, because the data from Side Scan Sonar is only one-dimensional space. Thus we must transform the data to two-dimensional space using the transformed line method which will be described in this paper.

The co-occurrence matrix is used as an estimator of the joint probability density function of gray-level pairs in an image. The matrix is in general symmetric and, when normalized, element values are bounded by [0,1], and the sum of all element value equal to 1. Features extracted from this matrix are so called the second-order statistical feature, for instance, energy, entropy, inverse difference moment, and etc.

The next section of this paper concerns about clustering algorithms based on the Self-Organizing Map (SOM) [1]. This method is frequently employed in various applications such as data mining [2], image segmentation [6] and also pattern recognition. The SOM is a neural network algorithm based on unsupervised learning. It is an efficient tool for visualizing the multidimensional numerical data. It represents high-dimensional data into low-dimensional grid in 1D or 2D. Several methods to visualize clustering base on the SOM can be found in the literature. The most widely used methods for visualizing the cluster structure of the SOM are distance matrix technique[2][3], especially the unified distance matrix or U-matrix as well as the data histogram method.

The aim of this paper is to detect the position of pipeline by means of the comparative model of pipeline signal which is derived directly from the data histogram method. To find the pipeline position, the penalty function is formed and the object of interest is found while its penalty value is the nearest zero.

2. Architecture of Seabed Recognition and Detection System for detecting a pipeline

The basic seabed recognition and detection system is composed of two main processes: training and testing process (Figure 1). The aim of the first one is to evaluate labeled patterns or pipeline image in order to obtain its models, so called a comparative model. During this phase, the labeled pattern are trained by the SOM network till the network is fold, and we have also the comparative model at this step. On the other hand, the testing phase evaluates the model of the arbitrary pipeline images by means of the SOM network of previous process. During the testing process, the comparative model and tested image model are compared by using the penalty function to estimate the position of pipeline.

Each process in the diagram below is consisted of three elements: pre-processing, features extraction and neural network. The role of the pre-processing module is to remove noise and normalize the pattern. Another ones, The line transformation, the Gray Level Co-occurrence

Matrix (GLCM) and the Self-Organizing Map (SOM) will be described in the next section.

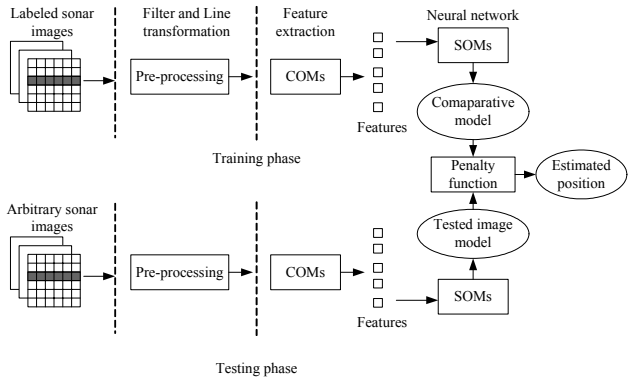


Figure 1. Architecture of seabed recognition and detection system

3. Line Transformation

In general, the sonar image is composed of many lines of the reflected signal returning from sea bottom. The main purpose of this topic is to find the position of pipeline locating on the line image by using the GLCM. But, in this case, we can not directly apply the GLCM, because the data is only one-dimensional space. Thus we solved this problem by introducing the line transformation method. This method is capable to transform the data from one-dimensional space to two-dimensional space , or from a line to an image of line. The image is so called the transformed line image. The method is illustrated step by step as follows:

- At first, the dimension of the image is given, the number of lines are equivalent to $Max(I)+3$ and the columns are equal to N*3. And then each point is put on the image, for instance, if I(n) is of 0, it will be put in the second line of the image, and I(n) = 1 must be in the third line of the image, etc.

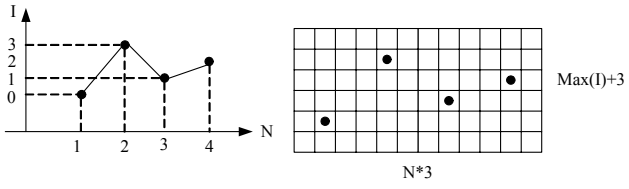


Figure 2. The data points present the amplitude of the signal vs. time.

- Each column is separated by a distance of 3 pixels so that we can put the 8 pixels around each point by the same value (Figure 3).

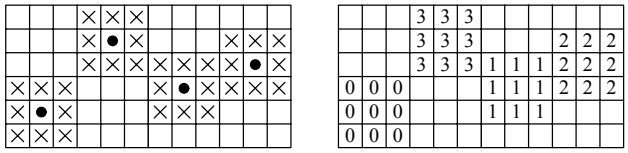
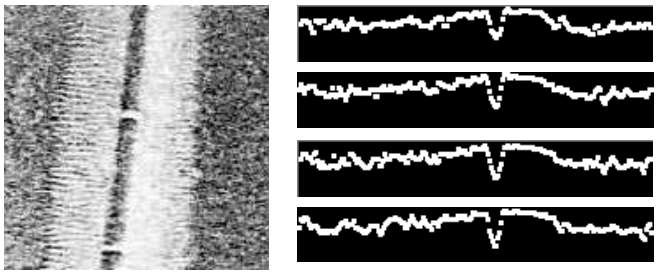


Figure 3.

- Finally the transformed line images are shown in figure below.



(a) (b)

Figure 4. Some transformed line images (right) extracted from the pipeline image (left)

4. The Gray Level Co-occurrence Matrix

The good texture feature extraction method should be capable of identifying the major groups of seabed patterns based on their prominent features to give the best information for texture classification. In the scientific literature, one of the most well-known and wildly used techniques is the G*ray Level Co-occurrence Matrix* (GLCM). The GLCM is based on the estimation of the second-order joint conditional probability density function, $P(i,j/d,\delta)$, derived from co-occurrence matrix.

3.1. Co-occurrence Matrix

The co-occurrence matrix, *P*, represents the repeated occurrence of pairs of pixels (*i,j*) going from gray level *i* to gray level *j* through distance *d* along direction δ. Let $I_x=\{1,2,...,N_x\}$ and $I_y=\{1,2,...,N_y\}$ be the **X** and **Y** spatial domains, where $I_x \times I_y$ is the set of resolution of square image, and the digital image I contain a finite number of gray-level value $g \in G\{1,2,...,N_g\}$ for every pixels, formally $I: I_x \times I_y \rightarrow G$. Let the distance *d* is the distance between two-pixel positions (x_1,y_1) and (x_2,y_2), which indicated by angular angle δ. The matrix, P, is $N_g \times N_g$ square matrix, where N_g-1 is gray value in the image.

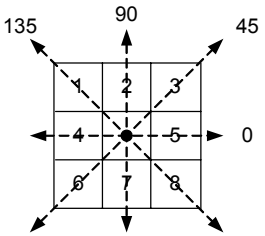


Figure 5.

The co-occurrence matrix allows us to derive four matrix for each given distance: $P(0,d)$, $P(45,d)$, $P(90,d)$ and $P(135,d)$, as indicated in Figure 5.

3.2 Statistical texture description functions

Prior to calculate the statistical texture descriptors, the matrices are normalized. They approximate the joint probability densities of the co-occurrence gray level.

$$P(i,j)=P(i,j)/N \text{ where } N=\sum_i\sum_j P(i,j) \quad (1)$$

From the normalized co-occurrence matrix, a set of textural features is extracted. In our experiments, the most relevant features used are listed below.

Energy:

$$\text{F1} = \sum_i\sum_j P(i,j)^2 \quad (2)$$

Entropy:

$$\text{F2} = -\sum_i\sum_j P(i,j)\log P(i,j) \quad (3)$$

Maximum probability:

$$\text{F3} = \max\{P(i,j)\} \quad (4)$$

Inverse difference moment:

$$\text{F4} = \sum_i\sum_j \frac{P(i,j)}{1+(i-j)^2} \quad (5)$$

Contrast:

$$\text{F5} = \sum_i\sum_j (i-j)^2 P(i,j) \quad (6)$$

Homogeneity:

$$\text{F6} = \sum_i\sum_j \frac{P(i,j)}{1+|i-j|} \quad (7)$$

In this case, we obtain texture feature vectors, $F=\{F_1,F_2,...,F_6\}$. Each element contains information of image texture calculating from statistical description functions above.

4. Self Organizing Map (SOM)

One of the most popular of the *Artificial Neural Network* (ANN), the self-organizing map (SOM), is the best one for pattern recognition and classification task. It belongs to the category of unsupervised learning neural networks. The SOM have only two layers of neurons, an input layer and a competitive layer (figure 6). Each node in the input layer is connected to every node in the competitive layer. The nodes in the competitive layer may also be connected to each other in the aspect of various models of connection, such as squared neighboring connection.

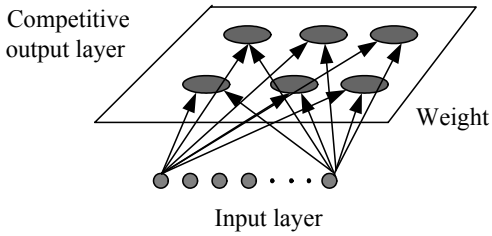


Figure 6.

The model of SOM used in our application is a two-dimensional array of k nodes. Each neuron k is represented by an n-dimensional vector $m_k=[m_{k1},...,m_{kn}]$, where n is the dimension of the input space. On each training step, a data sample x is randomly selected and the best-matching unit (BMU or m_c) is found on the map unit:

$$\|x-m_c\|=\min_k\{\|x-m_k\|\} \quad (8)$$

And then, the vector m_c and its neighbors on the grid are updated by closing to the sample vector:

$$m_k=m_k+\alpha(t)h_{ck}(t)(x-m_k) \quad (9)$$

where t denotes time, $\alpha(t)$ is learning rate and $h_{ck}(t)$ is a neighborhood kernel centered on the winner unit c:

$$h_{ck}(t)=\exp\left(-\frac{\|r_c-r_k\|^2}{2\sigma^2(t)}\right) \quad (10)$$

and

$$\alpha(t)=\frac{\alpha_0}{1+100t/T} \quad (11)$$

where $\|r_c-r_k\|$ is distance between map units of neurons c and k on the SOM grid. In equation (11), α_0 denotes initial learning rate and T is the total iterative time. Both learning rate function $\alpha(t)$ and neighborhood kernel radius decrease monotonically with time.

During the iterative training, the SOM adapt to input data set in such a way that the model vectors which belong to units close to each other on the map unit, are also close to each other in the data space.

4.1. Data histogram method

The aim of the data histogram method is to display the number of hits in each map unit. It means that each unit of map unit belongs to a number of the best-matching units of any given input vectors. For instance, if we have 20 input vectors and 2×2 map unit, the first unit possesses 6 of the best-matching units, the other ones have 4, 2 and 8 of the best-matching units respectively. And then the matrix of map unit which contains the number of the best-matching unit is formed , shown in Figure 7, Finally the normalization of this matrix, so called the model of network, is employed in the next section.

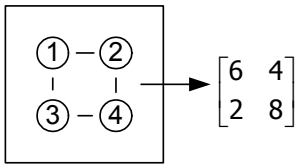


Figure 7. The matrix of the best-matching unit in the map unit

4.2 Penalty function

In this section, we address the penalty function based on the data histogram visualization method. In this paper, we do not use directly the SOM to classify the data, but it is used for evaluating a comparative model. It means that the SOM network generally contains a number of categories of given input in one model. These categories can be perhaps clustered by using the well-known method such as the U-matrix. But, in this topic, we consider only one group of interested data, for instance, the group of pipeline data. Therefore the model will contain only the category of pipeline data. Finally the model is used for evaluating the penalty function shown as the equation below.

$$E^k(i,j)=\sum_{i=1}^{n}\sum_{j=1}^{m} I_w(i,j)\otimes\{I^k(i,j)-I_w(i,j)\} \quad (12)$$

Where, I_w is the matrix model or the comparative model of specific data, I^k is the one of tested sample, *k* denotes the index of sliding-window and $\otimes$ is product of matrix in term by term. The best-matching sample is found while the value of *E* is the nearest zero.

5. Methods

The system introduced in this paper proceeds in two phases (Figure 1). The training phase has a set of the transformed line images which each sample contains only the pipeline data. And then the training-window is defined in the standard size. Its structure is shown in Figure 8. During the training-phase, the training-window is firstly trained by SOM network in order to obtain a comparative model of pipeline. In case of two-dimensional map units, this model is the matrix of probability density as I_w in eq.12.

Figure 8. The structure of training-window

During the testing phase, the matrix model of sliding-window, I^k, is calculated from the arbitrary transformed line images by means of the trained SOM model in previous section. After the matrix model of I^k, is compared with the one of I_w. To find the object location, the penalty value E^k for every sliding-window from left to right is calculated. Finally the pipeline is located on the sliding-window *k* which has the penalty value the nearest zero.

Figure 9. Real transformed line image of pipeline

- Remark: The angle (θ) between the scanning line or the transformed line image and the position of pipeline should be perpendicular for the best result, or it should not touch at 0^o or 180^o .

6. Experimental results

The experiment follows the seabed recognition block diagram illustrated in section 2. In training step, the transformed line image of 30 lines of pipeline image is cut from the testing image for creating the matrix model or the comparative model of pipeline (see Figure 10).

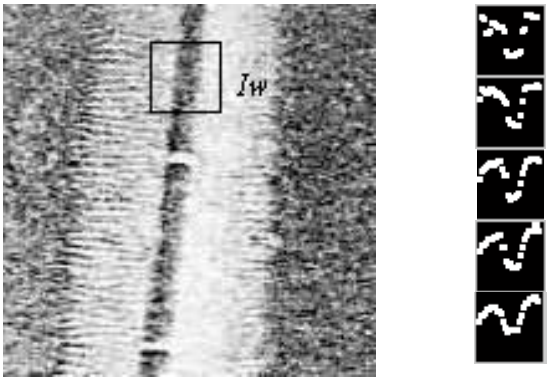
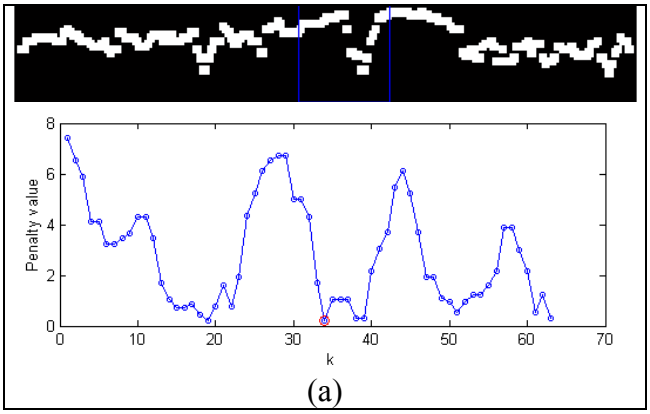
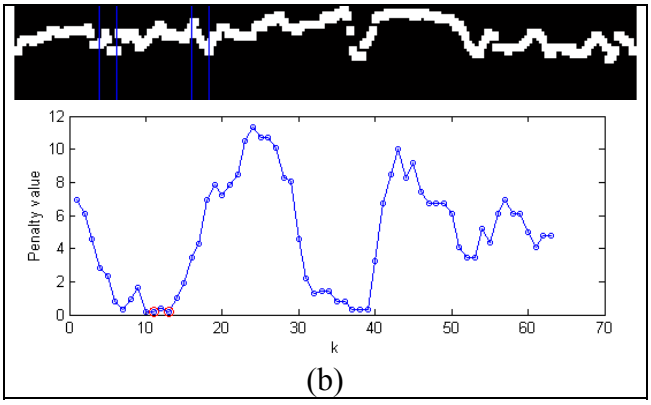


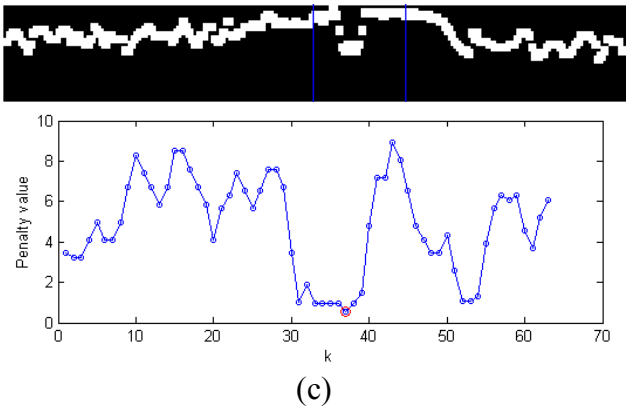
Figure 10. The pipeline image (left) and some transformed line images of pipeline (right)

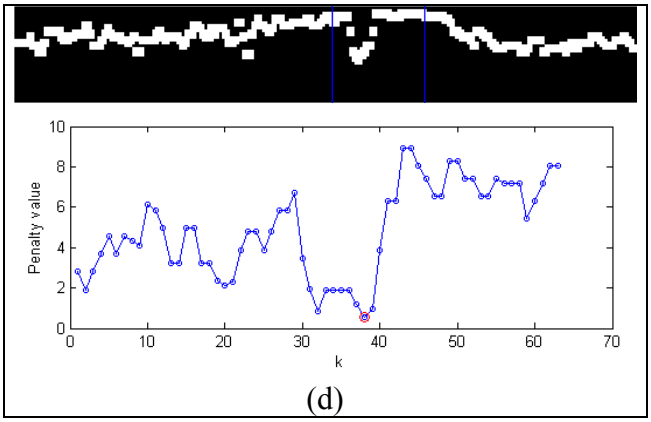
A size of 2×2 units of SOM grid is selected for the best result from a number of experiments. The experiments has tested with the five consecutive lines of sonar image. The results are shown in figure as follows:

- Remark: The accuracy of experiments is about 70 %.









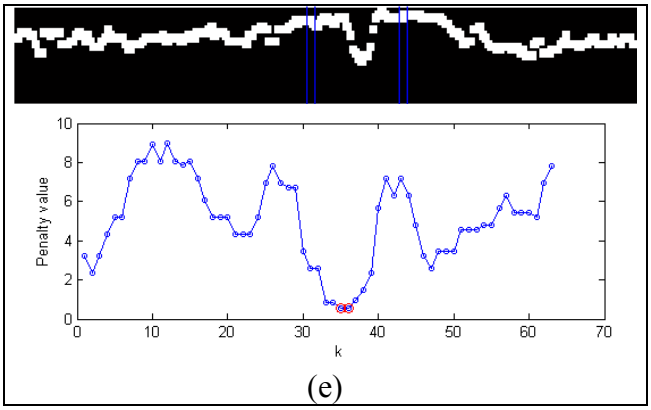


Figure 11.(a-e). Each picture shows the pipeline position indicated by the best-matching window marked in the transformed line images above.

7. Conclusion

This paper proposes a new idea for detecting the position of pipeline in sonar image by using the comparative model based on the SOM. The main purpose is to find the position of pipeline located on one line of the image. The technique which we described above performed well in the real world sonar images.

This technique is designed for a standard size of sliding-window. In addition, the scanning line or transformed line image should not be 0^o or 180^o with

respect to the position of pipeline. The angle should be between 0^o and 180^o. The main advantage of this technique is simple and robust. However this method has the high computational time due to co-occurrence matrix calculation.

For future work, we will attempt to improve this technique and also penalty function to identify more precisely the best-matching window. Moreover this technique will be applied on the real experiment for detecting the position of pipeline in real time.

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