OIL SPILL DETECTION USING RBF NEURAL NETWORKS AND SAR DATA

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ABSTRACT:

Illegal oil spill discharges cause serious damage to marine ecosystems. Synthetic Aperture Radar (SAR) images are extensively used for the detection of oil spills in the marine environment, as they are not affected by local weather conditions and cloudiness. However, radar backscatter values for oil spills are very similar to backscatter values for very calm sea areas and other ocean phenomena because dampen capillary and short gravity waves is caused by the presence of an oil spill. Several studies aiming at oil spill detection have been conducted. Most of these studies rely on the detection of dark areas, which are objects with a high Bayesian probability of being oil-spills. The drawback of these methods is a complex process, because there are many non linearities involved. The use of Neural Networks (NNs) in remote sensing has increased significantly as NN can simultaneously handle non-linear data of a multidimensional input space. Furthermore, NN do not require an explicitly well-defined relationship between input and output as they determine their own relationships based on input/output values. In a previous study, the potential of the Multilayer Perceptron (MLP) neural network and different training algorithms for oil spill classification were investigated. In this paper another approach of NN use in oil spill detection is presented. The Radial Basis Function (RBF) neural network is investigated in order to be compared with the Multilayer Perceptron. For both networks, several topologies are examined and their performance is evaluated. MLPs appear to be superior than RBFs in detecting oil spills on SAR images.

1. INTRODUCTION

Oil spills are seriously affecting the marine ecosystem and cause political and scientific concern since they have serious affect on fragile marine and coastal ecosystem. The amount of pollutant discharges and associated effects on the marine environment are important parameters in evaluating sea water quality. Satellite images can improve the possibilities for the detection of oil spills as they cover large areas and offer an economical and easier way of continuous coast areas patrolling. Synthetic Aperture Radar images have been widely used for oil spill detection. The presence of oil film on the sea surface damps the small waves and drastically reduces the measured backscatter energy, resulting in darker areas in SAR imagery (Martinez and Moreno, 1996; Pavlakis et al, 1996; Kubat et al, 1998; Anne et al, 1999; Frate et al, 2000; Gade et al, 2000). However, dark areas may be also caused by other phenomena, like locally low winds, currents or natural sea slicks called 'lookalikes'.

Several studies aiming at semi-automatic or automatic oil spill detection can be found in literature (Martinez and Moreno, 1996; Ziemke, 1996; Kubat et al, 1998; Anne et al, 1999; Frate et al, 2000 ; Gade et al, 2000, Benelli and Garzelli 1999; Lu, 1999, Topouzelis et al, 2002). These studies first detect manually or with threshold filtering dark areas on the image which could be oil spills. If not supported by visual inspection (Lu et al, 1999; Frate et al, 2000), dark areas detection prerequires a threshold wind speed (Anne, 1999; Gade et al, 2000) sufficient to generate the sea state (Frate et al, 2000). The extent of the sea state conditions is consequently included in the estimation of the strength of the contrast signal that an oil spill yields. When dark areas are detected, statistical classification methods (e.g. Bayesian) are applied to characterize the dark areas as oil spills or 'lookalike' objects. For this purpose, estimation of a number of spectral and spatial features of the dark areas (geometric, surrounding, backscattering, etc.) is prerequired. In relevant studies, classification methods are usually applied only on the dark areas, considering them as objects (Anne, 1999; Frate et al, 2000), whilst dark areas detection methods are based on pixel-basis processing. The transition from the detection step to the characterization one needs user interference in terms of masking, coding, and selecting the dark objects in order to proceed to classification processing (Topouzelis et al, 2002).

Neural networks have been employed to process remote sensing images and have achieved improved accuracy compared to traditional statistical methods (Kanellopoulos, 1997; Kavzoglu and Mather, 2003). This success derives from neural network characteristics. A single neuron can be compared with a multivariance linear regression model, which works without any *a priori* assumptions concerning the statistical nature of the data set. The massive parallel work of several neurons gives further capabilities for solving complex problems in the remote sensing area. Moreover, NN are able to learn from existing examples, making the classification adaptive and objective (Kanellopoulos, 1997).

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Neural networks differ from statistical approaches in four main aspects (Bishop, 1995; Kanellopoulos 1997): i) problem and model complexity: NN deal with large amounts of training data with higher complexities whereas statistical methods use much smaller training sets, ii) goal of modelling: when using neural networks, the main objective is the representation of complicated phenomena rather than explanation. iii) no assumption about data distribution: NN do not make any explicit *a priori* assumptions about the underlying distribution of the data, iv) robustness and quality of prediction estimation: NN methods appear more robust than statistical ones with respect to parameter tuning.

The general objectives of this project have been to describe, demonstrate and test the potential of artificial neural networks (NNs) for oil spill detection using SAR satellite images. In this paper, we investigate two different NN architectures and compare their performances. Two well known NN models, Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks are examined in order to evaluate their performance in oil spill detection. The main difference between the two architectures lies in the nature of the input–output relations of their nodes. In a previous study (Topouzelis et al, 2003) a first attempt to examine the efficiency of MLP-NN was performed. MLP networks are based on nonlinear sigmoid functions and on combinations between them. RBF networks are three-layer networks, whose output nodes form a linear combination of the basis functions (usually of the Gaussian type) computed by the hidden layer nodes. The main aim of the present work is to detect the best topology for our network and the algorithm better fit to our classification problem. The term topology refers to the structure of the network as a whole, specifying how its input, output and hidden units are interconnected.

The paper is organized in six sections. In next section (section 2) we state the problem of oil spill detection from SAR images. Section 3 presents a brief summary of MLP and RBF neural network architectures and training algorithms. In Section 4 a dataset description is given, presenting SAR images and datasets derived from them. Results and conclusions follow is sections 5 and 6, respectively.

2. PROBLEM DESCRIPTION

In this section, we briefly state the problem of oil spill detection from remote sensing data acquired by active sensors. We start by defining the direct problem on oil slick detection. Then we describe the general methodology used and we compare it with the neural network approach.

Oil is one of the major pollutants of the marine environment. It may be introduced in diverse ways, such as natural sources, offshore production, sea traffic, tanker accidents, atmospheric deposition, river run off and ocean dumping (Pavlakis 1996). The aim of the present work is to describe a methodology for monitoring illicit vessel discharges to the sea surface, including ballast water, tank washings and engine room effluent discharges.

SAR systems are extensively used for the determination of oil spills in the marine environment, as they are not affected by local weather condition and cloudiness and occupy day to night. SAR systems detect spills on the sea surface indirectly, through the modification spills cause on the wind generated short gravity – capillary waves (Alpers et al, 1991). Spills damp these waves which are the primary backscatter agents of the radar signals. For this reason, an oil spill appears dark on SAR imagery in contrast to the surrounding clean sea. Other phenomena which could cause dampen of short gravity-capillary waves are (Alpers, 1991): organic film, grease ice, wind front areas, areas sheltered by land, rain cells, current shear zones, internal waves and upwelling zones. The existence of a light wind, sufficient to generate short gravity – capillary waves (Alpers et al, 1991) is necessary in order to detect spills. It is well known that oil spill detection by radar is limited by the sea state. Too low sea states (≈2m/sec), as mentioned above, will not produce sufficient sea surface roughness in the surrounding area to contrast to the oil, and very high sea states (≈12m/sec) will break up the oil spills, creating scatters sufficient to block detection. In their vast majority, the ships discharge their oily effluents en route, leaving back linear oil spills. This linearity is the most targeted feature by SAR image interpreters when they trace oil spills (Pavlakis, 2001).

Several studies aiming at oil spill detection have been implemented (Martinez and Moreno, 1996; Ziemke, 1996; Kubat et al, 1998; Anne et al, 1999; Frate et al, 2000 ; Gade et al, 2000, Benelli and Garzelli 1999; Lu, 1999, Topouzelis et al, 2002). Most of these studies rely on the detection of dark areas, which are objects with a high probability of being oil-spills. Once the dark areas are detected, classification methods based on Bayesian or other statistical methods are applied to characterize dark areas as oil spills or 'lookalike' objects. Characteristics (geometric, surrounding, backscattering, etc.) of spectral and spatial features of the dark area are used in order to feed the statistical model. The drawback of these methods is a complex process not fully understood, as it contains several nonlinear factors. The development of an inverse model to estimate such parameters turns out to be very difficult.

Recent work has demonstrated that neural networks (NNs) represent an efficient tool for modelling a variety of nonlinear discriminant problems. NNs may be viewed as a mathematical model composed of several non-linear computational elements called neurons, operating in parallel and massively connected by links characterized by different weights (Bishop, 1995; Ziemke, 1996; Kanellopoulos et al, 1997; Frate et al, 2000). NNs have been successfully used for remote sensing applications (Bishop, 1995; Kanellopoulos et al, 1997; Frate et al, 2000; Kavzoglou and Mather 2003; Uiu and Jensen, 2004)

For oil spill detection NNs have been used (Zimke and Athley, 1995; Ziemke, 1996; Frate et al, 2000) in different perspective from the present work; one using airborne data (SLAR) and another for dark object classification. The innovation of the present study is the use of the original SAR image and some features derived from it as inputs to NN. The network is called to determine if the image contains an oil spill or not.

3. NEURAL NETWORK ARCHITECTURE AND TRAINING ALGORITHMS

In the present study two different networks are tested in order to evaluate the one most suitable for oil spill detection: Multilayer Perceptron (MLP) and Radial Basis Function (RBF) networks. Both of them belong to the feed-forward networks where there is no feedback connection between layers and no connections between units in the same layer. Moreover, both work in a supervised manner, are very good in classification and inversion problems, easy to use, work as universal approximators, have very good nonlinearity capabilities and are the most used in the feed forward network family.

3.1 MLP neural networks

The most popular class of multilayer feedforward networks is multilayer perceptron. MPL usually comprises one input layer, one or two hidden layers and one output layer. As an example, a four-layer network with two hidden layers can be seen in Figure 1. In the present study, input nodes correspond to bands of imagery, hidden layers are used for computations and output layers correspond to the classes to be recognised. Each individual neuron is the elemental unit of each layer. It computes the weighted sum of its inputs, adds a bias term and drives the result thought a generally nonlinear activation function to produce a single output. The most common activation function is the sigmoid activation function, also used in the present study. There are several training algorithms for MLP. In a previous study (Topouzelis et al, 2003), four algorithms of the gradient decent family were examined: Backpropagation (BP), Conjugate Gradient (CG), Resilient back propagation (Rprop) and Quick Backpropagation (Quickprop). A hybrid algorithm of backpropagation algorithm and conjugate gradient found to work fast and reliably (Topouzelis et al, 2003) was selected for the present study.

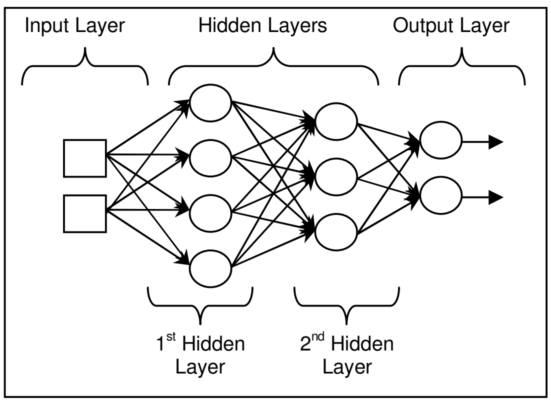


Figure 1. An example of MLP network

3.2 RBF neural networks

The Radial Basis Function neural network, which has three layers, can be seen as a special class of multilayer feed-forward networks. Each unit in the hidden layer employs a radial basis function, such as Gaussian Kernel, as the activation function. The output units implement a weighted sum of hidden unit outputs. The input into a RBF network is nonlinear. The output is linear. The radial basis function (or Kernel) function is centered at the point specified by the weight vector associated with the unit. Both the positions and the widths of these kernels are learned from training patterns. Each output unit implements a linear combination of these radial basis functions. Figure 2 illustrates the architecture of RBF network. Coefficients μ_{ji} represents the centers of radial basis and w_{kj} are the weighting coefficients of the linear combination.

There are a variety of training algorithms for the RBF networks. In the present study, Dynamic Decay Adjustment (DDA) Algorithm is used. DDA algorithm uses constructive training where new RBF nodes are added whenever necessary. It is characterized by fast training (because a few epochs are needed to complete training) and guaranteed convergence (SNNS 1998). The main characteristic of the algorithm is that when a training pattern is misclassified, either a new RBF unit introduced or the weight of an existing RBF is incremented.

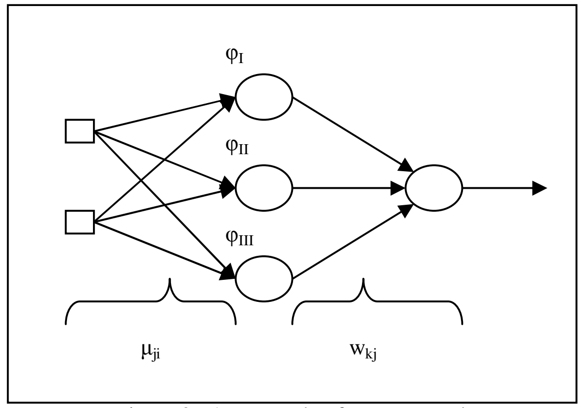


Figure 2. An example of RBF network

Because of the combination of their non-linear characteristics, RBF networks are commonly used in complex applications and are considered superior to perceptrons networks. In complicated cases perceptrons require many neurons, computational power and time in order to calculate the hyperplanes which distinguish the classes wanted. The main difference in the way that the two neuron network models try to solve a classification problem is illustrated in figure 3. MLP calculates hyperplanes in order to separate classes while RBF uses kernels to group pixels from the same class. To our knowledge, comparisons of different neural network models for the problem of oil spill detection are not available in the literature. In this paper, we present a comparison between the two commonly used neural network models, RBF and MLP neural networks.

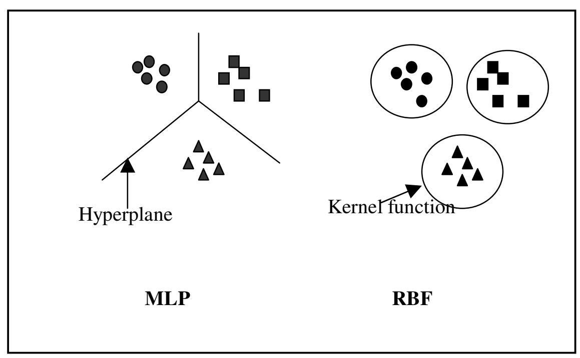


Figure 3. MLP and RBF classification approach

4. SAR IMAGES AND DATASET DESCRIPTION

4.1 General overview

The method developed was applied on an ERS 1 image captured on 1/6/1992 (orbit 4589, frame 2961). The image represents a rough sea surface, efficient to produce a strong contrast signal in the presence of oil spills. It also contains lookalikes in the left part, caused by different sea state (local wind falls in a big swell wave). In the experiments implemented, it was observed that the number of inputs significantly affects the computational time, due to the increased size and complexity of the neural network. An ERS scene (120Mb approximately) requires 5 hours for processing while an image window of 4-16Mb size, requires 2-5 minutes. The method was applied on image windows of 4-16Mb, to test its performance in terms of time requirements and result quality.

The main aspects considered for oil spill detection using neural networks were data preparation, network architecture decision, parameters estimation and network performance accession. The general overflow of the method developed for both networks (MLP and RBF) is illustrated in Figure 4.

In a previous study, a detailed examination of the features contribution to oil spill detection has been performed (Topouzelis et al, 2002). Features, which have been led to successful oil spill detection, were extracted from the SAR image. A preparation was necessary in order these features to be functional to neural network. Moreover, an initial network was chosen and trained for each network. Image results were compared with reference data to assess method accuracy. Network architecture continuously changed, adding a node (input layer or neuron) and re-evaluating the method. Figure 5 presents the methodology used.

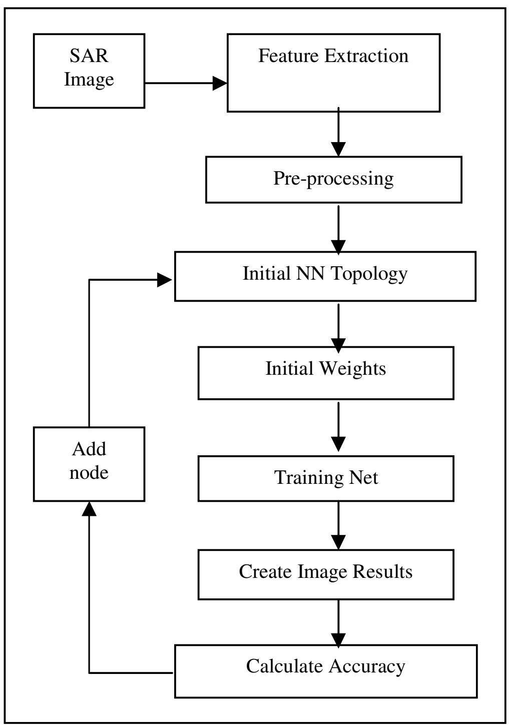


Figure 4. Methodology used

4.2 Preparing the data

Preparing the data involves feature extraction and normalize the data into a certain interval (for example [0,1]) according to the minimum and maximum values of the feature. The purpose of feature extraction is to map the image to a feature space that could serve as the basis for further processing (Kanellopoulos 1997). In order the neural network to be functional and the classification procedure to be simple, the inputs of the neural network were images. Thus, several images were generated from the original SAR, each one presenting a texture or geometry key-feature. Five images were selected according to their performance in oil spill classification (Topouzelis et al, 2002): the original SAR image, the shape texture, the asymmetry, the mean difference to neighbours and the power to mean images (Figure 5). Shape texture image is referred to the texture which is based on spectral information provided by the original image layer and calculated as the standard deviation of the different mean values of image objects already produced. Asymmetry can be expressed as the ratio of the lengths of minor and major axes of an ellipse which can be approximated for image objects. Mean difference to neighbours can be expressed as the mean difference for each neighbouring object multiplied by the shared border length of the object concerned. Power to mean ratio is defined as the ratio of the standard deviation and the mean value of the objects.

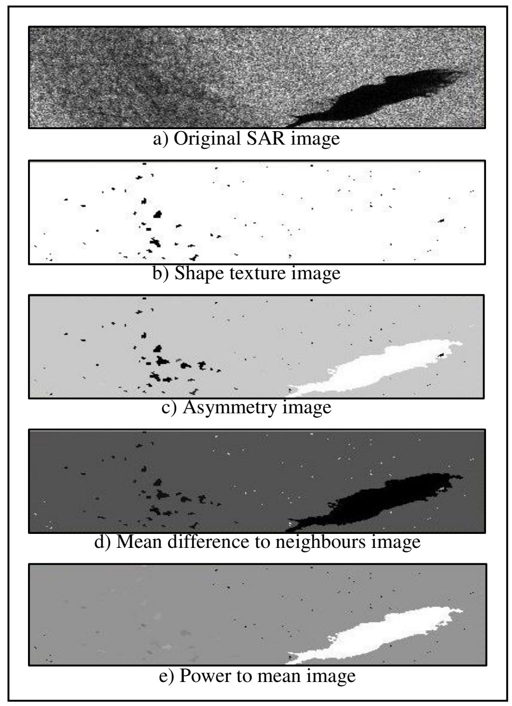


Figure 5. Inputs to Neural Networks

4.3 Network Topology

For both MPL and RBF neural networks an initial network topology was selected. The selection of the best suited topology for each NN was designed through the hill-climbing approach, which for a search point uses a solution created from a previous topology. The contractive algorithm was used, in which initial topology was the simplest one and nodes were added afterwards. The performance of each topology was evaluated and the process was repeated iteratively until a predetermined stopping criterion was achieved. Constructive algorithm was chosen among other hill-climbing algorithms (e.g. pruning) because it was very easy to specify the initial NN topology and it was significantly faster in terms of training time.

In the present study, was chosen a layer with one input node - the original SAR image - and one output node as initial network topology for MLP. The process continued until a complicated network with five input nodes, two hidden layers with five and four neurons respectively and an output layer with one neuron were created. The nature of RBF network requires a strictly three-layer network. A two input initial network was selected but without luck as the training algorithm had relatively good performance with 14 RBFs, which makes the classification procedure very complex. Three input topology was better suited as initial network with the hidden layer of 3 RBFs and 2 output nodes. From the process, a complicated network with 13 RBFs was constructed. Network performances can be viewed to next session of the paper.

A classified image identifying the presence of oil spill was produced for every network topology. For each image produced a comparison with a reference dataset was made. The reference dataset was produced by photo-interpretation methods and techniques (Topouzelis et al, 2002). A comparison was made using confusion matrices. For each image produced the confusion matrix and overall accuracy were calculated. Overall accuracy was calculated by dividing the total number of the pixels correctly classified by the total number of the pixels of a sample.

5. EXPERIMENTAL RESULTS

Figures 6 and 7 show results of different network topologies in terms of input nodes for MLP and RBF respectively. For MLP it can be seen that topologies with one (original SAR image) or with two input nodes do not classify the image correctly. On the contary, topologies using more than two input nodes have much better performance. If we concentrate in the latter, we can see that there is a special performance to topologies containing 7 nodes. Also, if we investigate the performance of accuracy due to neurons we can assume that the topologies having the better performance are 3:3:1, 4:2:1, 5:1:1 (Table 1).

Network - Topology	Accuracy %
MPL - 3:3:1	99.37
MLP - 4:2:1	99.43
MLP - 5:1:1	99.49
RBF - 3:2:2	98.45
RBF - 3:3:2	98.48
RBF - 3:4:2	98.19
RBF - 4:2:2	99.08

Table 1. Best network accuracies

Due to the fact that for each input node the size of the original data increases by 20% and the needs of computational time and power are significantly increased, the topology that is proposed is 4:2:1. The accuracy of this topology is strongly connected with the specific inputs as these are presented in paragraph 4.2. Four input nodes topology, where the inputs were the predetermined images, was proved the appropriate topology for classifying the oil spill very accurately. Looking at the five input nodes topology in details, we can see that the information in the borders of the oil spill was lost. Furthermore, more computational power and training time were needed.

For RBF we observe that their performance is poorer than MPL. It starts nearly from 45% while only four topologies can be compared with the majority of MLP, which are above 95% (small window in Figure 8 – Table 1). Topology with 3 input units is the only with relative stability close to 98.5 and is bounded from 7 to 9 nodes (3:2:2, 3:3:2, 3:4:2, 4:2:2). Better performance was observed for 4:2:2 topology with 99.08% while the performance of all the other topologies is under 99%. From the above it can be concluded that the MLP network has better performance in oil spill detection than the RBF network.

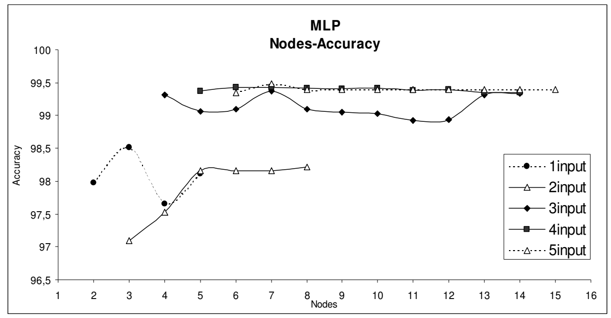


Figure 6. MLP overall accuracy according to nodes

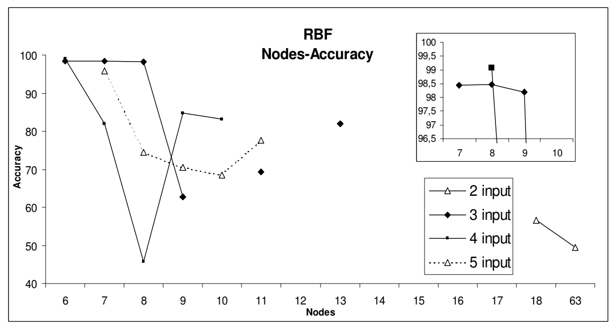


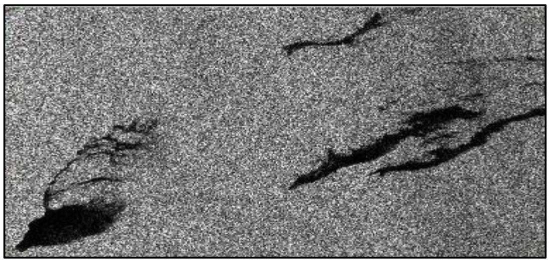
Figure 7. RBF overall accuracy according to nodes

For evaluation reasons, the method was tested on a broader area. Figure 8 contains a SAR image window with several oil spills. Oil spills can easily be identified but it is extremely difficult, even for an expert, to specify the border of oil spill and sea. Classification was performed using the MLP – 4:2:1 topology. The classification total accuracy was 99,291%. There was a very good discrimination between sea and oil spill but some of the linearities were lost, especially in cases that oil spill covers very thin areas.

6. CONCLUSIONS

In this study a neural network approach for oil spill identification was investigated using SAR images. Two types of neural network were used: the feed forward Multilayer Perceptron and Radial Basis Function. Original images and other images generated from them were used as inputs to a neural network. The method was tested on SAR image windows, containing oil spills and lookalikes.

In general, RBF networks work faster than LMP. RBF almost guarantee convergence while MLP some times stick in local minima. The use of a hybrid algorithm of backpropagation and conjugate gradient seems to solve this problem. Moreover, MLP has smaller memory requirements for the classification and has better generalization than the RBF.



a) Original SAR image

b) Classified image

Figure 8. Image result of the developed method

From the two neural network models examined MLP works more reliably than RBF for oil spill detection. The mean performance for all RBF topologies examined was 77.62% while for MPL 98.98%. Several topologies were examined using the constructive method. The topology best suited for the classification procedure was the MLP 4:2:1 according to specific inputs. Classification accuracy was 99.433% for the above topology. The high performance of neural networks as classifiers was confirmed by producing accuracy 99,29 – 99,60% when applied to other images, which contain oil spills and are captured under the same wind conditions. For RBF, the best performance achieved was 99.08% with 4:4:2 topology but the more reliable topology was topology with 3 inputs (3:3:2, 3:4:2, 3:5:2) with a mean performance of 98.37%.

Further examination is needed using images containing different sea states and different types of oils spills. Moreover, the performance of other neural network types like Support Vector Machines (SVM) and Recurrent networks (like Hopfield) need to be investigated.

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