IL NUOVO CIMENTO Vol. 24 C, N. 1 Gennaio-Febbraio 2001

Classification of sea-ice types in SAR imagery (*)(**)

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(ricevuto il 26 Ottobre 1999; revisionato l' 8 Settembre 2000; approvato il 20 Settembre 2000)

Summary. — We present a supervised three-stage classification (labeling) scheme applied to SAR images of polar regions for detecting different sea-ice types. The three-stage labeling procedure consists of: 1) a speckle noise filtering stage, based on a sequence of contour detection, segmentation and filtering steps, which removes SAR speckle noise (and texture information as well) without losing spatial details; 2) a second stage providing Bayesian, maximum-*a-posteriori*, hierarchical (coarse-to-fine), adaptive (data-driven) and contextual labeling of piecewise constant intensity images featuring little useful texture information; and 3) an output stage providing a many-to-one relationship between second stage output categories (types or clusters) and desired output classes. Modules 1) and 2), which demonstrated their validity in several applications in the existing literature, are briefly recalled in the current paper. The proposed labeling scheme features some interesting functional properties when applied to sea-ice SAR images: it is easy to use, *i.e.* it requires minor user interaction, is robust to changes in input conditions and performs better than a non-contextual (per-pixel) classifier. Application results are presented and discussed for a pair of SAR images extracted, respectively, from an ERS-1 scene acquired on November 1992 over the Bellingshausen Sea (Antarctica) and from an ERS-2 scene of the East Greenland Sea acquired on March 1997 when a field experiment by the research vessel "Jan Mayen" was conducted in the same area.

PACS 92.10 – Physics of the oceans.
PACS 92.10.Rw – Sea ice.

Acronym list

MRGMAP: Modified Refined Gamma Maximum *A Posteriori*
PAC: Pappas Adaptive Clustering
MPAC: Modified PAC

(*) Paper presented at the Workshop on Synthetic Aperture Radar (SAR), Florence, 25-26 February, 1998.
(**) The authors of this paper have agreed to not receive the proofs for correction.

HCM: Hard c-Means
SEM: Stochastic Expectation Maximization
RMS: Region Merging Step

1. – Introduction

Satellite SAR imagery provides an excellent tool for continuous observation of sea-ice in polar regions. These regions are almost in the darkness for half of the year and quite often covered by clouds, thus their observation is nearly impossible with optical and thermal sensors.

The mapping of sea-ice characteristics has great scientific and economic importance: it is important for weather and climate studies and it has economic relevance for transportation and ship routing among ices.

In recent years several works have been published on segmentation and classification of SAR imagery, some of them specifically oriented to sea-ice parameter extraction [1-10]. This paper describes a contextual and easy to use three-stage supervised classification (labeling) scheme for sea-ice–type detection in SAR images. This three-stage labeling sequence consists of:

1) A pre-processing filtering stage, based on a sequence of contour detection, segmentation and speckle filtering steps, capable of removing SAR speckle noise (and texture information as well) without losing spatial details.

2) A Bayesian contextual labeling procedure exploiting an adaptive and multiresolution estimate of system parameters which applies to piecewise constant or slowly varying intensity images, *i.e.* to images with little useful texture information, that may be corrupted by an additive white Gaussian noise field independent of the scene. This module is robust to changes in initial conditions and requires few and intuitive user-defined parameters to run.

3) An output stage equivalent to a multiple-prototype classifier exploiting a many-to-one relationship between second-stage output categories (types, clusters or labels) and supervised output classes. The relationship between label types and output classes is either user-defined (when the user initializes classification stage 2 with supervised reference vectors) or based on majority voting (when initial reference vectors in classification stage 2 are detected by means of unsupervised clustering algorithms). Since this third stage is trivial, it will not be further discussed in the rest of this paper.

Functional properties of modules 1) and 2), which are taken from the literature, are summarized in sects. **2** and **3**. Section **4** presents the data set to be classified and the training procedure adopted for the classifier. Application results are presented and discussed in sect. **5**. Conclusions are reported in sect. **6**.

2. – First stage: speckle noise removal

Our first processing stage consists of a SAR speckle filtering procedure, identified as MRGMAP [11], which is a Modified version of the Refined Gamma Maximum *A Posteriori* SAR speckle filter proposed in several states of development in recent years [5-7]. MRGMAP consists of three functional boxes which are processed in sequence and whose characteristics are summarized below:

1) A SAR contour detection box, proposed in [7], where speckle noise is considered a multiplicative random process, *i.e.* speckle is supposed to be fully developed. Since the fully developed speckle hypothesis does not hold true across image boundaries, this contour detector employs adaptive (multi-scale, oriented) rectangular masks collecting local statistics to assess whether these masks cross image boundaries.

2) A segmentation box capable of detecting closed image segments out of nonconnected contour pixels. This procedure is based on a region growing mechanism exploiting geometric information exclusively, *i.e.* no intensity information is employed here.

3) The SAR filter box, which applies the Gamma Maximum *A Posteriori* SAR speckle filter equation [7] to local areas of increasing size within the segment boundaries detected at segmentation box 2. The input data to this box are: i) the speckled raw image; and ii) the segmented image obtained with segmentation box 2. Around a central pixel of interest, the implemented filter scheme grows a local area that must be part of the segment to which the central pixel belongs. Thus, local statistics are extracted within segment boundaries, *i.e.* within spectrally homogeneous regions in which the fully developed speckle hypothesis holds.

The output product of the MRGMAP module is a de-speckled, slowly varying or piecewise constant intensity image (*i.e.* this image features little useful texture information) where spatial details are preserved (due to speckle low-pass filtering within segment boundaries). This output image satisfies the functional constraints required by the second stage of our three-stage classification scheme.

3. – Second stage: Contextual labeling for image segmentation

The second stage of our classification scheme employs a Modified version, identified as MPAC [12], of the well-known Pappas Adaptive Clustering (PAC) algorithm for image segmentation [13]. MPAC differs from PAC in its spectral class-conditional model where global and local (*i.e.* multi-scale) estimates of intensity averages are employed simultaneously. Advantages of MPAC with respect to other segmentation algorithms found in the literature are [12]

1) Compared with other (noncontextual) clustering algorithms like Hard c-Means (HCM) [13, 14], MPAC is less sensitive to changes in the user-defined number of input clusters as it allows the same region (label) type to feature different intensity averages in different parts of the image, as long as they are separated in space.

2) Although it employs no Markov Random Field model supporting special image features (*e.g.*, thin lines [15, 16]), MPAC has demonstrated to preserve image details better than i) HCM, which is a hard-competitive, Bayesian, noncontextual, Maximum-Likelihood labeling procedure [12]); ii) Stochastic Expectation Maximization (SEM), which is a soft-competitive, Bayesian, contextual labeling procedure) [12]; and iii) PAC.

Fig. 1. – A) ERS-1 SAR scene over the Bellinghausen Sea (Antarctica) of November 22, 1992 (Orbit: 7078, Frame: 5733). B) ERS-2 SAR scene over the Odden Ice Tongue, East Greenland Sea, of March 8, 1997 (Orbit: 9840, Frame: 2115).

4. – Data set and classification training procedure

The proposed processing scheme is applied to two test images extracted from two different SAR scenes of polar regions (see figs. 1A and B). The two scenes are georeferenced by means of the commercial software TeraScan (by SeaSpace, Poway, U.S.A.) and calibrated by means of the European Space Agency SAR image Toolbox.

Test image A, 512 × 512 pixels in size (equivalent to a surface area of about 6 × 6 km), is taken from an ERS-1 scene of the Bellingshausen Sea (Antarctica) acquired on

Fig. 2. – Test images A and B exctracted from the SAR scenes of figs. 1A and B. A) full resolution window, 512 × 512 pixels in size. B) Full resolution window, 1000 × 1000 pixels in size.

Fig. 3. – Reference data, selected by an expert sea-ice photointerpreter, for the test images of figs. 2A and B. The 3 different gray-levels correspond to the 3 classes. A) C1 (floes), C2 (mixed sea-ice) and C3 (open water); B) C1 (frazil ice), C2 (pancake ice) and C3 (open water).

November 22, 1992. Test image B, 1000×1000 pixels in size (equivalent to a surface area of about 12×12 km), is taken from an ERS-2 scene of the Odden Ice Tongue region in the East Greenland Sea acquired on March 8, 1997, at the time when a field experiment by the research vessel "Jan Mayen" was conducted in the same area as part of the EU funded ESOP-2 Project [17].

Our aim is to distinguish sea-ice types: floes, mixed sea-ice and open water (no ice) in test image A (fig. 2A), and pancake ice, frazil ice and open water (no ice) in test image B (fig. 2B).

To evaluate the accuracy of our classification procedure by means of an error (or confusion) matrix [18], test images A and B are supplied with ground truth data, shown in figs. 3A and B, respectively, selected by an expert sea-ice photointerpreter of the Scott Polar Research Institute, University of Cambridge (U.K.). In deeper detail, in test image A 55924 (= 46313 + 5198 + 4413) reference pixels are selected for classes C1 (floes), C2 (mixed sea-ice) and C3 (open water) respectively, while in test image B 302319 (= 47814 + 94455 + 160050) reference pixels are selected for classes C1 (frazil ice), C2 (pancake ice) and C3 (open water).

In both test cases, to train the second-stage of our classifier only three labeled pixels are interactively selected by an expert photo-interpreter to be used as MPAC's initial cluster templates, each supervised pixel belonging to class C1 to C3, respectively. In the case of test image B, this supervised pixel selection is validated by the "Jan Mayen" ground truth data.

5. – Results

When the MRGMAP filtering box is applied to the two test images, which visually look very fragmented, it detects a large number of spectrally homogeneous segments. To reduce segment-based computation time, MRGMAP is provided with a post-processing step to merge small segments (*e.g.*, whose area is ≤ 4 pixels). In table I, the number of detected segments before and after the Region Merging Step (identified as RMS) is

TABLE I. – *No. of segments in output images.*

Test Image	MRGMAP	MRGMAP + RMS	MPAC
A	106207	5812	655
B	254547	15218	965

TABLE II. – *Test image A. Three-stage sea-ice classification with MPAC.*

Category	C1	C2	C3	Misclas.	% Error
R1	45937	358	21	379	0.82
R2	1456	3432	310	1766	33.97
R3	5	722	3686	727	16.47
Total Error				2872	5.13

TABLE III. – *Test image B. Three-stage sea-ice classification with MPAC.*

Category	C1	C2	C3	Misclas.	% Error
R1	47683	131	0	131	0.27
R2	4694	89454	307	5001	5.29
R3	0	4434	155616	4434	2.77
Total Error				9566	3.16

TABLE IV. – *Test image A. Three-stage sea-ice classification with HCM.*

Category	C1	C2	C3	Misclas.	% Error
R1	45935	360	21	381	0.82
R2	1768	2856	574	2342	45.05
R3	10	677	3726	687	15.56
Total Error				3410	6.09

TABLE V. – *Test image B. Three-stage sea-ice classification with HCM.*

Category	C1	C2	C3	Misclas.	% Error
R1	47495	299	20	319	0.66
R2	7811	85490	1154	8965	9.49
R3	0	6736	153314	6736	4.21
Total Error				16020	5.29

Fig. 4. – A and B, output images of the MRGMAP module applied to the test images of figs. 2A and B, respectively.

reported in the second and third column. The two de-speckled output images are shown in figs. 4A and B. Next, MPAC, provided with three initial reference vectors corresponding to classes C1 to C3, is applied to figs. 4A and B to generate labeled output images 5A and B, respectively, whose number of segments (equivalent to connected areas featuring the same label type) is reported in the fourth column of table I.

Tables II and III represent the confusion matrices of test images 2A and B, respectively, where R1, R2 and R3 are the reference data pixels while acronyms C1, C2 and C3 identify the classified data pixels. For result comparison, the same three-stage classification scheme is employed when its second stage is implemented as the well-known Hard c-means (HCM) non-contextual (per-pixel) algorithm (see tables IV and V). In line with a visual inspection of the labeled output images generated by the two tested classifiers, the quantitative comparison of tables II to V confirms that, by exploiting contextual information, MPAC is capable of reducing the well-known salt-and-pepper classification noise effect which typically affects non-contextual (per-pixel) classifiers. This result is also in line with other MPAC applications [12].

6. – Conclusions

A three-stage classification procedure, whose blocks are taken from the literature, is employed to classify sea-ice types in SAR imagery of polar regions.

The first processing stage is a speckle filtering block which removes textural information from the original SAR image while preserving small details (*i.e.* this block generates a piecewise constant or slowly varying intensity output image). This output image can be successfully labeled through a second stage, named MPAC, which makes use of a spectral, contextual, iterative, hierarchical clustering algorithm for 2-D data (image) segmentation. This second stage preserves small but genuine regions, is quite robust to changes in the number of initial clusters, intuitive to use and effective in reducing the salt-and-pepper classification effect which typically affects non-contextual (per-pixel) classifiers. In the detection of three sea-ice types in two SAR test images, the contextual clustering classifier performs 16% and 40% better than a non-contextual classifier.

Fig. 5. – A and B, final result of the classification procedure applied to the test images of figs. 2A and B, respectively.

Some theoretical weaknesses and limitations of the MPAC algorithm are: i) MPAC applies only to images with little useful texture and additive Gaussian noise, independent of the scene; ii) it is unable to detect outliers which may affect the estimate of spectral parameters. iii) Although it is less sensitive to changes in the user-defined number of input clusters than traditional (noncontextual) clustering algorithms, MPAC is still a suboptimal labeling procedure sensitive to initial conditions; therefore, one main issue in the user interaction with MPAC remains the choice of the number of clusters to be detected.

Further applications of the proposed classification scheme for SAR images of polar regions will regard: i) first- and multi-year sea-ice detection; ii) position and character of the ice edge in the Marginal Ice Zone; iii) size and dynamics of ice floes; iv) ship routing in sea-ice areas.

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The work described in this paper was supported by the Italian Space Agency (ASI) and by the Italian National Programme for Antarctic Research (P.N.R.A.). We are also grateful to the European Space Agency (ESA) for providing SAR imagery.

REFERENCES

[1] Sun Y., Carlström A. and Askne J., *Int. J. Remote Sensing*, **13** (1992) 2489.
[2] Sephton A., Brown L., Macklin J., Partington K., Veck N. and Rees W. G., *Int. J. Remote Sensing*, **15** (1994) 803.
[3] Nezry E., Lopes A., Ducrot-Gambart D., Nezry C. and Lee J.S., *IEEE Trans. Geosci. Remote Sensing*, **34** (1996) 1233.
[4] Smits P. C. and Dellepiane S. G., *IEEE Trans. Geosci. Remote Sensing*, **35** (1997) 844.
[5] Lopes A., Touzi R. and Nezry E., *IEEE Trans. Geosci. Remote Sensing*, **28** (1990) 992.
[6] Lopes A., Nezry E., Touzi R. and Laur H., *Int. J. Remote Sensing*, **14** (1993) 1735.
[7] Touzi R., Lopes A. and Bousquet P., *IEEE Trans. Geosci. Remote Sensing*, **26** (1988) 764.

[8] Ulaby F. T., Kouyate F., Brisco B. and Lee Williams T. H., *IEEE Trans. Geosci. Remote Sensing* , **24** (1986) 235.
[9] Smith D., *Int. J. Remote Sensing*, **17** (1996) 2043.
[10] Lee J. and Jurkevich I., *IEEE Trans. Geosci. Remote Sensing*, **27** (1989) 674.
[11] Baraldi A. and Parmiggiani F., *IEEE Trans. Geosci. Remote Sensing*, **33** (1995) 1245.
[12] Baraldi A., Blonda P., Parmiggiani F. and Satalino G., *Opt. Eng.*, **34** (2000) 907.
[13] Pappas T. N., *IEEE Trans. Signal Processing*, **40** (1992) 901.
[14] Bishop C. M., in *Neural Networks for Pattern Recognition* (Clarendon Press, Oxford, UK) 1995.
[15] Geman D. and Jedynak B., *IEEE Trans. Pattern Anal. Machine Intell.*, **18** (1996) 1.
[16] Jhung Y. and Swain P. H., *IEEE Trans. Geosci. Remote Sensing*, **34** (1996) 67.
[17] Wadhams P., Gascard G. C. and Miller L. (Guest Eds.), *Deep-sea Research*, **46** (1999) No. 6-7.
[18] Congalton R. G., *Remote Sensing Environ.*, **37** (1991) 35.