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Multi-segmentation of sonar images using belief function theory

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Today side scan sonar is one of the most efficient sensors for Rapid Environment Assessment missions. Unfortunately, features extracted from a given area are strongly dependent on the relative position of the sensor (*e.g.* due to the shadow or the gain variation). That could conduct to a bad segmentation of the seabed. However, due to the fact that operational systems give very often multiple views of the same area we use the redundancy.
In this work, we propose to fuse multi-view segmentations in order to outperform the seabed classification. First we present a way to characterize the seabed using as a start point, a texture analysis in order to extract parameters on images. Then, a classification method allows allocating a class according to the type of sediment for the different standpoints. The proposed classifier fusion is based on the belief function theory. We present results from a set of experiments conducted to evaluate the proposed approach with real sonar images and we discuss them.

1 Introduction

Today side scan sonar is one of the most efficient sensors for Rapid Environment Assessment missions. Unfortunately, features extracted from a given area are strongly dependent on the relative position of the sensor (*e.g.* due to the shadow or the gain variation). That could conduct to a bad segmentation of the seabed.

Many approaches have been proposed in order to outperform the texture analysis methods for marine sediments characterization. Indeed, sonar images present various homogeneous zones of sediments which we can consider as entities of texture. The interest of the texture analysis within the framework of the treatment of image is indisputable. In [1, 2], matrices of cooccurrences, filter of Gabor and the wavelet decomposition have been employed. Hence, many features can be extracted from the images for classification, and many classifiers can be used to provide a good classification [3].

However, due to the fact that operational systems give very often multiple views of the same area we use the redundancy of the classification on this same area. In this work, we propose to fuse multi-view segmentations in order to outperform the seabed classification.

The rest of the paper is organized as follow: First we present the characterization method based on a process of Knowledge Discovery on Database (KDD). The texture analysis in order to extract parameters on images is first detailed. Then, the classification method based on the prototype classifier, allows allocating a class according to the type of sediment. Image registration is supposed made in order to fuse the corresponding parts of the multiple views of the same area. The proposed classifier fusion is based on the belief function theory. In the last section, we present results on one real sonar images and we discuss them.

2 Method

The classification chain following the KDD process is showed in (cf. Fig. 1). In this process, all images are stored in a database which can be voluminous or still badly informed. The first stage of the chain consists in selecting the necessary and sufficient data for the application of recognition by selecting a party of them for the learning phase and the other one for the test phase. It is then important to prepare the data for the classification. Images pre-treatment according to our application is based on Time Variation Gain (TVG) correction and reducing the speckle noise. Once these data have been pre-treated, they must be then transformed to allow extracting of the textures of sediments; this will be the object of the next stage. Classification algorithm is based on prototypes classifier. Finally we used the belief function theory to fuse all obtained classification results and to provide an appropriate classification of registered sonar images.

2.1 Texture analysis

There are several definitions of texture; it is so difficult to give a precise definition. But we can say that the texture is a zone of the image which presents certain characteristics of homogeneity which creates as an unique zone. Texture analysis methods have been utilized in a variety of application domains and have been a subject of intense study by many researchers. In some of the mature domains (such as sonar [1,2,3]) texture already has played a major role, while in other disciplines such as remote sensing and medical imaging. The purpose consists in extracting from an image presenting only texture, a number of parameters, supposed to be representative of the texture. This texture will have to be as well little sensitive as possible in transformations of the image which leave the unchanged texture for a human observer. In order to extract irrelevant information in sonar images, we develop here the used method based on the cooccurrences matrix. This approach was originally proposed in [4] and developed by Haralick [5, 6]. Cooccurrences matrix, knew a very big success in analysis of texture. Often, it is taken as reference method in spite of its cost importing in compute time and in space memory. Cooccurrences matrices are based on the estimation of density use the second order joint probability. We consider here the mean of the four directions: 0°, 45°, 90° and 135°. This method will provide us 6 parameters which are homogeneity, contrast, correlation, entropy, directivity, uniformity and defined by the following equations:

$$Homogeneity = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P^2(i,j) \quad (1).$$

$$Contrast = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} (i-j)^2 P(i,j) \quad (2)$$

$$Correlation = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \frac{ijP(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y} \quad (3)$$

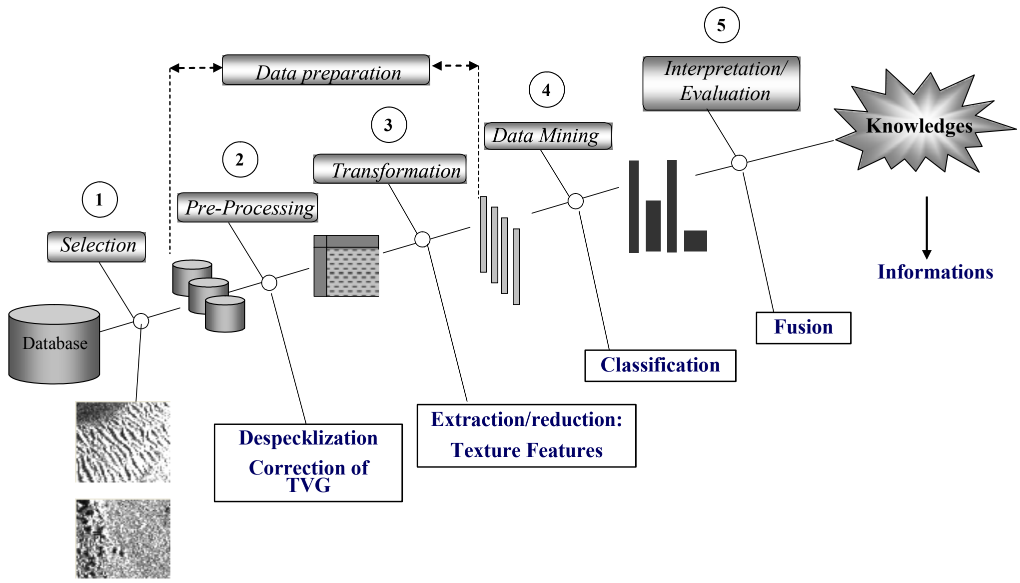


Figure 1: KDD process of multi- segmentation fusion

$$Entropy = -\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P(i,j)\ln(P(i,j)) \qquad (4)$$

$$Directivity = \sum_{i=0}^{N_g-1} P(i,i) \qquad (5)$$

$$Uniformity = \sum_{i=0}^{N_g-1} P^2(i,i) \qquad (6)$$

where N_g is the number of gray level and $P(i,j)$ is the estimation of transition probability of the pixel i to the pixel j, (μ_x, μ_y) describe the mean on rows and columns of P and (σ_x, σ_y) are the standard deviations.

These features are extracted from small tiles of 32x32 pixels. The set of features is considered as the input of a prototypes classifier described in the next step.

3 Classification

Classification is the process of sorting the small tiles of 32x32 pixels into a finite number of individual classes. If a tile satisfies a certain set of criteria, then the tile is assigned to the class that corresponds to that criterion. Supervised classifier has been extensively analyzed and for which many learning algorithms have been developed. In this work we used classification approach based on supervised classification using prototypes classifier. Other classifiers are possible [3]. This method consists in determining the distances separating new tile of those of the learning whose type of sediment is known. In this work we keep only all classes center, and we use the Mahalanobis global distance represented by the below equation:

$$d^2_{Mah}(x,\mu_c) = (x-\mu_c)'\Sigma^{-1}(x-\mu_c) \qquad (7)$$

where Σ and $\mu_c = \frac{1}{n_c}\sum_{k=1}^{n_c} x_k$ are respectively the covariance matrix and the center of class.

3.1 Fusion

In literature we can find many fusion theories whose can be used for the experts in image classification such as voting rules [7, 8], fuzzy and possibility theory [9, 10], and belief function theory [11, 12]. As a result, probabilities theories such as the Bayesian theory or the belief function theory are more adapted. Indeed, the possibility theory is more adapted to imitate the imprecise data whereas probability-based theories are more adapted to imitate the uncertain data. For this reason, we adopt the fusion based on the belief function theory; know also by the Dempster-Shafer theory (DST) [11].

The belief functions theory is more and more employed in order to take into account the uncertainties and imprecisions in pattern recognition. The belief functions framework is based on the use of functions defined on the power set 2^D (the set of all the subsets of D), where $D=\{C_1,\ldots,C_n\}$ is the set of exclusive and exhaustive classes. These belief functions or basic belief assignments, m_j are defined by the mapping of the power set 2^D onto [0,1] with generally:

$$\sum_{A\subseteq D} m_j(A) = 1\,, \qquad (8)$$

The first difficulty is the choice of a mass function. We have shown in [3] that the proposed approach in [13] is well adapted for sonar image classifiers fusion. This mass function is defined by:

$$\begin{cases} m_j^i(\{C_i\})(x) = \alpha_{ij} R_j p(q_j / C_i)/(1 + R_j p(q_j / C_i)) \\ m_j^i(\{C_i\}^c)(x) = \alpha_{ij} /(1 + R_j p(q_j / C_i)) \\ m_j^i(D)(x) = 1 - \alpha_{ij} \end{cases} \qquad (11)$$

Where q_j is the j^{th} classifier (supposed cognitively independent), α_{ij} are reliability coefficients on each classifier j for each class i, and R_j is the maximum of the probabilities given by:

$$R_j = (\max_{q_j,i}(p(q_j / C_i)))^{-1}, \tag{12}$$

Hence a mass function is defined for each source and each class. In this approach, we have to estimate the probabilities:

$$p(q_j / C_i), \tag{13}$$

The estimation of these probabilities can be easily made by the confusion matrix on a learning database.

To combine all mass functions we use the orthogonal Dempster-Shafer's rule, given for two mass functions by:

$$m(A) = \frac{1}{1-k} \sum_{B_1 \cap B_2 = A \neq \emptyset} m_1(B_1) m_2(B_2) \tag{14}$$

with k=$m(\emptyset)$. Finally the last step is the decision step. Different solutions are possible; we propose here the use of the pignistic probability, which is a good compromise. It is given by:

$$betP(A) = \sum_{X \in 2^D, X \neq \emptyset} \frac{|X \cap A|}{|X|} m(X) \tag{15}$$

4 Experimental results

4.1 Sonar image data base

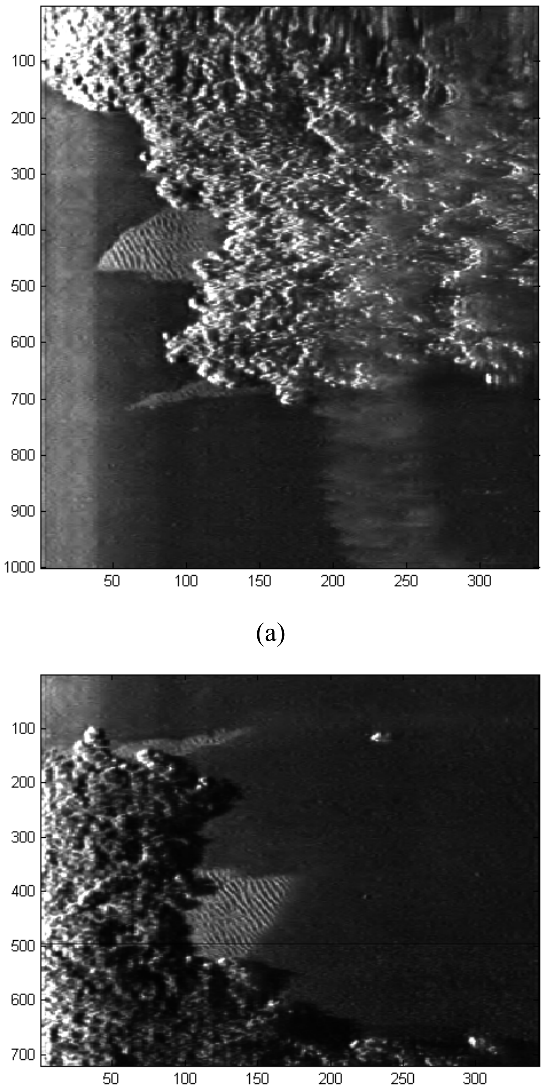
In order to train the classifier, we use a real database composed by sonar images. It consists of 42 sonar images provided by GESMA (*Groupe d'Etude Sous Marine de l'Atlantique*).

To evaluate the proposed approach, we use two images, with posidonia with the same area (*cf.* figure 2). These images are obtained with a Klein 5500B data recorded on "*la Grande Vaille*" in France by SEMANTIC-TS and by the GESMA (*Groupe d'Etudes Sous-Marines de l'Atlantique*) within the DGA\D4S\MRIS contract n° 05.34.011.00.470.75.65 entitled "*cartographie de la couverture du fond marin par fusion multi capteurs*".

Note that such database is quite difficult to realize. Indeed, the expert has a subjective experience, and he can make mistakes on some small-images, even if he has a perception of the global sonar image. So we only have a subjective perception of reality [14].

The manually segmentation by one expert of both images of the figure 2 is given on figure 3. Note that on the image (b), the shadow of the posidonia is clearly marked; this shadow is not on the other view of the image (a). The border between sand and posidonia is also different according to the view angle.

In order to fuse both images we must first to register them. The registration is here simply made manually indicating remarked points, and applying an affine transformation. This manual registration is made on the manually segmented images and given in the Fig. 4. Automatic registration is possible but not so easy with sonar images [15].



(a)

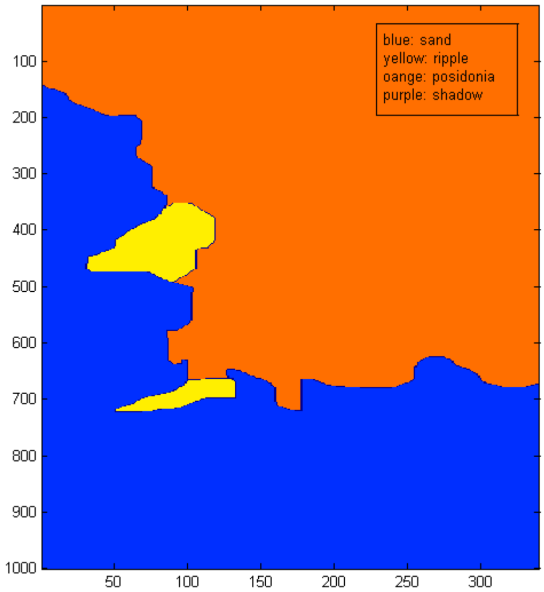
(b)

Fig. 2 Sonar images in (a) and (b) with the same area.

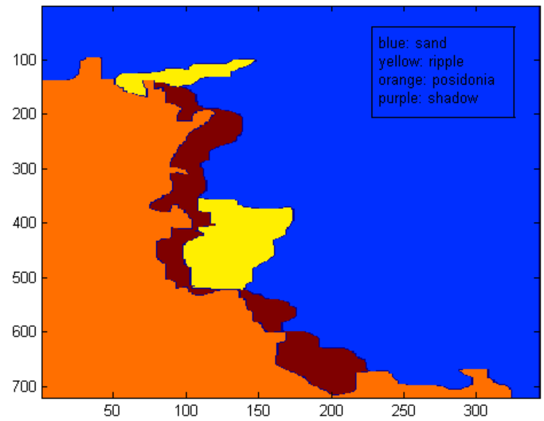
The training is made only on 4000 homogeneous tiles of size 32×32 pixels, on which the kind of sediments is indicated. We consider four classes of sediments: sand, silt, ripple and other. Note that on the training images there is no posidonia. The posidonia is learning with the ''other'' class. The obtained confusion matrix for this classifier is given by the table 1.

		Found			
		Ripple	Sand	Silt	Other
Real	Ripple	60.32	11.09	0.00	28.59
	Sand	2.35	65.29	26.28	6.09
	Silt	0.26	27.64	70.69	1.42
	Other	9.14	8.97	0.46	81.43

Table 1 Confusion matrix of the prototype classifier.



(a)



(b)

Fig. 3 The manually segmentation by one expert in (a) and (b) of both images of Fig. 2.

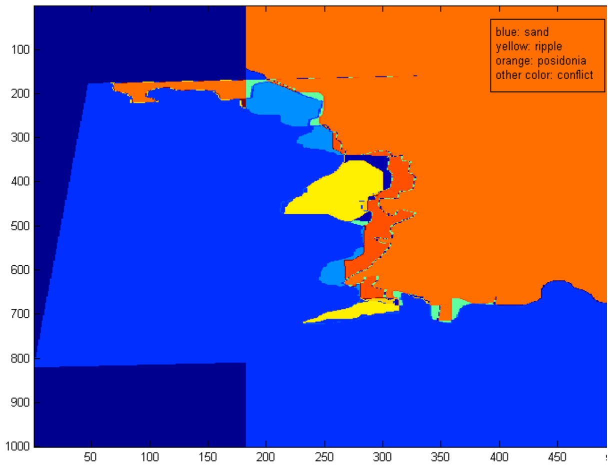
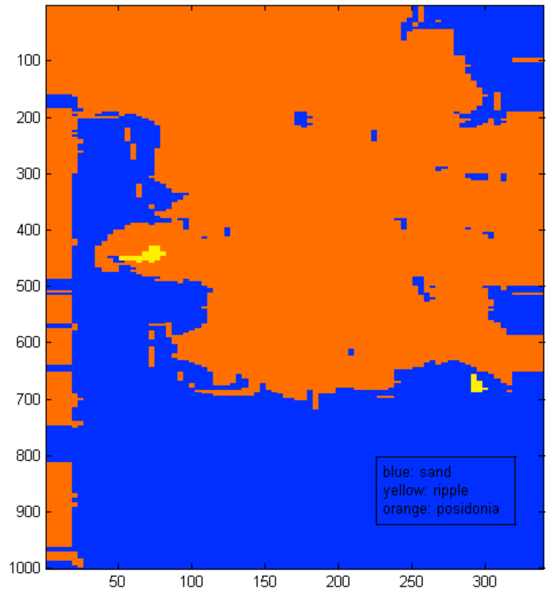
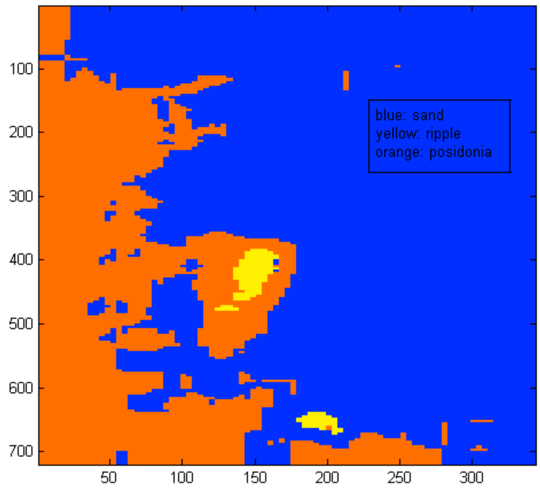


Fig. 4 Manual registration of both images manually segmented.

Hence, the classification on both test images according to the KDD process is given on the figure 5. Note that we cannot find separated shadow and posidonia, but only other that correspond more to the posidonia. There is some artefact on the left part of the image (a). The artefacts are the cavitations' bubbles doing by the helix of the ship during a previous acquisition.



(a)



(b)

Fig. 5 Automatic classification obtained by the KDD process applied to two sonar images based on texture analysis to extract features for existents sediments characterization (a): first view and (b) second view.

The corresponding registration is given on the figure 6. The colours blue, orange and yellow show the sediment type and the others the conflict between the two images.

Finally, the figure 7 shows the fusion of the classifiers on the common area of both images. The class other, corresponding here to the posidonia is well learning on the learning database. And even if the ripple triangular zone (dimensions are 18m, 17m and 16m) in the centre of the images are not entire well classified, the boundaries between sand and others sediment seem to be robust.

Hence the artefact on the left of the image (a), is conserved. A third image could suppress these artefacts.

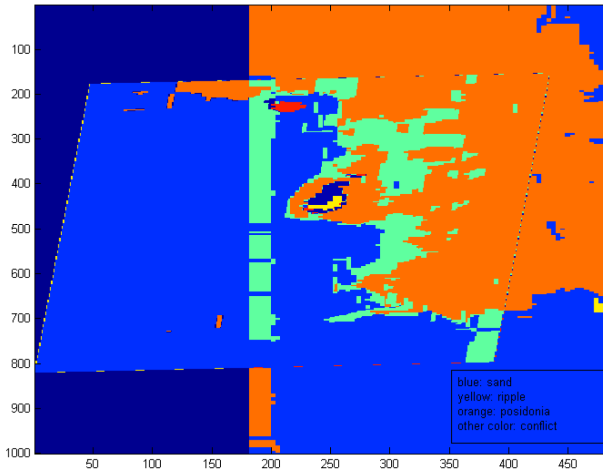


Fig. 6 Registration of both classified images.

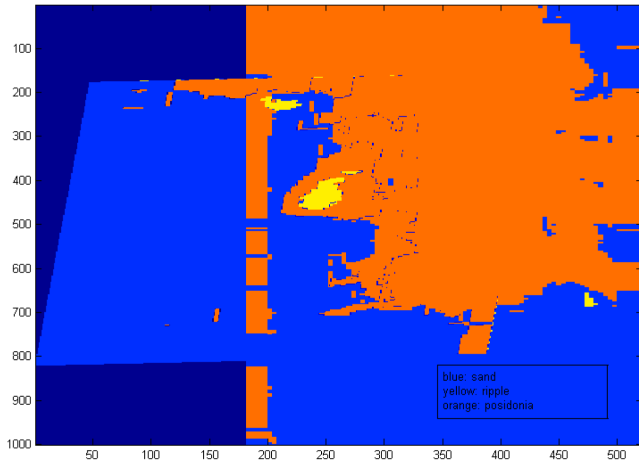


Fig. 7 Fusion of both classified images.

5 Conclusion

We have proposed here an original method for multi-segmentation coming from classifier fusion applied to a sea-bottom characterization. The fusion approach is based on the belief function theory. The KDD process will be improved upgrading each step (pre-processing, transformation, classification and fusion) as regard of the expert segmentation.

This work shows the interest of multi-segmentation of sonar images by fusion. And we expect at the end provide texture map of the seabed for navigation map-matching and for mine warfare sonar performance indicator.

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