Texture Analysis for Seabed Classification: Co-occurrence Matrices vs Self-Organizing Maps

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Abstract— **This paper considers two well-known pattern recognition techniques using texture analysis. The first is the co-occurrence matrix method which relies on statistics and the second is the Kohonen Map which comes from the artificial neural networks domain. Both methods are used as feature extraction methods. The extracted feature vectors are fed to a second Kohonen map used as classifier. We report briefly some results of our experimental assessment of the merit of each technique when applied to the problem of classifying seabed from sequences of real images.**

I. INTRODUCTION

This paper addresses the unsupervised classification of real, underwater imagery using co-operative texture and colour analysis. The applicative context is the automatic detection of objects of interest in sequences of colour images of the seabed, acquired by a Remotely Operated Vehicle (ROV) during scientific missions at depths between some hundreds and some thousands meters. The target objects are mainly organisms and plants lying on or attached to the seabed (as opposed to floating or swimming in the water column), for instance rocks, plants, molluscs or particular sediment types.

The classification problem at hand is very difficult for several reasons. First, imaging conditions like illumination and magnification undergo continuous (if slow) change. Second, several noise sources contribute to decrease image quality, including floating particles, disturbances during transmission of the video signal to the surface, and digitisation. Third, instances of the target objects may occur in very different shapes and sizes.

For these reasons, our basic design choices were (1) to employ a self-organising architecture to discover relevant classes automatically, and (2) to combine several features to characterise object classes. The self-organising architecture adopted is the *Kohonen self-organising map* (SOM), which we train using a large database of real, subsea video. We compared our method with another well-known texture analysis technique, the it Co-Occurrence Matrices (COMs).

After a brief overview of both techniques we report and evaluate results obtained with our implementations, applied to the classification of various textures in real seabed images.

II. TECHNICAL OVERVIEW

One of the aims of pattern classification techniques is to classify a pattern using its texture characteristics. Thus the problem is to extract textural features that give the greatest information pertaining to each texture. Several well-known techniques exist in this field, e.g., Markov Random Fields, co-occurence matrices, self-organizing maps, fractal components and 2-dimensional FFT [7]. The choice of a suitable method depends on the constraints of the application in terms of nature of the textures and processing time.

The main idea of COMs [4], [3] is to characterise image textures by a set of statistics for the occurences of each gray level at different pixels and along different directions. The term *feature* is used, in texture classification, to describe a set of statistics extracted from a co-occurence matrix, characterising the texture. For instance, energy, entropy and contrast can all be used as features.

Artificial Neural Networks used in combination with unsupervised training algorithms have proven capable to extract automatically the most relevant features from a set of data in several applications. We apply them here to the automatic characterisation of image textures. The SOM algorithm is typical for this task.

A. CO-OCCURRENCE MATRICES

The grey level COM technique [4], [3] sketched in this section is based on the repeated occurrence of some grey level configuration in the texture. Let f: $Lx \times Ly \rightarrow I$ be an image, with dimensions $Lx = 1, 2, \ldots, n_x$ and $Ly = 1, 2, \ldots, n_y$, and grey levels $G = 0, 1, \ldots, m-1$. Let d be the distance between two pixel positions (x_1, y_1) and (x_2, y_2). The immediate neighbours of any pixel can lie on four possible directions: $\theta = 0°$, $45°$, $90°$ and $135°$, as indicated in Figure 1. The COM is constructed by observing pairs of image cells distance d from each

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other and incrementing the matrix position corresponding to the grey level of both cells. This allows us to derive four matrices for each given distance: $P(0°, d)$, $P(45°, d)$, $P(90°, d)$, $P(135°, d)$.

For instance, $P(0°, d)$ is defined as follows:

$$P(0°, d) = \{p_0(i, j); i \in [0, m[, j \in [0, m[\}$$

where each $p_0(i, j)$ value is the number of time when: $f(x_1, y_1) = i$, $f(x_2, y_2) = j$, $|x_1 - x_2| = d$ and $y_1 = y_2$ append simultaneously in the image. $P(45°, d)$, $P(90°, d)$, $P(135°, d)$ are defined similarly.

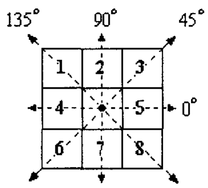

Fig. 1:

The matrices are normalised and features derived from them. Many features can be derived directly; an experimental investigation pointed us to a set of 5 most relevant features, listed below.

Angular second moment:

$$f_1 = \sum_i \sum_j p(i, j)^2 \tag{1}$$

Contrast:

$$f_2 = \sum_{n=0}^{m-1} n^2 \sum_{i=1}^{m} \sum_{j=1}^{m} p(i, j) \text{ with } |i - j| = n \tag{2}$$

Correlation:

$$f_3 = \frac{\sum_i \sum_j p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{3}$$

where μ_x, μ_y are the means and σ_x, σ_y the standard deviations of p_x and p_y.
Variance:

$$f_4 = \sum_i \sum_j (i - \mu)^2 p(i, j) \tag{4}$$

Inverse Difference Moment:

$$f_5 = \sum_i \sum_j \frac{p(i, j)}{1 + (i - j)^2} \tag{5}$$

Finally, the four values that one feature takes on in the four directions shown in Figure 1 are averaged to produce a rotation-invariant feature that we use.

In this paper we are concerned with colour images of the seabed, and for this reason we extended the COM technique to consider the three colour planes (red,green,blue) individually, in order to provide the additional colour information. As three distances $d = \{1, 3, 5\}$ are used, the final feature vector, $\boldsymbol{\beta}$, has 45 components: 3 distances $\times$ 3 colours $\times$ 5 averaged features.

Colour analysis [1], [8] has been rather neglected in ROV applications, probably because, in practice, non-blue components are lost for distances greater than a few meters. Work exists on unsupervised systems for texture segmentation (e.g., [5]) and on unsupervised colour-texture combination [2], but we are not aware of colour-texture classifiers for unstructured subsea objects.

B. SELF-ORGANIZING MAPS

The Kohonen SOM [6] is frequently used to determine the distribution of n-dimensional data, and map them onto a lower-dimensional space (say m-dimensional, with, commonly, $m < n$ and $m = 1, 2$ or 3).

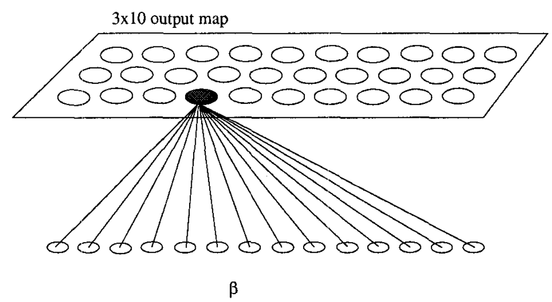

Fig. 2: SOM architecture, with $\boldsymbol{\beta}$ input vector and a 3×10 output grid. Layers are fully connected, though only the connections of one output neuron are shown.

The architecture of a SOM can be sketched as a two-layered neural network (Figure 2) in which the first layer is a set of n input neurons, and the second layer is a set of C output neurons arranged in a m-dimensional space. Each output neuron, i, is fully connected to the inputs. The input layer does not perform any computation; outputs are equal to inputs. The second layer computes the Euclidean distance d_i between the input $\boldsymbol{\beta}$ and each $\mathbf{w_i}$, where $\mathbf{w_i}$ is the n-dimensional weight vector of the connections of output neuron i. The smallest distance defines the winner neuron i^* in the output map. For a classification task, the outputs of neuron i of the second layer are set to 1 if $i = i^*$ and 0 otherwise. For the feature extraction task the outputs are set to distance d_i and thus represent the feature values extracted from the current input.

The training algorithm to tune each $\mathbf{w_i}$ is an iterative loop which, for each input presented, updates $\mathbf{w_i}$ by adding $\Delta\mathbf{w_i} = \eta\Lambda(\mathbf{i}, \mathbf{i}^*, \sigma)(\boldsymbol{\beta} - \mathbf{w_i})$, where η is a coefficient controlling the learning rate; $\Lambda(i, i^*, \sigma)$ is a continuously decreasing function with the distance between i and i^* and equal to 1 for $i = i^*$ (typically a Gaussian function is used); σ reflects the range of effect of the updates. η and σ decrease with the number of iterations.

Notice that, unlike COMs, unsupervised training *discovers automatically* the image features characterising different textures.

III. ARCHITECTURE

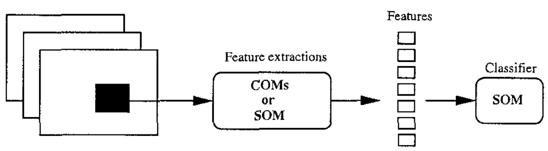

Fig. 3: Architecture of the unsupervised classifier, showing process applied to each image window.

The hardware system is composed of a underwater colour camera, a frame grabber at (1 image/sec) with a resolution of 704 $\times$ 576 pixels, a Pentium II 300MHz computer with Solaris 2.6 Operating System. The system (Figure 3) downloads an image from the sequence. Each 16×16 square window of the image feeds the feature extraction tool (Co-Occurence Matrices or Kohonen-Map), thus the resulting computation of the feature vector feeds the classifier, another Kohonen-Map wich gives the class of the texture in the input window. The final result is presented as a segmented and labeled image.

The SOM for feature extraction has 768 inputs (3 colours $\times 16 \times 16$ pixel window) and 45 output nodes arranged in wire. The SOMs used as classifier, for both feature extraction methods, has 45 inputs and 30 output nodes arranged in an array of 3×10.

IV. RESULTS

For testing with real data we have used a set of images (330×231) in 18 different image sequences extracted from a 1-hour videotape recorded in various benthic trials between [10, 200]-metre depths in the Mediterranean. The training phases needed for the SOMs architectures have been done on all the sequences but on different images used in the test phase. 20,000 times a 16×16 window have been presented to the input of the system during the training phase. For the test, the system labels each 4×4 window by analysing a 16×16 window centered on it. Thus 4,674 windows are analysed by the system for each image.

We report only two examples for reasons of space. Figure 4 shows an image containing various scientific targets. The resulting classes are shown in Figures 5 for the Kohonen SOM technique. The figure shows the resulting labelled image where each grey level is associated to one of the 30 classes. The results indicate a consistent choice

Fig. 4: Image A of the Mediterranean seabed, from a sequence acquired by a scientific ROV (original in colour). Courtesy of the Institute of Marine Biology of Crete.

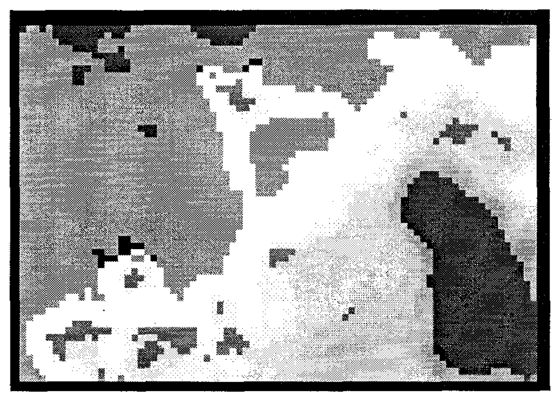

Fig. 5: Segmented image A using a Kohonen map for feature extraction.

Fig. 6: Segmented image A using COMs for feature extraction.

of classes for the Kohonen SOM, which defines classes automatically, and good segmentation performance for both methods. For comparison, results obtained by the COM technique are shown in Figure 6.

The other example (Figure 7) is a less coloured image. In this case COMs (Figure 9) give the best labelling, because the texture brings more information than the colours, for which the SOM method (Figure 8) is more relevant.

V. CONCLUDING REMARKS

We have built an unsupervised image segmentation system using Kohonen SOMs, capable of identifying automatically the most prominent texture-colour features in sets of real subsea images. Once classification targets are made explicit by scientists, training will be designed to optimise target-specific classification. The results show the systems promise in terms of segmentation quality (e.g., homogeneous regions corresponding to a same type of seabed or flora are kept together).

We have compared the system with a COM-based classifier, using real data. COMs appear to catch better texture than SOMs, which however are better for catching colour variations. COM performance seems less affected by typical subsea noise like marine snow. But the time taken to compute COMs (and features from COMs) is larger than for SOM. Moreover, the optimum set of features from COM have to be determined a priori and is highly dependent on the kind of seabed observed, whereas SOMs can find *automatically* the most relevant features in a large set of images.

The image processing problem posed by our project is very difficult; this paper has reported an initial, if promising, solution. Future work must address issues critical in guaranteeing reliability during real, prolonged missions, including invariance to scale, rotation, illumination, and filtering effects introduced by the water.

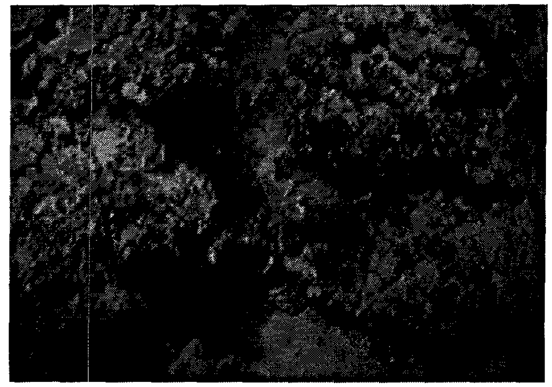

Fig. 7: Image B of the Mediterranean seabed, from a sequence acquired by a scientific ROV (original in colour). Courtesy of the Institute of Marine Biology of Crete.

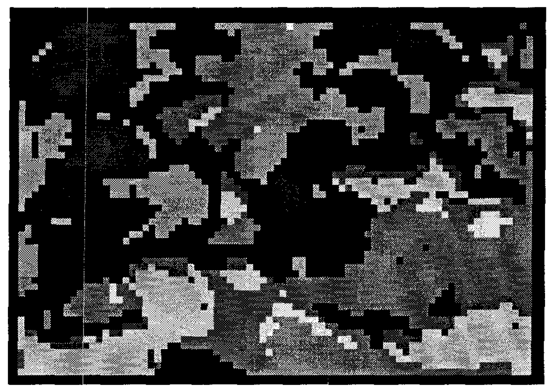

Fig. 8: Segmented image B using a Kohonen map for feature extraction.

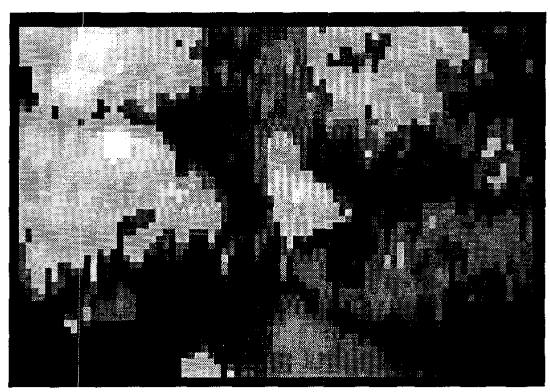

Fig. 9: Segmented image B using COMs for feature extraction.

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