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A non-parametric 2D deformable template classifier

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SUMMARY

We introduce an interactive segmentation method for a sea floor survey. The method is based on a deformable template classifier and is developed to segment data from an echo sounder post-processor called RoxAnn.

RoxAnn collects two different measures for each observation point, and in this 2D feature space the ship-master will be able to interactively define a segmentation map, which is refined and optimized by the deformable template algorithms.

The deformable templates are defined as two-dimensional vector-cycles. Local random transformations are applied to the vector-cycles, and stochastic relaxation in a Bayesian scheme is used. In the Bayesian likelihood a class density function and its estimate hereof is introduced, which is designed to separate the feature space.

The method is verified on data collected in Øresund, Scandinavia. The data come from four geographically different areas. Two areas, which are homogeneous with respect to bottom type, are used for training of the deformable template classifier, and the classifier is applied to two areas, which are heterogeneous with respect to bottom type.

The classification results are good with a correct classification percent above 94 per cent for the bottom type classes, and show that the deformable template classifier can be used for interactive on-line sea floor segmentation of RoxAnn echo sounder data. Copyright © 2004 John Wiley & Sons, Ltd.

KEY WORDS: sea floor segmentation; RoxAnn echo sounder; deformable templates; classification method

1. INTRODUCTION

An online sea floor survey on board a ship needs a segmentation procedure which can handle a couple of challenges. One of the major challenges is the measuring equipment's relative changes or drift in value levels. Changes in measurement values may be caused by the instruments, exogenous variables or local variations in the sea, and the corresponding transformations, in order to restore or normalize data, may be unknown.

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We will introduce an interactive segmentation method based on a deformable template classifier. The method is applied on sea floor data collected by an echo sounder instrument called RoxAnn. The RoxAnn echo sounder gives two measures, which are the first and second echo sounder backscatter, and displays them as a 2D feature space image. Today the ship-master has to rely on his own experience and a predefined 2D feature space classification map, which do not take exogenous variables, local variation or instrumental setup into account, when he has to explore the sea floor. A reliable online sea floor classification would be an improvement of state of the art.

We introduce a classifier which is able to handle the changes and transformations in value levels from a RoxAnn echo sounder measuring equipment. An online segmentation procedure could be as follows. A classified map in feature space is manually defined by a specialist. It could be a 2D predefined feature space map as today, or the ship-master could interactively define his own classes. This map is a start classifier. Every time the ship starts logging new data, the first amount of data should be logged on areas where the sea floor is well known. These data will be regarded as training data, and used by the deformable template classifier to transform the start classifier onto a current classifier. The current classifier can then be used for a reliable automatic classification.

The more training data from different types of sea floor, the better the transformation of the start classifier will be. It is, however, not always possible to obtain training data representing the full feature space. Therefore we need a method which will always give a classifier map almost similar to the start classifier map when training data are missing, but which also changes properly according to the apparent training data. We introduce a class density function in the deformable template framework so a deformable template classifier is able to change or deform based on start classifier templates and training data. A major strength is that, although the classifier is highly data-driven, the classifier templates are able to stay very similar to the starting classifier templates even if the training data in the feature space area are very sparse.

We apply and verify the deformable template classifier on RoxAnn echo sounder data collected in Øresund, Scandinavia, under the European Union project 'Sonar technology for monitoring and assessment of benthic communities' (BioSonar). Given data from four geographical areas, we use two areas, which are homogeneous with respect to bottom type, as training areas. The other two areas, which are heterogeneous with respect to bottom type, are classified by the new classifier.

2. THE RoxAnn ECHO SOUNDER

The RoxAnn device is an add-on to a conventional echo sounder. It is easy to install and not very expensive. The device consists of a head amplifier, a parallel receiver and a software package. The frequency range for the echo sounder is 20 to 250 kHz.

RoxAnn uses the first and second echo sounder backscatter. The first echo, E1, is considered as a measure of the roughness of the sea bed, and the second echo, E2, is considered as a measure of the hardness of the sea bed. E1 is defined as the integral over the tail of the first echo, and E2 is defined as the integral over the second echo (see Figure 1).

A relationship between the sea floor and the sea bed's morphology and the first and second echo from an echo sounder backscatter was explored in Chivers *et al.* (1990), where a RoxAnn system was described, and further discussed in Chivers and Burns (1992). In Heald and Pace (1996) the assumed relationship between the first and second echo and the morphology and sea floor of the sea bed is theoretically justified. A field evaluation of RoxAnn in Schlagintweit (1993) gave promising results and showed that the choice of frequency is important. A low frequency causes a generalization of the

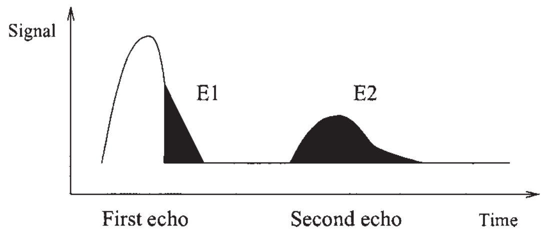

Figure 1. First and second echo sounder backscatter. The black areas illustrate the RoxAnn measures E1 and E2

sea bed. A high frequency is preferred when the sea floor in small areas is studied. The data described and analysed in this article were obtained with a frequency of 200 kHz.

3. COLLECTION OF DATA

Data were obtained under a field campaign in Øresund in 1997. Øresund is the narrow straight between Denmark and Sweden. A complete description of the field campaign can be seen in Conradsen (1999). A map of the area is shown in Figure 2.

The data come from four geographical areas. Two areas are homogeneous in respect to bottom type, which is either mussels or sand. They are called bottom type area mussels, respectively sand. The size of each area is approximately $100 \times 100\,\mathrm{m}^2$. The two other areas are heterogeneous in respect to bottom type, and are called test areas 1 and 2. Each test area is approximately $2\,\mathrm{km}^2$. We do, however, only have data from a sub-area of test area 2. This is because a previous field campaign showed that the

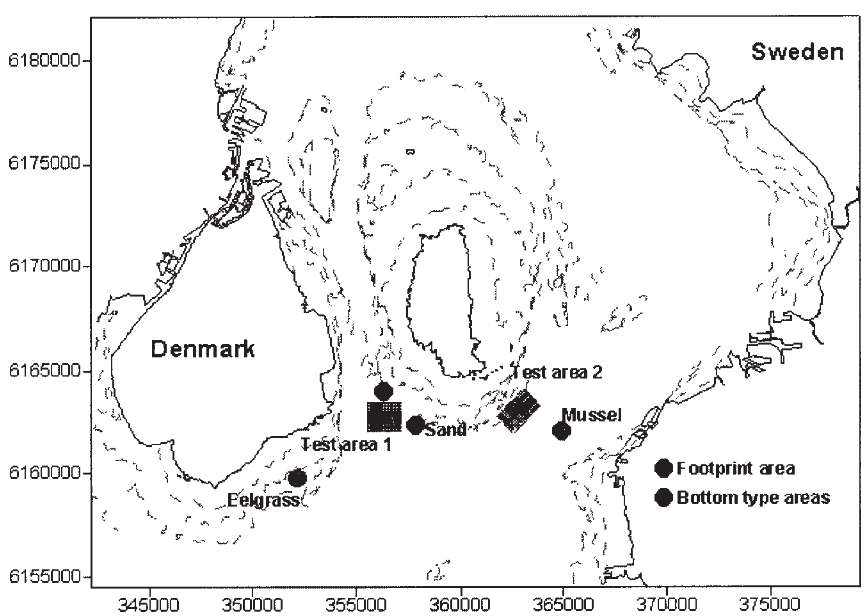

Figure 2. A map of Øresund

area was nearly homogeneous, the sea floor was covered by mussels all over, and therefore it was decided only to cover a part of the area under the next campaign.

Different sampling strategies were applied to the two different types of areas in Øresund. For the bottom type areas data were obtained by 5 sailing transects with an intended spacing of 20 m in two orthogonal directions. For the test areas the sampling strategy was as follows: In the centre of a test area there were seven sailing transects spaced by 20 m in two orthogonal directions. Around these transects eight transects were placed, four on each side, spaced by 60 m in two orthogonal directions. Finally, around these transects the remaining transects were spaced by 120 m in two orthogonal directions.

Ground truthing in the test areas was performed as follows. Every fifth sailing transect was recorded with a video camera mounted on a sledge moving just above the sea bottom. Inside the test areas 10 stations were randomly selected, under the constraint that they were placed on intersection nodes of the actual sailing transects. From every station ground truth data were obtained by both video camera, photo sampler and a divers description of the sea bed.

For each observation we have a position and the two RoxAnn measurements E1 and E2. E1 and E2 are in the range from 0.0 to 2.0 V. The deformable template classifier is represented in a two-dimensional image space. Therefore we will transform data to a 2D image, which is a limited 2D discrete feature space set S, S($E1$, $E2$), where rows represent E1 and columns represent E2 and the pixel-value is the number of observations, in a given data set, having the specific values $(E1 = e1, E2 = e2)$.

In Figure 3 the 2D feature space for observations from bottom type area mussels and sand are shown. The 2D feature space is here represented by an image of size 500×500, where the rows represent E1 and the columns represent E2, both in the range 0 to 0.5 V. This corresponds to 0.001 V per pixel in the feature space image. If we compare the two feature spaces, we can see that mussel and sand observations are well separated, although there is an overlap between the classes. We will use the RoxAnn measurements from bottom type area mussels and sand as training data to the deformable template classifier. The classifier will be used in the obtained RoxAnn measurements from test areas 1 and 2.

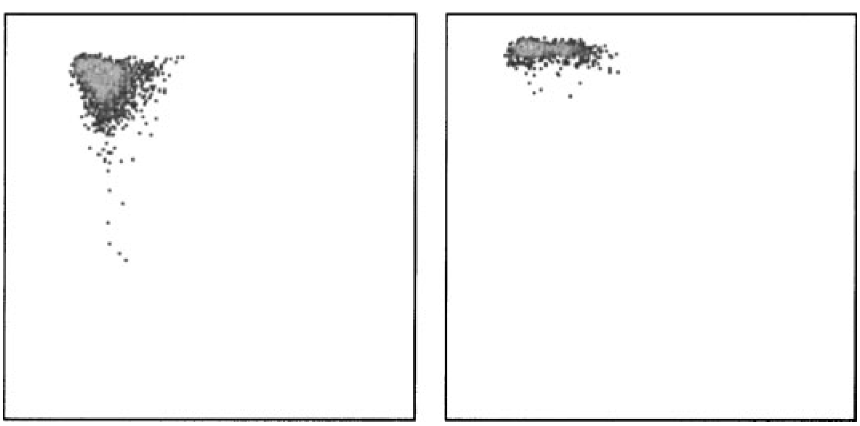

Figure 3. The left image is a 2D feature space for mussels. The right image is a 2D feature space for sand. Rows represent E1 and columns represent E2, both in the range 0–0.5 V. Dark areas represent few observations and lighter areas represent many observations

4. THE DEFORMABLE TEMPLATE CLASSIFIER AND SEGMENTATION PROCEDURE

We could have used other types of classifiers, such as Bayesian discriminant analysis, classification and regression trees, nearest neighbours and neural networks, but in order to properly fulfil the following conditions for a good RoxAnn classifier:

- It has to be interactive, and easy to use for an operator with a primary knowledge and understanding of the parameters E1 and E2, so that he can paint his own start template classes.
- We cannot assume that a class fits to a given statistical distribution.
- The classifier is not allowed to vary very much from the painted start class if the data are very sparse.

We chose to develop a new 2D deformable template classifier which fulfils these conditions.

4.1. Deformable templates as a classifier

Deformable templates, originated in Grenander (1983), are normally used for segmentation of biological objects. We will, however, use them in feature space, in order to achieve a classifier which does not assume any distribution on the data and is able to handle few training data in feature space.

We define a template as a two-dimensional vector-cycle. The template is deformed by global and local transformations applied to the vector-cycle. The global transformations apply Gaussian distributed changes in overall scale, orientation and displacement. The local transformations apply local changes of a given subset of connected vectors. A first order neighbourhood dependence is imposed on the vector-cycle, which means that a given vector is dependent on its two neighbours. The distribution induced by local random transformations converges weakly to a Gaussian distribution, which makes the simulation procedure relatively quick. Only a part of the vector-cycle is changed for each iteration, and stochastic relaxation in a Bayesian scheme is used. In Schultz and Conradsen (1998) the theory is thoroughly described.

Given a k-class classification task, we have k templates each representing a class. The templates are simultaneously simulated, i.e. they are deformed independent of one another. These simulated templates are used in the segmentation of the feature space. The Metropolis algorithm (Metropolis *et al.*, 1953) and simulated annealing (Geman and Geman, 1984) are used to get a maximum a posteriori estimate for segmentation. In the Bayesian likelihood we apply a class density function and an estimate hereof, which is designed to segment the feature space. First a density function for each class based on the data has to be estimated.

4.2. The class density function

We define the class density function as follows.

Definition 1. *Let π_i represent a class i for $i \in \{1, \ldots, k\}$, and let π_r represent the reject class*. Then for a point $\mathbf{x}$ *in the two-dimensional discrete set S the class density is defined as*

$$f_{\mathbf{x}}(c) = p_{\mathbf{x}}\{C = c\} \tag{1}$$

for $c \in \{\pi_1, \ldots, \pi_k, \pi_r\}$, *iff*

$$0 < f_{\mathbf{x}}(c) < 1 \quad \text{for } c \in \{\pi_1, \ldots, \pi_k, \pi_r\} \tag{2}$$

and

$$\sum_{c=\{\pi_1,\ldots,\pi_k,\pi_r\}} f_{\mathbf{x}}(c) = 1 \tag{3}$$

We will impose the following conditions to an estimate of a class density function:

- The estimate of a class density function gives equal probabilities for all classes in a point **x** if there are no observations in this point.
- If there are observations from different classes at a point **x**, the largest class density function estimate at point **x** will always belong to the class with the largest number of observations in **x** relative to its spatial size.

The following theorem describes a class density function estimate $\hat{f}_{\mathbf{x}(c)}$ which takes care of the above-mentioned conditions.

Theorem 1. *Given a training dataset* $D = \{d_1, \ldots, d_n\}$, *where* $d_j = (\mathbf{x}, c)$, **x** *belongs to the two-dimensional discrete set* $S, c \in \{\pi_1, \ldots, \pi_k\}$ *and* $k > 0$.

Then a class density function estimate $\hat{f}_{\mathbf{x}(c)}$ can be

$$p_{\mathbf{x}}, \pi_i = \frac{\frac{nobs_{\mathbf{x},\pi_i}}{\alpha_i} + \frac{1}{k+1}}{1 + \left(\frac{nobs_{\mathbf{x},\pi_1}}{\alpha_1} + \left(\frac{nobs_{\mathbf{x},\pi_2}}{\alpha_2} + \cdots + \frac{nobs_{\mathbf{x},\pi_k}}{\alpha_k}\right)\right.} \quad for\ i = \{1, \ldots, k, r\} \tag{4}$$

Here, $nobs_{\mathbf{x},\pi_i}$ *is the number of observations* d_j *in point* **x** *belonging to class* π_i *and*

$$\alpha_i = \frac{number\ of\ observations\ in\ S_{\xi i}}{area\ of\ S_{\xi i}} \quad for\ i = \{1, \ldots, k\} \tag{5}$$

where S_{ξ_i} *is the two-dimensional discrete set enclosed by the start template vector cycle* ξ_i *for class* π_i.

The templates are constrained to be non-overlapping.

Note that a kind of normalization is done by α_i, *i.e. if there are few observations in a large area in one class and many in another small area.*

We define

$$\alpha_r = 1 \tag{6}$$

Note that $nobs_{\mathbf{x},\pi_r} = 0$.
Proof:
We have

$$\hat{f}_{\mathbf{x}}(c) = p_{\mathbf{x},c} \quad for\ c = \{\pi_1, \ldots, \pi_k, \pi_r\} \tag{7}$$

Because $nobs_{\mathbf{x},\pi_i} \geq 0$ *and* $\alpha_i > 0$ *for* $i = \{1, \ldots, k, r\}$, *we have*

$$0 < \hat{f}_{\mathbf{x}}(c) < 1 \quad for\ i = \{1, \ldots, k, r\} \tag{8}$$

Further, we have

$$\sum_{c=\{\pi_1,\ldots,\pi_k,\pi_r\}} \hat{f}_{\mathbf{x}}(c) = \sum_{i=\{1,\ldots,k,r\}} \frac{\frac{nobs_{\mathbf{x},\pi_i}}{\alpha_i} + \frac{1}{k+1}}{1 + \bigg(\frac{nobs_{\mathbf{x},\pi_1}}{\alpha_1} + \bigg(\frac{nobs_{\mathbf{x},\pi_2}}{\alpha_2} + \cdots + \frac{nobs_{\mathbf{x},\pi_k}}{\alpha_k}\bigg)} \tag{9}$$

$$= \frac{\sum_{i=\{1,\ldots,k\}} \left(\frac{nobs_{\mathbf{x},\pi_i}}{\alpha_i} + \frac{1}{k+1}\right) + \frac{1}{k+1}}{1 + \left(\frac{nobs_{\mathbf{x},\pi_1}}{\alpha_1} + \cdots + \frac{nobs_{\mathbf{x},\pi_k}}{\alpha_k}\right)} \tag{10}$$

$$= 1 \tag{11}$$

QED.

When we have the estimated class density functions which are designed to separate the feature space, we can maximize the joint probability for the data given the templates and an energy function.

4.3. *Likelihood function*

Now assume that the density $f_{\mathbf{x}}(c)$ for an occurrence $\mathbf{x} \in S$ belonging to a class $c \in \{\pi_1, \ldots, \pi_k\}$ is known, and that the densities for each of the classes $\pi_1, \ldots, \pi_k$ are independent. Let the feature space be a limited and discrete system in two dimensions. Assume that we have a classifier for each class π_i represented as a closed vector-cycle template $\mathbf{z}^i$, and let the vector-cycle be non-self-intersecting and non-overlapping.

Then the joint probability for the data D given the templates $\mathbf{z}^1, \ldots, \mathbf{z}^k$ is

$$p(D \,|\, \mathbf{z}^1, \ldots, \mathbf{z}^k) = \prod_{\mathbf{x}\in S_1} p_{\mathbf{x},\pi_1} \times \cdots \times \prod_{\mathbf{x}\in S_k} p_{\mathbf{x},\pi_k} \times \prod_{\mathbf{x}\in S_R} p_{\mathbf{x},\pi_R} \tag{12}$$

S_i is the two-dimensional discrete set enclosed by $\mathbf{z}^i$. $\boldsymbol{x}$ is a point belonging to the limited set $S = S_1 \cup \ldots \cup S_k \cup S_R$. $p_{\mathbf{x},\pi_i}$ is the probability that $\mathbf{x}$ belongs to the class π_i, i.e. has probability $f_{\mathbf{x}}(c)$. We can split the set S_i into two subsets, $S_i = SA_i \cup SB_i$, where SB_i is the closed set bounded by the m neighbouring vectors $\mathbf{z}^i_m$ and the straight edge back to start (see Figure 4).

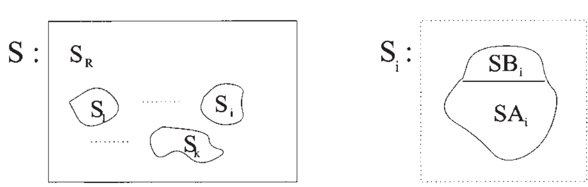

Figure 4. The limited two-dimensional discrete set $S = S_1 \cup \ldots \cup S_k \cup S_R$. S_i is enclosed by $\mathbf{z}^i$. $S_i = SA_i \cup SB_i$, where SB_i is the closed set bounded by the m neighbouring vectors z^i_m and the straight edge back to start

Now assume that a vector segment $\mathbf{z}_m^j$ changes, then we can write (12) as

$$
\begin{aligned}
p\left(D \mid \mathbf{z}^1, \ldots, \mathbf{z}^j, \ldots, \mathbf{z}^k\right) \\
&= \prod_{\mathbf{x} \in SA_1} p_{\mathbf{x},\pi_1} \times \cdots \times \prod_{\mathbf{x} \in SA_k} p_{\mathbf{x},\pi_k} \times \prod_{\mathbf{x} \in S \setminus (SA_1 \cup \ldots \cup SA_k)} p_{\mathbf{x},\pi_R} \\
&\times \prod_{\mathbf{x} \in SB_1 \cap S \setminus SA_1} \frac{p_{\mathbf{x},\pi_1}}{p_{\mathbf{x},\pi_R}} \times \cdots \times \prod_{\mathbf{x} \in SB_{j\,new} \cap S \setminus SA_j} \frac{p_{\mathbf{x},\pi_j}}{p_{\mathbf{x},\pi_R}} \times \cdots \times \prod_{\mathbf{x} \in SB_k \cap S \setminus SA_k} \frac{p_{\mathbf{x},\pi_k}}{p_{\mathbf{x},\pi_R}} \\
&\times \prod_{\mathbf{x} \in SB_1 \cap SA_1} \frac{p_{\mathbf{x},\pi_R}}{p_{\mathbf{x},\pi_1}} \times \cdots \times \prod_{\mathbf{x} \in SB_{j\,new} \cap SA_j} \frac{p_{\mathbf{x},\pi_R}}{p_{\mathbf{x},\pi_j}} \times \cdots \times \prod_{\mathbf{x} \in SB_k \cap SA_k} \frac{p_{\mathbf{x},\pi_R}}{p_{\mathbf{x},\pi_k}}
\end{aligned} \tag{13}
$$

Note that $SA_i = S_i \setminus SB_i$ for $i \neq j$ and $SA_j = S_j \setminus SB_{j_{old}}$.

The likelihood ratio given the new and old template vector segment for a template $\mathbf{z}^j$ will then be

$$
\frac{p\left(D \mid \mathbf{z}^1, \ldots, \mathbf{z}^j_{new}, \ldots, \mathbf{z}^k\right)}{p\left(D \mid \mathbf{z}^1, \ldots, \mathbf{z}^j_{old}, \ldots, \mathbf{z}^k\right)} = \frac{\prod_{\mathbf{x} \in SB_{j\,new} \cap S \setminus SA_j} \frac{p_{\mathbf{x},\pi_j}}{p_{\mathbf{x},\pi_R}} \times \prod_{\mathbf{x} \in SB_{j\,new} \cap SA_j} \frac{p_{\mathbf{x},\pi_R}}{p_{\mathbf{x},\pi_j}}}{\prod_{\mathbf{x} \in SB_{j_{old}} \cap S \setminus SA_j} \frac{p_{\mathbf{x},\pi_j}}{p_{\mathbf{x},\pi_R}} \times \prod_{\mathbf{x} \in SB_{j_{old}} \cap SA_j} \frac{p_{\mathbf{x},\pi_R}}{p_{\mathbf{x},\pi_j}}} \tag{14}
$$

The classifier optimization algorithm differs from the traditional deformable template algorithm (Schultz and Conradsen, 1998) in the following ways:

- A class density function estimate (4) is calculated based on training data and painted start template classes.
- The new classifiers likelihood ratio (14) is used as the chosen energy function in the stochastic relaxation scheme.

4.4. Start templates and deformable template model parameters

In the actual case the start templates are painted manually on the RoxAnn feature space map as a rough guess based on the training data. The curvatures of the start templates are further smoothed by a median filter because small hand movements from the operator can induce unwanted sharp edges. These start templates are, of course, very dependent on the painter. This means that the operator–ship-master or predefined map–may influence the classification.

The deformable template model parameter choice can give a looser or harder constraint to the template's deformability, e.g. if some part of the template border is very well defined, then the parameters in this area could be set to give a very little vector deformability at this border. The two start templates can be seen in Figure 5.

The template parameters are as follows (for details see Schultz and Conradsen, 1998):

Global iterations, local iterations	0, 1000
Number of vectors, segment vector size	120 (mussels) 50 (sand), 3
Energy function	Class density function, likelihood
Annealing constant α, temperature	0.98, 5
Local parameters $(\alpha_{v_i}, \phi_{v_i}, \alpha_{a_i}, \phi_{a_i})$	200 200 0.01 0.01 (deformability parameters)

We have chosen not to use global iterations, because overall change in size and rotation is unnecessary in the actual case. The number of local iterations is set to 1000. The mussel template is

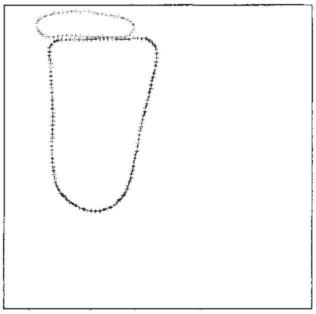

Figure 5. The two start templates. The darker template represents mussels and the lighter template represents sand. Rows represent E1 and columns represent E2, both in the range 0–0.5 V

defined by 120 vectors and the sand template is defined by 50 vectors. The segment size for the templates is 3, which means that 3 neighbouring vectors are deformed at a time. We use a class density function, and the simulated annealing constant is 0.98 with the start temperature 5. The local parameters determine the distribution parameters for the vector deformability. α is normally inducing changes in vector length, and ϕ is normally responsible for change in vector orientation. The local parameters are set equal for all vectors, and are chosen in order to give stable deformable template simulations.

In Figure 6 simulation iteration numbers 200, 400, 600 and 800 are shown. It is seen that the simulated deformable templates are stable. This is important if we have areas in the feature space where training data are missing.

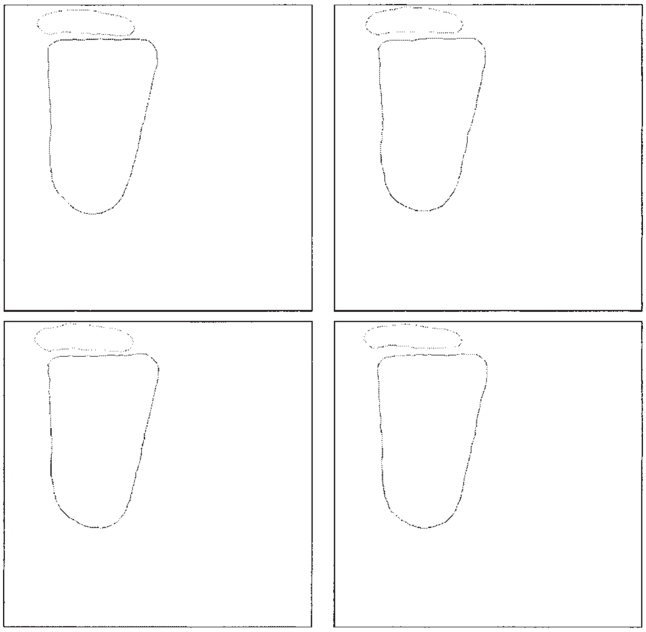

Figure 6. From top left, by rows, to bottom right the images show simulation results after 200, 400, 600 and 800 iterations. The darker template represents mussels and the lighter template represents sand

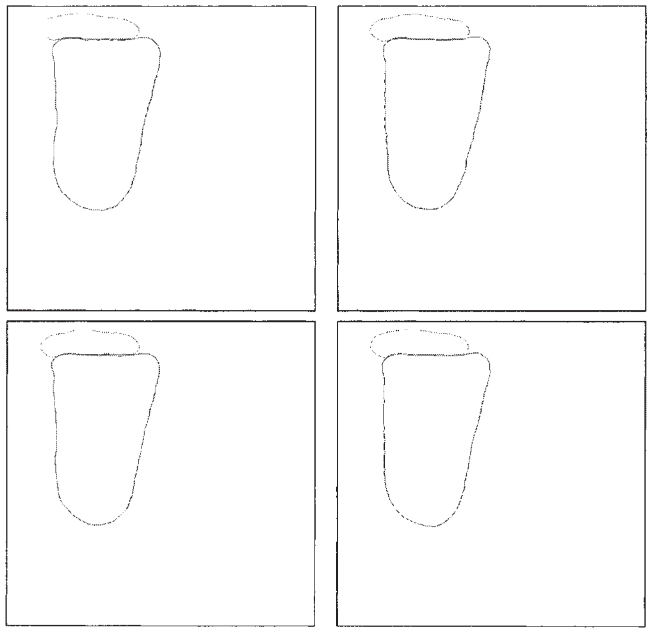

Figure 7. From top left to bottom right, by rows, the images show the segmentation results after 250, 500, 750 and 1000 iterations. Rows represent E1 and columns represent E2, both in the range 0–0.5 V. The darker template represents mussels and the lighter template represents sand

4.5. Deformable template segmentation

We can now apply the deformable templates on training data. Figure 7 shows how the templates are deformed and become stable during the segmentation. After 1000 iterations the templates have reached a stable state and are constant, especially where classes nearly overlap.

4.6. Classification procedure

The result from the deformable templates gives a segmented feature space which is the classifier.

In Figure 8 the feature space map is shown. The white area in the feature space map, which is not covered by a template, is reject class. The sand class is represented by light grey, and the mussels class is represented by dark grey. The classification procedure is as follows: given an observation with the RoxAnn measurement values $e1$ and $e2$, then the observation belongs to the class which is on the feature space map at point ($e1$,$e2$).

Note that in the feature space areas with few training data the template classifiers are very similar to the start templates, and in the areas with many training data the templates have been deformed to fit the data.

5. CLASSIFICATION RESULTS

Classification results for training data from the bottom type area mussels and sand are shown in Tables 1 and 2. The classification results of training data are good. There are no observations which are rejected, and misclassification rates of 0.5 per cent for mussels and 5.4 per cent for sand are low.

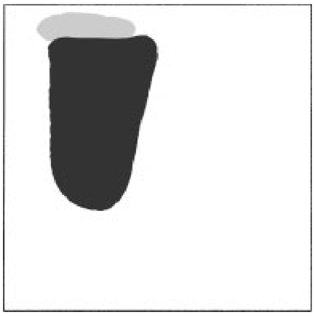

Figure 8. The dark template area represents mussels and the light template area represents sand. Rows represent E1 and columns represent E2, both in the range 0–0.5 V

Table 1. Classification results table for training data belonging to the mussel class

	Mussel classification table			
	Reject class	Mussel class	Sand class	Total
Number	0	3078	16	3094
Percentage	0.0000	99.4829	0.5171	100.0000

Table 2. Classification results table for training data belonging to the sand class

	Sand classification table			
	Reject class	Mussels class	Sand class	Total
Number	0	88	1536	1624
Percentage	0.0000	5.4187	94.5813	100.0000

If we inspect the classifier templates in Figure 8, we can see that the start templates have been deformed according to the previously described conditions, namely that the templates should be deformed to minimize the classification error in the feature space areas where training data are present. In the areas without training data the templates should be stable and very similar to the start templates.

Figure 9 shows the classified sailing transects for the two bottom type areas. The geographic allocation of the misclassified observations seems reasonable from a biological point of view.

We will now validate the classifier by classifying test areas 1 and 2. Figure 10 shows the classified sailing transects for test areas 1 and 2.

As expected, the classified maps are very homogeneous, with only small areas of other classes than the specific bottom type class. If we look at the right side at test area two, there are relatively many observations classified as sand. This fits well to the fact that the depth is very low in this area, the upper right corner has no observations because the boat could not sail closer to the coast, and therefore there normally will be sand.

From ground truth we know (Conradsen, 1999) that the sea floor in test area 1 is mostly covered by mussels with sand areas to the east and eelgrass spread over the middle of the area. The classification

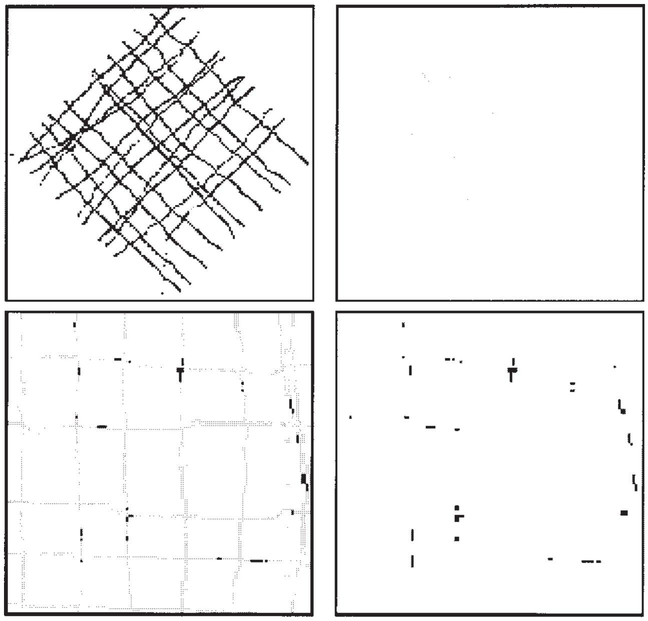

Figure 9. Classified sailing transects for the bottom type areas mussels, first row, and sand, second row. The first column shows all the classified observations and the second column shows only the misclassified observations. Dark areas represent mussels and lighter areas represent sand

result for test area 1 is similar, although we miss an eelgrass class. The classification could be improved if we had had eelgrass training data; eelgrass is now classified as either mussels or rejected.

Ground truth (Conradsen, 1999) shows that the sea floor in test area two is covered by mussels. The classification shows a similar result.

The classification results are in general good. One may argue that eelgrass observations, which are present in test area one, should be rejected and not classified as mussels, which seems to happen. The reason for this is the mussels start template, which is probably too big, i.e. the mussel observations with high E1 values are probably outliers.

This kind of classifier is highly data-dependent and can also be operator-dependent, which induces a bias/variance dilemma (see, for example, Geman *et al.*, 1992), causing models that may be improperly conditioned due to, for instance, too small data sets. However, the advantage of the classifier is its flexibility and capability to handle different kinds of data.

6. CONCLUSION

In order to improve a sea floor survey on board a ship equipped with a RoxAnn echo sounder we have introduced a deformable template classifier for sea floor segmentation. We have described how the segmentation method enables the user to interactively define a segmentation map, which is then refined and optimized by the deformable template classifier. We have defined and used a new class density function and an estimate hereof in a Bayesian scheme, for segmentation of the deformable templates in feature space. This enables us to maximize the global joint probability for the training data given the classifier templates.

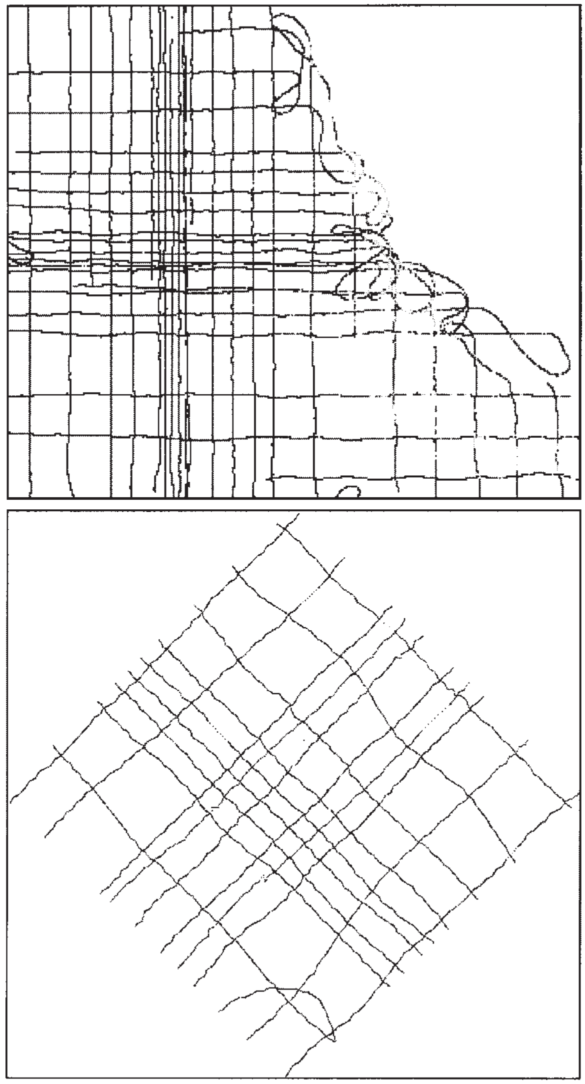

Figure 10. Classified sailing transects for test area one, top image, and test area two, bottom image. Dark grey represents mussels and light grey represents sand

The deformable template classifier has been trained on training data from two different homogeneous areas—a mussels area and a sand area. The correct classification percent for mussels is 99.5 per cent and that for sand is 94.6 per cent. The final classifier templates have deformed properly in the feature space areas where the training data are present, and have properly stayed similar to the start templates in the areas where no training data were present. The classifier has been applied to two test areas, where the classified areas have been compared to ground truth, and the classification results are in general good. Therefore, we conclude that the deformable template classifier applied on RoxAnn echo sounder data can be used to segment the sea floor.

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