SOME IMPROVEMENTS OF A ROTATION INVARIANT AUTOREGRESSIVE METHOD. APPLICATION TO THE NEURAL CLASSIFICATION OF NOISY SONAR IMAGES

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This paper presents some improvements of a rotation invariant method based on AutoRegressive (AR) 2D Models to classify textures. The basic model and our improved version are applied to natural sidescan sonar images (with multiplicative noise) in order to extract a reduced set of relevant rotation invariant features which are then used to feed a MultiLayer Perceptron (MLP) for identification task. Some analysis are conducted over these features to evaluate their interest. Classification results on four types of sidescan sonar images illustrate the efficiency of the proposed approach.

Introduction

Classification of seafloor areas has two applications : the cartography of seafloors and the improvement of detection/classification steps of manufactured objects lying on these seafloors. The key step of a recognition system lies in the appropriate feature calculation. Sonar images are highly textured and strongly noisy. Good reviews on texture analysis methods are given in [4][15]. The Grey Level Cooccurrence Method (GLCM) [5] and the Run Lengths Method [2] are widely used in satellite imagery [9][11] or in sidescan sonar imagery [12][13].Other approaches concern the Gibbs Random Field Models [1], the Gabor filters [3] and the AutoRegressive (AR) models [6][7]. We are specially interested in the 2D AR rotation invariant modelisation reported in [7] for the four following advantages: 1) spatial interactions are efficiently taken into account; 2) AR rotation-dependent models presented in [6] have shown good classification results on our sonar images; 3) the method is rotation invariant and seems to be efficient; 4) a reduced number of relevant features is provided by this method.
To improve the efficiency of the rotation invariant method presented in [7], we introduce three additional AR similar parameters which describe a larger neighbourhood. Spatial interactions are then better taken into account. Other studies in the fields of Markov Random Fields [10] and AR Models [8] have shown the interest of extending the neighbourhood size. A MLP is used to perform identification of four types of seafloors (see Fig. 1).

Models and Feature Estimation

In the paper, we recall the basic method and then describe the improvements we have proposed to take a 5×5 pixels neighbourhood (see Fig.2) and additional directions into account. We have noted in a recent study [14] that a 5×5 pixels neighbourhood is required to obtain good classification results. The method provides three new rotation invariant parameters in addition to the three of the basic method.

Feature Analysis

We first analyze the behaviour of each of the six extracted features over 301 natural 64×64 sonar images belonging to the categories: pebbles (77), dunes (70), ridges (77) and sand (77) (see Figure 3). The calculation of the correlation coefficients between the six features (see Table 1) shows explicitly that some of the features are highly correlated. Then we evaluate the ability of some combinations of these features to separate the four considered seafloors. Figure 4 shows 301 natural sidescan sonar images in the space defined by $E_1 = \{\alpha_{11}, \beta_{11}, \zeta_{11}\}$ (feature set issued from the basic method) and by $E_2 = \{\alpha_{22}, \beta_{22}, \zeta_{22}\}$ (additional feature set issued from the proposed improved method). Finally we investigate the degree of invariance of E_1 and E_2 over a *rotated database* (see Figure 5).

Classification Results and Conclusion

The performances of the three feature sets E_1, E_2 and $E_3 = E_1 \cup E_2$ are evaluated through a neural classifier (a MLP) with one hidden layer. Classification results are also given for a K-Nearest Neighbour Algorithm (K-NNA) for comparison (the K-NNA requires about ten more multiplications than the MLP). Tables 2 and 3 give some classification results which illustrate the

European Signal Processing Conference - EUSIPCO'98, Vol. 4, pp. 2001-2004, Rhodes, Greece, Sept. 1998

efficiency of the improved method over the basic method. Comparative study has finally been conducted. The comparated method is a rotation invariant version of the Grey Level Cooccurrence Method. The improved method performs as good as GLCM for the identification of sand, ridges (strongly directional) and pebbles seafloors and a little better for dunes identification (see Tab. 4). Furthermore, the rotation invariant method produces a reduced set of relevant features so it is more profitable. Through this study, we have demonstrated on four types of seafloors that the proposed approach performs better than the basic method and slightly better than the GLCM, with the advantage over the last one to provide a very compact parameter set.

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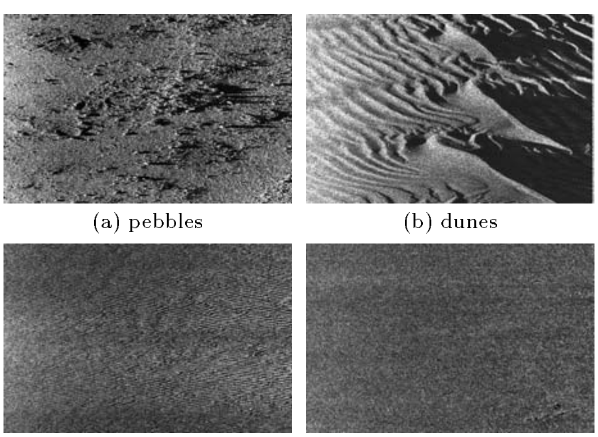
Figures



(a) pebbles (b) dunes (c) ridges (d) sand

Figure 1: Four types of seafloors (512×768 pixels). One pixel represents about 100cm² on the seafloor.

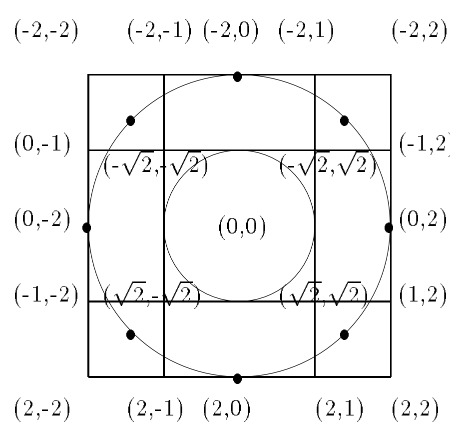
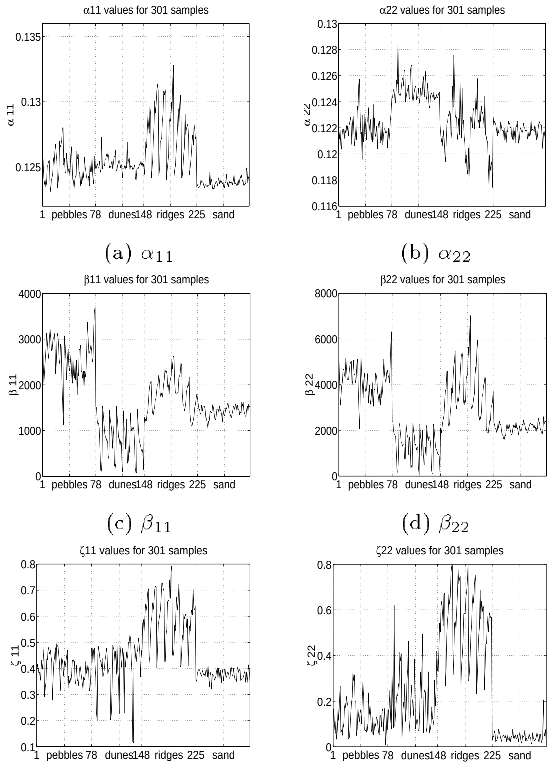


Figure 2: Circular neighbourhood of the improved model.



(a) α_{11} (b) α_{22}

(c) β_{11} (d) β_{22}

(e) ζ_{11} (f) ζ_{22}

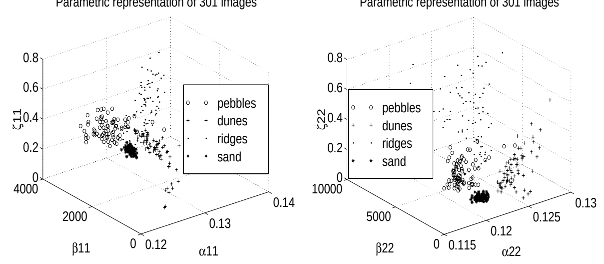
Figure 3: Values of the six rotation invariant features over 301 samples divided into four classes.

$$
\begin{array}{c}
(\alpha_{11}) \\ (\beta_{11}) \\ (\zeta_{11}) \\ (\alpha_{22}) \\ (\beta_{22}) \\ (\zeta_{22})
\end{array}
\begin{pmatrix}
1.00 & 0.12 & 0.84 & 0.06 & 0.45 & 0.91 \\
0.12 & 1.00 & 0.16 & -0.48 & 0.93 & 0.02 \\
0.84 & 0.16 & 1.00 & -0.14 & 0.44 & 0.83 \\
0.06 & -0.48 & -0.14 & 1.00 & -0.43 & 0.05 \\
0.45 & 0.93 & 0.44 & -0.43 & 1.00 & 0.33 \\
0.91 & 0.02 & 0.83 & 0.05 & 0.33 & 1.00
\end{pmatrix}
$$

Table 1: Matrix of the correlation coefficient values calculated between the six parameters estimated over 301 images.

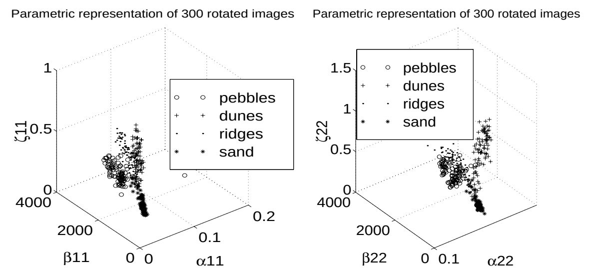
Recognition Rates in %						
		PE	DU	RI	SA	GLOBAL
E_1	MLP	100	56	93	100	87
	K-NNA	100	52	94	100	86
E_2	MLP	100	74	100	100	93
	K-NNA	97	73	100	100	92
E_3	MLP	100	62	100	100	90
	K-NNA	100	64	100	100	91

Table 3: Recognition rates obtained with two classifiers for the three feature sets E_1, E_2 and E_3 and for the four classes PEbbles, DUnes, RIdges and SAnd. Learning set (resp. testing set) is *database_lrn2* (resp. *database_test2*).



(a) α_{11}, β_{11}, ζ_{11} (b) α_{22}, β_{22}, ζ_{22}

Figure 4: Parametric representations of 301 images divided into the four classes : pebbles, dunes, ridges and sand. 4(a): an image is represented by a point defined by the α_{11}, β_{11} and ζ_{11} features; 4(b): an image is represented by a point defined by the α_{22}, β_{22} and ζ_{22} features.



(a) α_{11}, β_{11}, ζ_{11} (b) α_{22}, β_{22}, ζ_{22}

Figure 5: Parametric representations of 300 rotated images divided into the four classes : pebbles, dunes, ridges and sand. 5(a): an image is represented by a point defined by the α_{11}, β_{11} and ζ_{11} features; 5(b): an image is represented by a point defined by the α_{22}, β_{22} and ζ_{22} features.

Recognition Rates in %						
		PE	DU	RI	SA	GLOBAL
E_1	MLP	98	87	68	100	88
	K–NNA	98	94	61	100	87
E_2	MLP	98	100	94	92	96
	K-NNA	97	100	93	95	96
E_3	MLP	98	97	90	100	96
	K-NNA	98	100	90	100	97

Table 2: Recognition rates obtained with two classifiers for the three feature sets E_1, E_2 and E_3 and for the four classes PEbbles, DUnes, RIdges and SAnd. Learning set (resp. testing set) is *database_lrn1* (resp. *database_test1*).

Recognition Rates in %					
	PE	DU	RI	SA	GLOBAL
GLCM	100	66	100	100	90
E_2	100	74	100	100	93

Table 4: Recognition rates obtained with a MLP classifier, for the GLCM method and the E_2 feature set, for the four classes PEbbles,DUnes, RIdges and SAnd. Learning set (resp. testing set) is *database_lrn2* (resp. *database_test2*).

European Signal Processing Conference - EUSIPCO'98, Vol. 4, pp. 2001-2004, Rhodes, Greece, Sept. 1998