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Recurrent modular network architecture for sea ice classification in the Marginal Ice Zone using ERS SAR images

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***Abstract* – A novel iterative approach based on a modular neural architecture [1] is presented for the classification of SAR images of sea ice. Additionally to the local image information the algorithm uses spatial context information derived from the first iteration of the algorithm and refines it in the subsequent iterations. The modular structure of the neural network is used with the aim to capture structural features of the SAR images of sea ice in the Marginal Ice Zone.**

I. INTRODUCTION

Following the Marr's paradigm, the different stages of image prepossessing, feature extraction, classification, and post-processing are usually treated separately and follow each other in a classification system. Such an approach is widely adopted because it allows decomposition of a complex problem into a number of simpler subtasks. The known drawback of the classical approach is that errors made at one of the processing steps will propagate further to the next stages of the algorithm increasing the classification error. For example, incorrect image segmentation will lead to the wrong class assignment of the segments. Another common problem is that segments are not "aware" of the surrounding segments so that complex objects consisting of several segments would not be treated as a single object. An observation is that the knowledge of classes of the segments surrounding the current segment could be useful for its classification. This is however difficult to implement in practice because the surrounding segments need to be classified first and this classification, supposedly, also should use the spatial context information. A general solution can be in organization of an iterative classification algorithm in which spatial context information is analyzed and used in subsequent iterations. In this presentation we propose an iterative algorithm that incorporates information on spatial correlations between classes in the image obtained from the first iteration and refines this information and the classification in the following iterations. The use of spatial context information derived from the surrounding segments in the classified image differs our approach from other iterative algorithms reported in the literature [2].

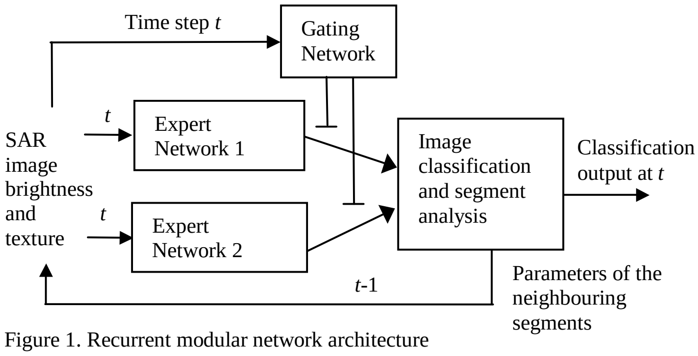

Figure 1. Recurrent modular network architecture

We apply the algorithm to classification ERS SAR images of sea ice in the Marginal Ice Zone (MIZ). Classification of sea ice in MIZ is important for navigation in these regions and for accurate evaluation of heat flaxes between ocean and atmosphere used in global climate modeling. MIZ is characterized by the transition from open water to thick ice types such as multi year ice. The classifier based on local information i.e. backscatter coefficients would show poor results because backscatter coefficients of several sea ice types and open water overlap significantly. The ice within the MIZ can be visually separated into at least two sub-zones. Classification of ice within these sub-zones can be done more accurately. This observation encouraged us to use a modular network architecture as classifier, as described in the next section. The modular network decomposes the complex task into two (in our application) subtasks. Because the task decomposition is done implicitly by the algorithm, each task does not necessarily correspond to a classification of ice within each ice zone. However, in Section V the results of our experiments reveal that the task decomposition is done in a sensible and interpretable way.

II. PROPOSED ARCHITECTURE

The proposed system architecture is presented in Fig 1. There are two main features determining its performance:

modularity of the classifier network and an iterative classification procedure described below.

A. Iterative classification procedure

The iterative training and classification can be realized independently of the type of the classifier network used in the study. Suppose that a single feed-forward neural network is initially trained by back-propagation using image brightness, texture, and other image features. After the first iteration of the algorithm the classified image still contains a number of misclassified regions in each of the ice sub-zones, as it will be shown later. To cope with this negative effect we propose to use an iterative classification scheme to incorporate context information on surrounding segments in subsequent iterations. The idea behind this approach is based on the observation that only particular combinations of ice classes coexist in some image areas. If an image segment surrounded by other segments represents a “non typical” combination of segments according to the training data, this segment should preferably be assigned to another class. The pseudo-code of the algorithm is given in the Table I.

In each iteration, the current classifier gets, as input, spatial context features calculated from the output of the previous classifier plus local image information. Thus, the better the classifiers become, the more exact are the context features calculated from their output and the better the input data for the next classifier. Eventually, this bootstraps better and better classifiers that provide better and better input data for the next classifier. Because during the all iterations of the algorithm the local image features are available, some form of relaxation should take place so that local image information and the context information derived from the image would agree well. An assumption made here is that sufficiently large number of test vectors is correctly classified at the first iteration of the algorithm.

To extract the context information, the segments in the output are identified using connectivity analysis. For each classification segment the following parameters are computed: 1) the total number of pixels in the segment, 2) the total number of pixels in the surrounding segments assigned to different ice classes and 3) the number of pixels in the surrounding segments located at the border with the current segment assigned to different ice classes. Six ice classes are used in an application, therefore there are 13 context features additional to the 16 local image features. The local features are histogram based features, grey level co-occurrence matrix (GLCM) texture, and autocorrelation function based features, all of them computed in a small 15×15 window. The interpixel distance used for computing the GLCM is set equal to 2. The GLCM is averaged for the three different directions 0°, 45°, and 90° to account for possible rotation of ice.

TABLE I
PSEUDO-CODE OF THE ALGORITHM (TRAINING)

Data: X - local texture and histogram based image features $\hat{X}_k$ - spatial context features extracted form the classification segments surrounding the current one Y_k - classifier output, T - target values
1. Initialize $\hat{X}_0 = 0$ and $k = 0$ 2. Initialize the network randomly 3. Train the network on $(X \oplus \hat{X}_k, T)$ 4. Evaluate the network on $X \oplus \hat{X}_k$ leading to Y_k 5. Recalculate $\hat{X}_{k+1}$ from Y_k (connectivity analysis) 6. Set $k = k+1$ and go to step 2 if stopping conditions are not fulfilled The sign $\oplus$ indicates concatenation of features in the data sets

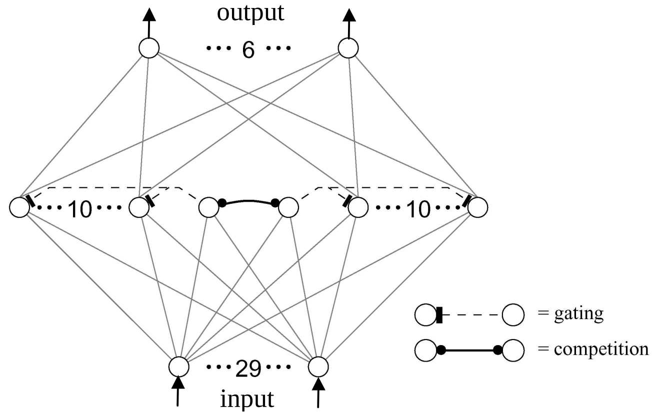

Figure 2. Structure of the network

B. A modular neural architecture

The modular network proposed in [1] consists of two types of networks: *expert networks* and a *gaiting network.* Its structure is shown in Fig 2. The expert neural networks are usual feed-forward neural networks. During classification they compete to classify the input feature vector x. The gaiting network assigns the decision (i.e. which expert neural network will produce the system’s output) to one of the experts.

As mentioned above we apply the modular network with the hope that, firstly, the experts would recognize the ice within particular image areas related to the ice structure and, secondly, a gaiting neural network would assign the task to one of the experts. The assignment may be possible based on spatial context information derived in the outer classification space.

The competition is realised by the so called competitive group of neurons. There are two neurons in the centre of Fig. 2 linked by a bi-directional competitive connection. To describe the neural network performance, suppose that the two classifiers and the gaiting network have been trained. When presenting a test vector x to the system, the expert i generates an output vector $y_i = f_i(x)$. The combined response y_c from the two experts (m = 2) is defined as the softmax linear combination:

$$y_c = \sum_{i=1}^{m} g_i y_i, \quad g_i = \frac{e^{\beta \hat{g}_i(x)}}{\sum_{j=1}^{m} e^{\beta \hat{g}_j(x)}}, \tag{1}$$

where $\hat{g}_i$ is the gaiting network output, g_i its weight in linear combination, and β is a parameter. The use of the softmax activation function ensures that the weights are non-negative and sum to one. The effect of the softmax competition is that it increases the weight g_i of the expert having higher output $\hat{g}_i$ than the others and decrease it for all other experts. As it is seen from (1) the gaiting network outputs have multiplicative effect on the expert output. For instance, by generating $g_i = 0$ or 1 the gaiting network completely discards or relies on the particular expert, respectively. The gaiting connections are shown by the dotted lines in Fig 2. Different learning methods for the modular architectures are described in [3]. In the current application we used the gradient based method.

IV. DATA

In the current experiments we used two stripes of ERS-1 SAR images, each consists of 6 images. The data was obtained on March 5 and 8, 1992 during the SIZEX92experiment. Sub-satellite in-situ data are available and have been generalized when defining ice classes and selecting training regions for each ice class as shown in Fig. 3a. The upper part of the images contains mostly thick ice types, except new ice in small polynyas. The lower part of the images contains new ice, pancake ice, and open water areas.

V. RESULTS AND DISCUSSION

The sea ice classification maps are given in Fig. 3b,c. The first iteration of the algorithm (Fig. 3b) produces a map containing a large number of small fragments often appearing as noise-like patterns. At this stage the spatial context information is not used. The typical classification errors are: some areas of multi-year ice in the upper part of the image are misclassified as open water and small floes of first year ice; some areas of open water areas are misclassified as pancake and first year ice in the lower part of the image. The second iteration of the algorithm, where the context information derived from the first iteration is used, largely improves classification results as seen from the Fig. 3c. We found that 2-3 iterations may be sufficient for the improvement of the results. A map of gaiting neural network states for one of the experts is presented in Fig. 3d. It shows that the expert specializes in classification of ice types located in the central part of the image (dark fragment). The other expert classifies thick ice types and open water. We would like to mention that this partitioning has internally emerged in the modular network in an unsupervised fashion. The training process is however completely supervised.

V. CONCLUSIONS

We have presented a sea ice classification algorithm that possesses two interesting features: iterative character and modularity. The application of the developed algorithm leads to improved ice classification. The classification emerges as a complex interaction of two processes, recursion and modularity. The analysis of this interaction is subject of future research. At the current stage we attribute a larger part of the

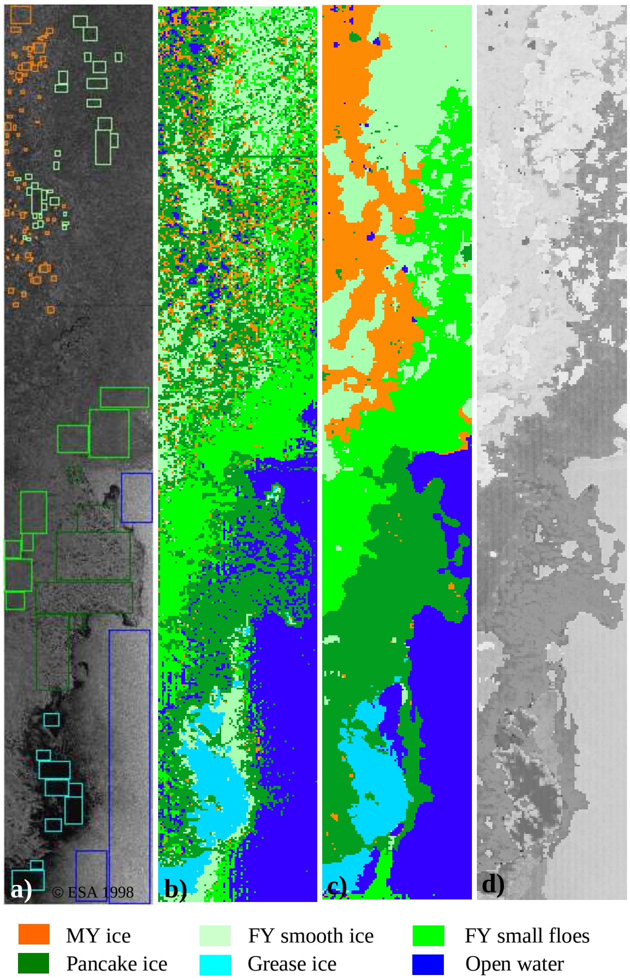

Figure 3. Mosaic of six ERS-1 SAR images 08.03.1992 (a), sea ice classification maps obtained after the first (b) and the second (c) iterations of the algorithm, and the map of the competitive neuron states (d).

improvement to the iterative classification, although the modular network shows a meaningful behavior. We believe that the algorithm could be applied and tested in other areas of remote sensing where some structural image information is preserved.

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