Consolidation of a Pixel-Based Classification Using Neighbourhood Information

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***Abstract* — A two-step consolidation process is presented that reduces the effect of speckle in the classification result. The degree of consolidation or smoothing can be adjusted using a classification confidence measure and a threshold for the amount of neighbourhood agreement needed. Results from AIRSAR ice data are shown and compared to a classification result from pre-filtered data.**

Keywords: classification, SAR polarimetry, Wishart distribution

I. INTRODUCTION

The use of SAR data for terrain classification has proved to be useful for a number of applications, particularly in areas such as ice monitoring where active microwave instruments provide the only reliable source of data [1]. A Bayesian pixel-based classifier for polarimetric SAR data based on the Wishart distribution is used, and a post-processing operation is applied to reduce the variability of the classification of individual pixels. The proposed method considers the distance used to classify the pixel as a confidence measure on the initial result, and the classification of neighbourhood pixels can be used to alter the result if the confidence is low.

II. PIXEL-BASED CLASSIFICATION

In a pixel-based classification technique, each pixel is classified separately based on its polarimetric scattering properties. Multi-looking is often used to reduce the effect of speckle on the variability of the result. The covariance matrix is used to express the averaged information of the scattering. A Bayesian approach based on the complex Wishart distribution of the covariance matrix proves to be very versatile and is used for unsupervised classification [2]. The classification process can be outlined as follows:

1. Pre-Processing – Speckle reduction can be applied using simple multi-looking or a more advanced edge preserving filter [3]. In this paper, the latter method is applied to provide a classification result for comparison with the proposed post classification operation.
2. Classifier initialization – Determination of a set of class means as input for the Wishart classifier. For land-based applications, the separation of groups of classes with different dominant scattering mechanisms (i.e. surface, volume, and dihedral) allows some automation of the class assignments [4]. The scattering properties of sea ice at C-band do not show as much variation in scattering mechanisms for this method to work well; however, a slightly simplified version of the Lee method results in faster convergence and better ice type separability over previous approaches.
3. Classification – Calculation of a distance measure from a pixel to a set of class means based on the Wishart probability distribution. Each pixel is subsequently assigned to the class with the minimum distance [2]. For unsupervised classification, an iterative approach is generally used where class means are updated after each iteration, although a manual step is required for the interpretation of the final classes.

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III. TWO-STEP CONSOLIDATION PROCESS

The proposed algorithm operates on the initial classification result to consolidate pixels with varying classification. It first considers the reliability of the classification, and then checks agreement with neighbouring pixels. The steps are described as follows:

A. Step 1: Selection of pixels that are allowed to be changed

The Wishart classifier uses a distance, and by considering only the mean V_m of the pixel's class, a simplified version of the distance can be used as a classification confidence measure:

$$d_{i,Vm} = Trace(\mathbf{V}_{\mathbf{m}}^{-1}\mathbf{C}_{\mathbf{i}}) - 3 \qquad (1)$$

where C_i is the covariance matrix representing the polarimetric scattering of pixel i and V_m is the average covariance matrix.

The standard deviation of the distribution of this new distance is computed, and the classification confidence measure is the distance divided by the standard deviation. Scaled distances close to zero indicate that the pixel value (i.e. covariance matrix) is close to the class mean. While all pixels of one class are correctly classified in the minimum distance sense, pixels with the larger distance can be interpreted as unreliable relative to the rest of the class. If a scaled distance is above a specified threshold, its classification is allowed to be changed by the next step. Otherwise, a change in classification is inhibited for this pixel (see Fig. 1(i)).

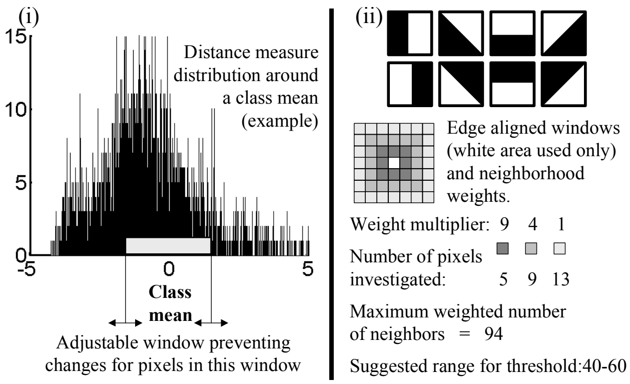

Figure 1. The two parameters used to adjust the algorithm (i) classification confidence measure; (ii) neighbourhood weight function

B. Step 2: Investigation of the pixel neighbourhood.

The classification of pixels in the neighbourhood of the target pixel is considered, to determine whether a change in classification is justified. The presence of edges is determined, and taken into account by only considering neighbouring pixels on the near side of the edge. Eight possible edge configurations are allowed within a 7x7 window, as shown in the top of Fig. 1(ii). Out of 48 neighbouring pixels, the 28 on the near side of the edge are used for analysis. There are 5 immediate neighbours, 9 neighbours with a one-pixel distance and 13 neighbours with a two-pixel distance. Pixels are weighted according to their proximity to the candidate pixel. A quadratic weight distribution is chosen to ensure the most impact of the direct neighbours. If the weighted total for one class exceeds a threshold, the candidate pixel is changed to this class. The maximum weighted number of neighbours, as well as a suggested threshold range is given in Fig. 1 (ii).

C. Implementation of the algorithm

The two adjustable parameters described above can be used to tune the algorithm performance. If desired, the consolidation algorithm can be applied in several iterations. The implementation of the algorithm can be summarized as follows:

1. Select an edge aligned window from the total power image as described in [3];
2. Calculate the distribution of the distance relative to the class mean for each class. Protect pixels within a pre-defined distance from changing classification;
3. If the weighted number of neighbourhood pixels belonging to the majority class exceeds a threshold, change the class of the target pixel to the majority class.

IV. Post Processing Results

Fig. 2a shows a 4-look AIRSAR C-band polarimetric image acquired in 1988 in the Beaufort Sea. The scene contains several ice types, as described in [5].

Figs. 2b and 2c show Wishart classification results for the unfiltered and Lee-filtered data. Eight classes are used in the classification, two for volume scatterers, two for dihedral scatterers, and four for surface scatterers. Within a scattering mechanism, classes are separated by their level of total power. In this simplified approach, scattering mechanisms are not kept separate during the Wishart iterations, to account for the generally strong surface component in the data relative to the other components. Using this method, better results can be achieved than with previous experiments [5]. For example, thin ice (shown in blue) and smooth first year ice (orange) are separated in the present case.

The 9 images with row/column annotation shown in the last 3 rows of Fig. 2 represent the results of the post processing applied with different parameter values. The consolidation algorithm is applied to the classification result shown in Fig. 2b (4-look data, no filter applied in pre-processing). From row to row, the size of the confidence window is varied. Threshold values of zero, ±1 and ±2 are used in rows 1, 2 and 3. The column number represents the threshold for the weighted number of agreeing neighbours, where values of 40, 50 and 60 are used in columns 1, 2 and 3.

Result 33 represents the most conservative approach. A considerable number of pixels are protected from change and a high neighbour threshold is chosen. The result is most similar to the original classification shown in Fig. 2b. This approach retains much of the granularity of the image (or resolution of the classification result), however, very few outliers are modified.

Result 11 on the other hand is obtained using the most aggressive approach. Here (and for the entire first row) the confidence window is set to zero, which means that no pixel is protected from change. In result 11, a low neighbour threshold is used and the result is most similar to the classification result of the pre-filtered data (Fig. 2c). While many outliers are removed and homogeneous areas can be identified, the granularity of the result is also reduced and finer detail may have been lost.

In the examples shown, a change of the neighbour threshold appears to have more impact on the result than an adjustment of the confidence window.

V. Discussion

The new method is not intended to replace the polarimetric filter but rather to provide an additional tool for improving the classification result. The algorithm can be used in iterations or on pre-filtered data (both options are not shown here). The two free parameters allow the method to be adjusted with respect to the input data (i.e. pre-filtered, level of multi-looking, or number of classes). When used in iterations, a change of parameters between two steps might also be beneficial.

A two-step post classification operation is presented that is developed to reduce the effect of speckle in the classification result. The performance of the method can be adjusted using a classification confidence measure as well as the weighted number of neighbouring pixels used. As no true solution is available for the example given in this paper, a quantitative measure for the quality of the operation requires further validation using simulated data. With modifications (mainly with respect to the confidence measure) it can essentially be used for classification results based on various data sources.

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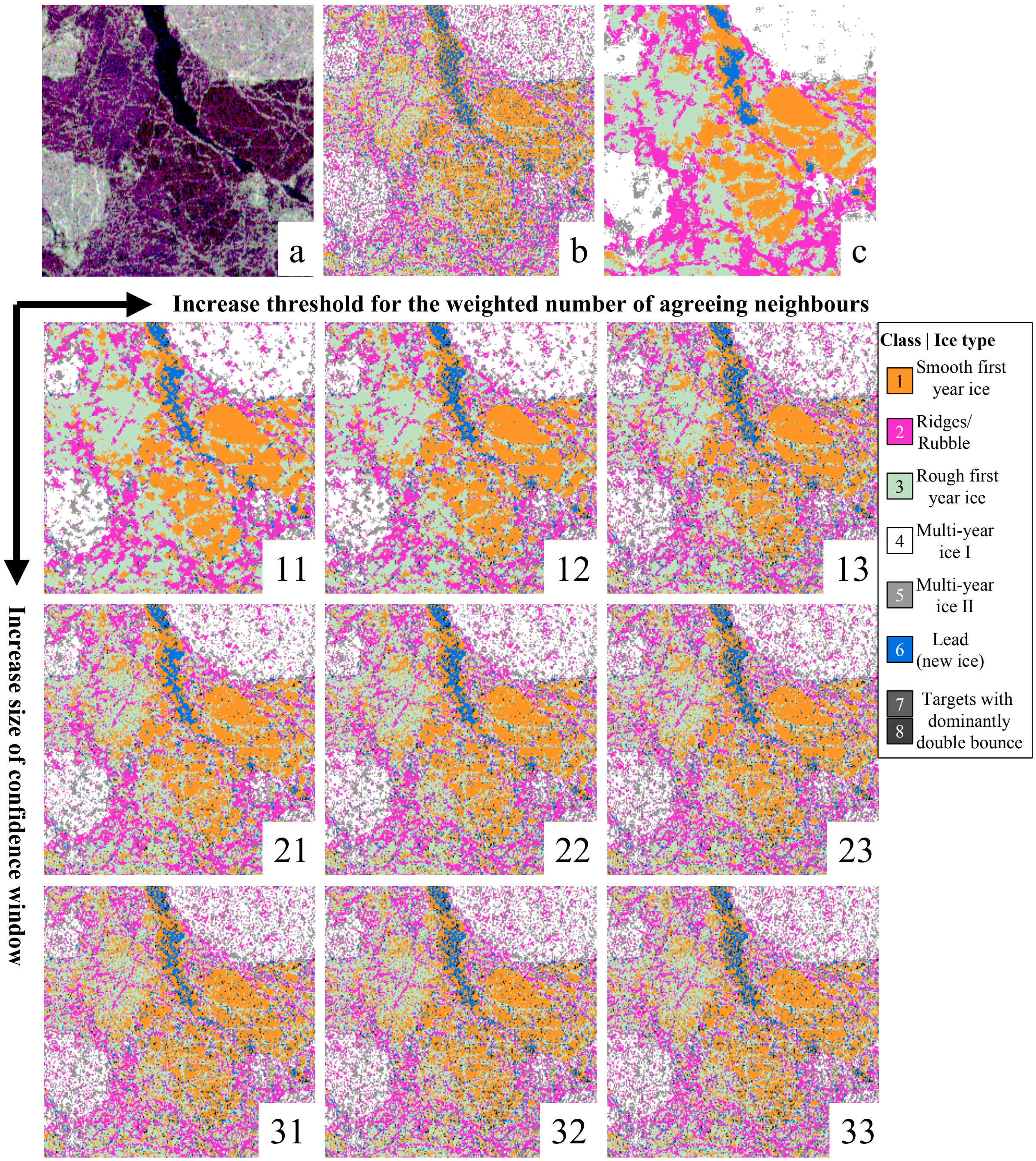

Figure 2. AIRSAR C-band data of sea ice (1988, Beaufort Sea): (a) RGB colour composite image, (b) classification of 4-look data, and (c) classification of Lee-filtered data. In the last 3 rows, results using the consolidation algorithm with varying parameters on the 4-look classification of Panel b (see CD-ROM for colour version).