Classification of GreenICE SAR data using Fuzzy Screening Method

Rashpal S. Gill and Rasmus T. Tonboe

Danish Meteorological Institute, Lyngbyvej 100, 2100-Copenhagen, Denmark.
Tel. (+45) 39157342, e-mail. : rsg@dmi.dk

Abstract: A semi-automatic SAR sea ice classification algorithm is described. It is based on combining the information in the original SAR data with those in the 'image' products derived from it, such as namely Power-to-Mean Ratio (PMR), the Gamma distribution and the second order texture parameter entropy, inertia and uniformity, respectively. The technique used to fuse the information in these products is based on a method called Multi Experts – Multi Criteria Decision Making (ME-MCDM) fuzzy screening. The Multiple Experts in this case are the above six 'image' products. The two criteria used currently for making decisions are the Kolmogorov-Smirnov (KS) distribution matching and the statistical means. The algorithm classifies an image into any number of pre-determined surface classes. The representative classes of the latter are manually identified by the user in the individual images.

In the context of the GreenICE project, this algorithm was tested using the Radarsat SAR acquired during the GreenICE 2003 – 2004 field campaigns. In this case the algorithm was used to estimate the percentage of open water, leads, ridges, new ice and old ice in the individual SAR images which have pixel size in the range 6.25 m – 25.0 m. The results obtained using the classification scheme were consistent with expectations such as, for example, detecting significantly more ridges in the 2004 data from north of Greenland (≈ 80 ºN) than in the 2003 ice camp from north of Spitsbergen. Further, ice types are indication of ice thickness and it was found that the region near the ice camps consists of ≈75 % - 85 % multiyear ice which typically has thickness ≈ 3m- 6 m. The possible strengths and weakness of the current classification algorithm and those based on SAR images in general are discussed.

Introduction

In recent years satellite image classification and multi sensor data fusion based on neural networks (NN) and fuzzy set theory have received much attention in the open literature (Zadeh, 1965, Kohonen et. al., 1995, Masselli et. al., 1995, Atkinson and Tatnall, 1997, Chanussot et. al., 1999, Solaiman et. al., 1999, Tupin et. al., 1999, Andrefouet et. al., 2000, Pal et. al., 2000, Tupin et. al., Melgani et. al., 2000, Wu and Linders, 2000, Moore et. al., 2001, Zhang and Foody, 2001). One of the main reason why NN has gained popularity over the more traditional statistical approaches is that the former is distribution free i.e., no prior knowledge of the distribution(s) underlying the different surface classes are needed for classification, only the actual data. There are several different types of NN and one thing they all have in common is that they all require the training of the network (Atkinson and Tatnell, 1997). The training can be supervised or un-supervised. The supervised training algorithms include those based on Multi-Layer Perceptron (MAL) using feed - forward concept and those using the feed – back neural network, for example the so-called Hopfield network (Atkinson and Tatnell, 1997). In these algorithms prior data sets of known classes are required. In the case of MAL, the training of the network involves the fine tuning of the weights of the connections, while in the case of the Hopfield network, the output from the nodes are fed back into the input. In the unsupervised training network no prior information is provided about the desired classification, the network learns itself so to speak. The Organising Topological Map is an example of this type of unsupervised network (Atkinson and Tatnell, 1997).

In the neural network approach a given unknown pixel or a region is classified into one of the predefined classes. In other words, a given pixel is either a full member of a particular class or is not a member. This is one of the disadvantage with using a NN approach, as in many cases data are mixed i.e., an unknown pixel may partially belong to several classes as the boundary between them may not be sharp. Fuzzy set theory explore this concept. In the fuzzy classification schemes, a given pixel can partially belong to several classes. In this case the contribution of each class in the pixel or a region must be estimated. Some of the most well known algorithms based on fuzzy theory are the hard and fuzzy-c means (HCM, FCM) clustering algorithms used for image segmentation (Pal et. al., 2000). Since its first introduction by Zadeh (1965), fuzzy set theory has invaded into many other fields beside fuzzy classifications, which include fuzzy control systems, fuzzy image processing (Melgani et. al., 2000).

One of main aim of the EU financed GreenICE project is to estimate the thickness of sea ice (Wadhams , 2001). In the context of this project, satellite Radarsat SAR data is to be used for, amongst others, to relate sea ice thickness to those measured by other sensors such as airborne laser profiling. Since direct measurement of sea ice thickness using SAR is not possible, if, however, the age of the ice is known then it can be used to infer its possible thickness. Typically, first, second and multi - year ice are ≈ 1m , ≈ 2m, $\approx 3 – 5$ m in thickness. This task of determining the observed ice types is best carried out using reliable SAR image classification algorithm.

The scheme used to classify SAR images acquired during the GreenICE field 2003 -2004 campaigns is called the Multi Experts – Multi Criteria Decision Making (ME-MCDM) (Gill, 2002a) fuzzy screening method. This method was selected as it was found to be very flexible with potential to include auxiliary information which could be relevant for image classification. In particular, it allowed for having multiple experts (the texture image products discussed below), any number of image surface classes (called alternatives), possibility to use multiple decision making criteria and to associate importance to each of them. The scheme also allowed the user to determine how many experts have to agree before a region is reliably classified. The method is originally due to Yager (1993) and "*is useful in environments in which we must select, from a large class of alternatives, a small subset to be further investigated*". It is well suited for SAR image classification because it allows for fusing the information in the original SAR image with that contained in the statistical and texture image products derived from it, namely, Power-to-Mean Ratio (PMR), Gamma probability distribution function (Gamma-pdf) and the second order texture parameters such as entropy, inertia and uniformity (Gill, 2001, 2002b, Gill and Valuer, 1999). The latter products are found to contain useful supplementary information which is often useful in discriminating between the different surface cover types (Gill, 2001).

The full details of the ME-MCDM fuzzy screening method has already been given and thus will not be given here (Gill, 2002a). However, it is useful to know the main components of ME-MCDM classification scheme. These are summarised below together with the computational procedure.

The main components of the ME-MCDM fuzzy screening method are the:

1. **Experts** – the image products (e.g., AMPLITUDE, GAMMA-pdf, PMR, ENTROPY (ENT), INERTIA (INER), UNIFORMITY (UNIF)) used in the image classification.
2. **Alternatives** – The number of different surface classes into which the SAR image is to be classified. In the present case 5 surface classes were chosen: open water, leads, ridges, new and old sea ice.
3. **Criteria** – necessary to make decisions by the experts about the possible alternatives. Currently 2 criteria are used and these are the Kolmogorov – Smirnov (KS) distribution matching and the statistical means comparison tests.

Computational procedure.

1. Compute the 6 image product (AMP; GAMMA-pdf, PMR, ENT, INER and UNIF).
2. Manually identify on a computer screen the surface classes into which the SAR image is to be classified. Store the values of these different classes.
3. By using a $N \times N$ test window in each of the 6 products, compute the scores of each of the above class using each of the above 2 criteria.

4. Use the fuzzy screening rules to aggregate the scores for each class from each of the 6 products for the test window. This will result in the overall scores for each class for the test window.
5. Hard classify the overall scores for the test window by de-fuzzying the results. This is achieved by taking the class that has the maximum overall score.
6. Steps 3 – 5 are repeated for the entire image by sliding the above N × N window across the image.

The SAR classification scheme discussed above is sketched in figure 1 below.

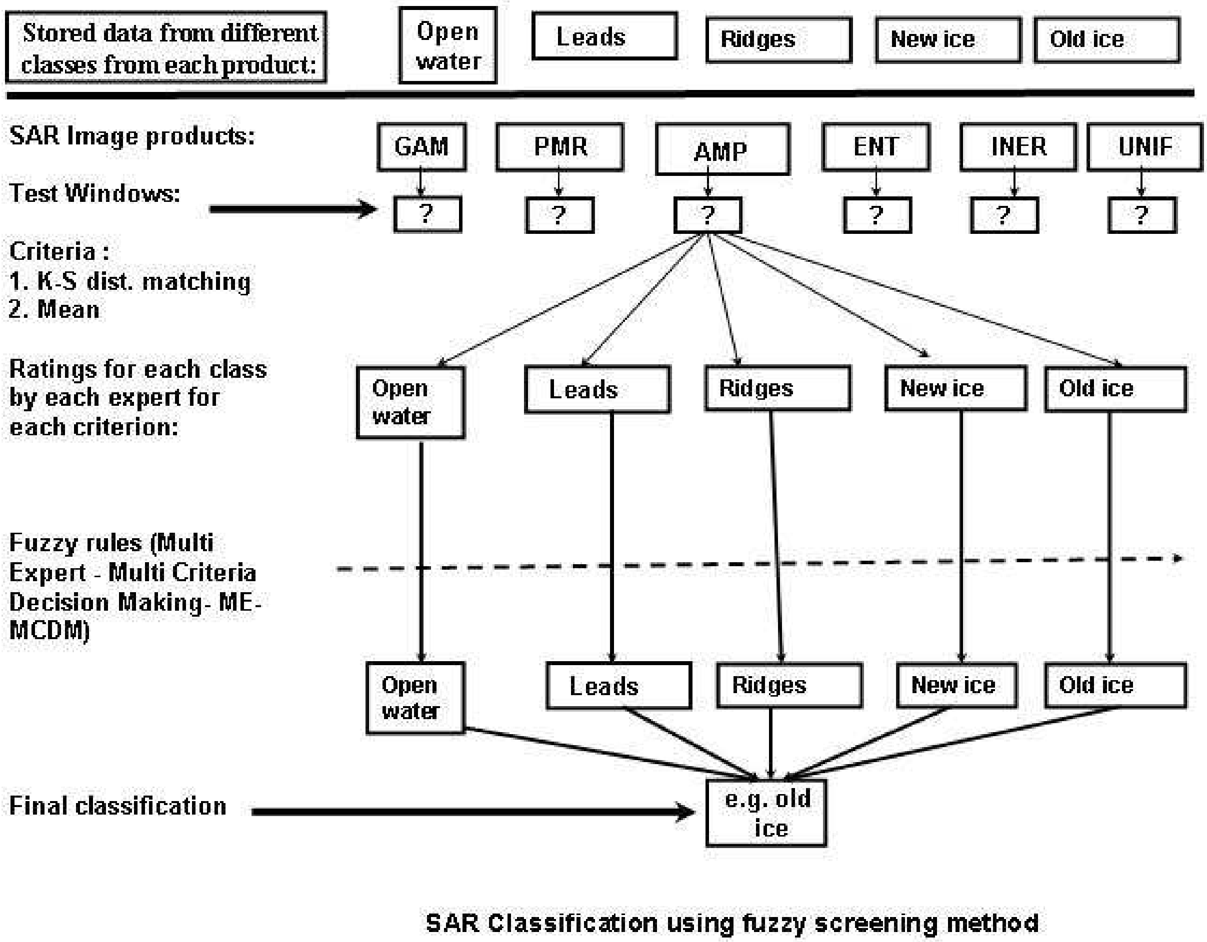

Figure 1. Shows the sketch of the SAR image classification using the fuzzy screening method. In the figure the number of surface classes are 5 (open water, leads, ridges, new and old ice), number of experts are 6 (AMP, PMR, GAM (=GAMMA_pdf), ENT, INER and UNIF. The 2 criteria used are the KS and the statistical means. For the sake of illustration only the ratings for each class by AMP is shown in the figure.

Results and discussion

This consists of, for the purpose of illustrating the method, a classification of the Radarsat Standard Mode (SGF) image from 11th April 2003 shown in Fig. 2 (left side). This image is from North of Spitsbergen acquired during the GreenICE 2003 ice camp. The image product is ≈100 km X 100 km in size with 12.5 meter pixel size. It has been chosen because it is relatively easy to interpret manually which can then be used to ascertain the performance of the algorithm qualitatively. Detailed examination of the image shows that it contains essentially 3 surface types: old multiyear ice floes, new ice and open leads. The classified image is shown on the right side in fig. 2. Qualitative comparison of the classified image with the original image shows that the classification appears to be reasonable.

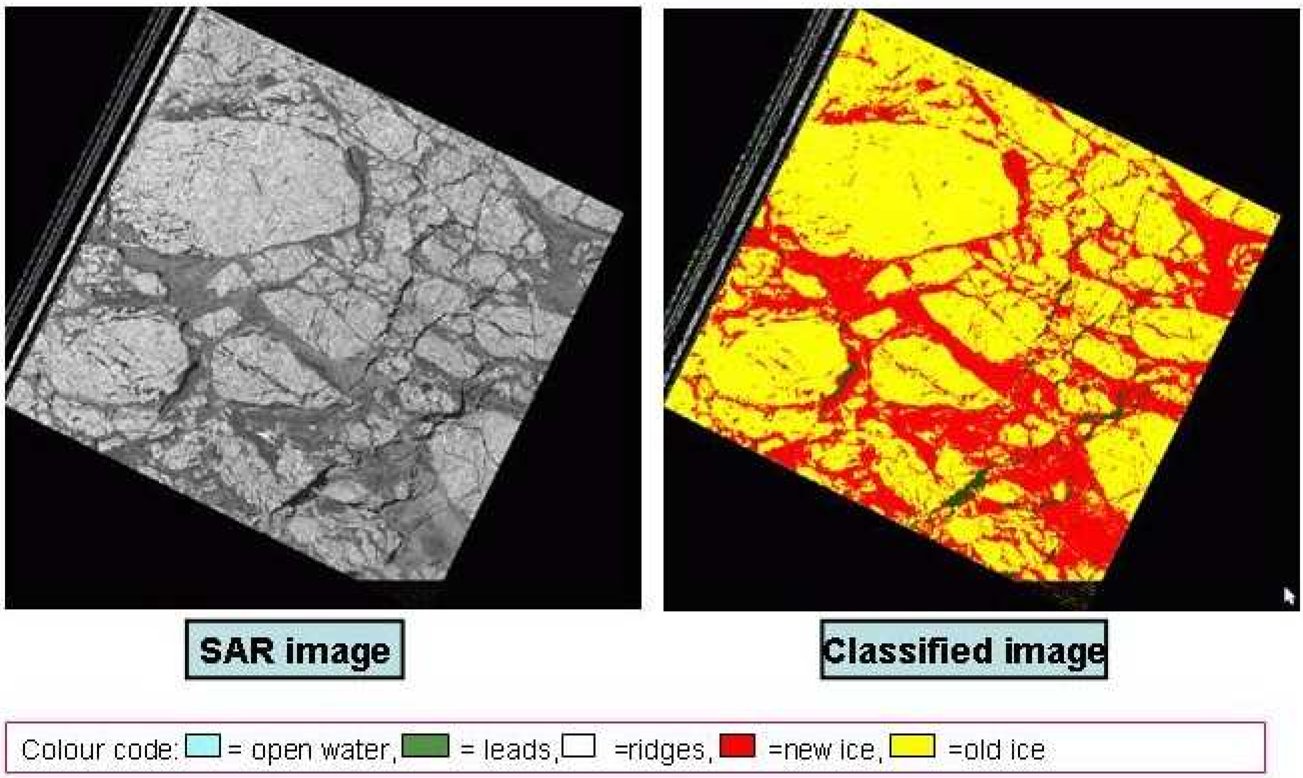

Figure 2 shows the geo-coded original SAR from 11th April, 2003 and its classification into 5 surface types. The image is approximately of size 100 km X 100 km.

According to the classification algorithm the image contained ≈ 64 % of old ice, ≈ 34% new ice, ≈ 0.7% ridges, ≈ 1.5% leads. The latter are a mixture of water and new ice pixels.

Similarly, the classification of the entire Radarsat data acquired during the GreenICE 2003 (north of Spitsbergen) and 2004 (north of Greenland at ≈ 80 ºN) ice camps were carried out. The results are summarised in table 1 below. In interpreting these results it is important to bear in mind that the ice regimes and their dynamical movements during the periods of the two camps were very different. The 2003 ice camp was established near the ice edge and was facilitated by the Polarstern cruise, while the 2004 ice camp was established near an aircraft landing airstrip ≈ 100 km north of the Canadian airport of Alert in nearly 100 % sea ice regime. This is reflected in the overall classified results for the 2 ice regimes. Namely that, as anticipated, the percentage of new ice which includes refrozen leads and open water is higher in the 2003 data than in the 2004 data. Further, as anticipated, the percentage of ridges, which are defined as regions with very high backscatter values, are much higher in the data from north of Greenland than from north of Spitsbergen. In particular, the percentage of ridges in the sea ice regime in north Greenland was in the range ≈ 3 % - 17 % while in the north of Spitsbergen it was < 1.4 % in all the Radarsat images. Finally, at first glace the classification results for the 14th April 2003 appear suspect as it only gives ≈ 58 % for old ice and ≈ 27 % for open water. However, the SAR image for that date was a lower resolution 25 m pixel size ScanSAR narrow image of a much larger area (≈ 300 km X 300 km) at the sea ice – open water boundary and contained significant open water regions.

Excluding the classification results from 14th April 2003 for the reason listed above, it can be seen from the table that the percentage of old multi-year in the vicinities of the ice camps were typically in the range ≈ 75 % - 85 %. These ice types are typically ≈ 3 m – 6 m in thickness, with average ≈ 3m for the entire Arctic. New ice types , ridges, and leads were in the range ≈ 3 % - 34 %, ≈ 0 % - 17 %, 0 % - 9%, respectively.

	Radarsat Product and pixel size (m)	Open water %	Leads or ice infested leads %	Ridges or ice infested ridges %	New ice %	Old ice %
2003-04-11_A	SGF (12.5 m)	0	1.5	0.7	33.9	63.9
2003-04-11_B	SGF (12.5 m)	0	0.4	1.4	9.3	88.9
2003-04-12	SGF (12.5 m)	0	1.0	0.2	15.6	83.2
2003-04-14	SCN (25.0 m)	27	8.5	0.0	6.6	58.0
2003-04-16	SGF (12.5 m)	0	0.2	0.1	11.7	88.0
2003-04-17	SGF (12.5 m)	0	5.8	0.04	20.0	74.2
2004-05-05	SCN (25.0 m)	0	4.5	7.5	4.8	83.3
2004-05-07 – badly processed	SCN (25.0 m)	0	3.8	17.3	6.3	72.7
2004-05-10	SCN (25.0 m)	0	2.2	16.4	16.1	65.3
2004-05-12	SCN (25.0 m)	0	4.2	9.3	12.6	73.9
2004-05-13	S7 (12.5 m)	0	0.8	3.4	14.8	81.1
2004-05-15	SGF (12.5 m)	0	1.3	11.4	2.9	84.4
2004-05-15	FN3 (6.25 m)	0	0.04	13.8	3.5	82.3
2004-05-20	W3 (12.5 m)	0	2.7	7.9	6.8	82.6

Table 1. Classification of RADARSAT data for 2003 – 2004 ice camps into 4 surface types in percentages. Radarsat product FN3 is of size 50 km X 50 km. S7, W3 and SGF are ˜100 km X 100 km. Finally SCN are of 300 km X 300 km.

Concerning the accuracy of the classification scheme it is important to ensure that the representative classes, identified manually by the user, do not contain impurities from other classes. This was clearly seen during the classification of the SAR images from the 15th May 2004 where 2 images, one a fine beam product (FN 3) with pixel size of 6.25 m and the other SGF image (pixel size = 12.5 m), were acquired over the same ground area but different acquisition times. It was found that the initial classification of the same sea ice regime observed in the 2 images did not agree too well. It was later found that the reason for this disagreement was that the representative classes of some ice types, identified by the user, were contaminated by impurities from other classes. Based on this experience the representative classes used to classify images were re-examined to ensure that they did not contain impurities from other classes. The main point to conclude from this is that the performance of the algorithm is only as good as the quality of the representative classes identified by the user.
Further, it was found that the classification results are not very reliable in the near range of the SAR images. The reason for this are the well known high pixel values due to steep radar incidence angles in the near range of the SAR images. This is one of the reason (the other is the low resolution of the SAR image product used) why the estimates of the ridges based on ScanSAR narrow images from 7th and 10th May 2004 are unusually high and should be treated with caution. The SGF and other high resolution Radarsat products acquired for the ice camps had radar surface incidence ≥ 30 ° which are sufficient for reliable classification. For improved classification the radar images should be corrected for this incidence angles effects prior to classification.

It was found that the KS criterion was more effective at discriminating between the different ice classes than the simple statistical means. To account for this fact more importance was accorded to the KS criterion in the algorithm. However, the KS test has its own limitations: (i) it is most sensitive around the

median of the cumulative distribution function and less sensitive at the tail ends, and (ii) it cannot discriminate between all types of distributions, such as a distribution with 2 maxima.
One of the main weakness of the current or for that matter any other SAR image classification scheme based on single polarisation or frequency data, is that unambiguous criteria or texture parameters that discriminate between different surface types in different meteorological surface weather conditions have, so far, not been identified. All the parameters used in the current classification; amplitude, power-to-mean ratio, Gamma-pdf, entropy, uniformity and inertia (and others), are also ambiguous. More specifically, none of them have unique values for the different ice types during the different weather conditions observed in the region, especially in different surface winds conditions and surface temperatures. Thus until more robust criteria and or parameters are found that are better at discriminating between the different surface types in different weather conditions, situations will arise when the classification schemes, such as the one used in here, do not give very reliable results.

The effectiveness of using surface types identified in one SAR image to classify a SAR image of the same (and different) region, from another day, was also investigated. The results found were not very encouraging. The main reason for this is that the different image classes are too sensitive to the radar incidence angles, i.e., their position in the across range direction. Another important reason is that the statistical characteristics of the surface classes can, in the time between the 2 images, undergo significant changes (due to meteorological conditions).

Finally it should be recalled that in the ME-MCDM model it is assumed that all experts are independent and have same importance. This assumption is not strictly satisfied as all the 6 products are derived from the same original SAR image. In the future it is planned to undertake combined Radarsat and ENVISAT -ASAR image classification and thus relaxing the above assumption. Results of this investigation will be reported in the near future.

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