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Improving cloud detection with imperfect satellite images using an artificial neural network approach

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Abstract— **The past few decades have seen an explosion of satellite remote sensing techniques for the monitoring of volcanic thermal features. Here, we propose an artificial neural network approach for improving the cloud detection through imperfect multispectral satellite images analysis. The cloud detection algorithm has been tested on a data set of MSG-SEVIRI images acquired over the area of Etna volcano in Sicily (Italy) before and during the 2008 eruption. Results show that this approach is robust in terms of percentage of correctly classified pixels.**

I. INTRODUCTION

Advances in satellite remote sensing techniques in the past decade have greatly assisted the observations of high-temperature volcanic features improving our understanding of volcanic phenomena and our ability to identify renewed volcanic activity [1], [2], [3]. Multispectral infrared observations carried out by satellite-based sensors have been proved particularly suited for the detection of the onset of volcanic eruptions [4], [5], [6], [7], [3] and for the mapping of total thermal flux and volcanic deposits from active lava flows with high refresh rates [8], [9], [10], [11], [12], [13]. Moreover, satellite-derived estimates of lava eruption rates have recently been employed to drive numerical simulations of lava flow paths [14], [15], [16], [17].

Although remote sensing techniques are fundamental for thermal monitoring of volcanic activity, the presence of clouds makes satellite images hard to analyze. In fact, cloud coverage could generate false alarms such as missing identifications and, whenever an eruption occurs, it may cause underestimation of the effusion rate computed from the radiative power retrieved by satellite data analysis [17].

Several techniques have been proposed for cloud classification. In particular, the most commonly used one is based on fixed threshold tests on multispectral satellite radiances, reflectance and brightness temperature or their combinations [18],[19]. However, because of the great variability in reflectance of both clouds and surface depending on solar zenith angle, seasonal effect, cloud type, presence of snow and many other variables, these simple theresehold-based techniques fail to rightly classify pixels in satellite images. Moreover, an optimal setting of thresholds is difficult to achieve since it requires several types of ancillary data. Statistical methods have been proposed as alternatives techniques for cloud detection. In particular, the variable threshold method based on the OCA (One-channel Cloudy-radiance detection Approach [20]; and principal component analysis (PCA) and independent component analysis (ICA) introduced by [21]; Support Vector Machines (SVM) described by [22]; a multicategory support vector machine classifier (MSVM) has been investigated with good results by [23].
Other techniques such as self-organizing map (SOM), back propagation (BPNN) and probabilistic (PNN) neural networks [24] are focused on recognizing the spectral features of clouds. Furthermore, the textural properties of clouds (i.e. the pattern of distribution of radiances) are often distinct and tend to be less sensitive to the effect of atmospheric attenuation or detector noise [25] thus being a suitable feature to be used for cloud detection [26].

Neural networks have been widely adopted as pattern recognition tool. In fact, much interests have been devoted to adopt artificial neural network models (ANNs) in order to classify complex data. ANNs mimic complex pattern of neuron interconnections in the brain. These have demonstrated excellent performance in tasks such as pattern recognition in digital image analysis. Among the wide scope of applications, ANNs have been used in a variety of fields such as medicine [28], nuclear fusion technology [29] and remote sensing [30]. In the latter case, ANNs have been used to classify multispectral remote sensing data; in particular, an ANNs-based pattern classification system for remote sensing data is described when using indipendent components (ICs) extracted from LANDSAT TM. ANNs have already been investigated for cloud detection in [31], [33] showing good performances.
Moreover, ANNs have to be flexible enough to model complex behaviours and this may result in ”overfitting”. In fact, an ANN may not be able to generalize well enough and, in these cases, it learns to well classify the training data but failing to generalize new input data. Thus, different methods have been proposed to avoid overfitting improving the robustness of ANNs [32]. One of the approaches that have been investigated is considering the effects of imperfections in the input data on the ANN performance. In particular, it is known that noisy training data helps improving ANN generalization capability. In [33] noise has been injected into the ANNs in order to improve ANN robustness and to prevent ANN over-fitting.

In this contribution, we propose a neural network pattern recognition approach for clouds detection based on imperfect

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satellite images. In particular, the effects of imperfections in the training input data are investigated as a mean to enhance the performance of the proposed ANN clouds classifier. The cloud detection algorithm has been trained and tested on a data set of MSG-SEVIRI images acquired over the area of Etna volcano in Sicily (Italy). We analyzed satellite images acquired before (in February) and during (in August) the Etna eruption began on 13 May 2008. This approach has been proved to be robust and effective both in terms of classification accuracy and generalization capability.

The paper is organized as follows: in Section II the data preparation stage is described; in Section III the proposed ANN-based approach for cloud detection is shown; in Section IV numerical results are presented and in Section V the conclusions are reported.

II. DATA

The SEVIRI radiometer is a geostationary imager providing high-quality data (10-bit quantization) in 12 narrow channels: 4 visible (VIS) and near-infrared (NIR), 8 infrared (IR), and one additional high-resolution visible (HRV). The sampling distance is 1 km for the HRV channel, while all other channels are designed to scan the Earth with a 3-km sampling distance at subsatellite point. The temporal resolution is very high, either 5 or 15 minutes.
However, instrumental data quantization limits the radiometric performance, thus radiometric noise values characterize each channel, i.e. 0.37K for 12um channel.

In order to apply the ANN-based method to MSG-SEVIRI data (downloaded by EUMESAT, http://www.eumetsat.int), we first divided nighttime and daytime images and selected those channels mainly involved in cloud discrimination as described in [26]. Consequently, the chosen data sets are daytime images of February and August 2008: VIS 0.6, VIS 0.8, NIR 1.6, IR 3.9, IR 10.8 channels.
In particular, the dataset is made by images from each of the first eleven days of August and February, starting with the one acquired at 7:00 on the first day and selecting the following ones 1 hour later on each subsequent day. In Fig.1 these five channels are shown.

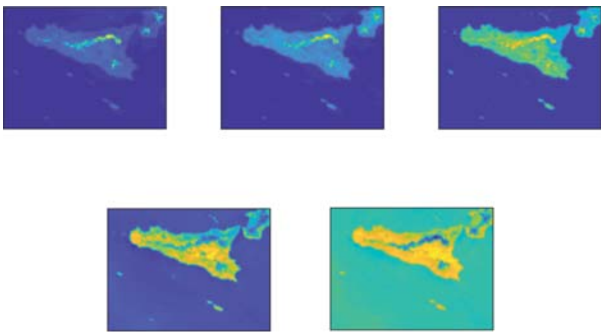

Fig. 1. MSG-SEVIRI data: VIS 0.6, VIS 0.8, NIR 1.6, IR 3.9, IR 10.8 channels.

As a pre-processing step, data are normalized between its minimum and maximum. As stated in the previous section, imperfect satellite images will be used, thus random noise is injected in the original satellite images. Different levels of noise have been explored; higher than 1%, performance starts getting worse. The noise level should be enough to improve neural network robustness while keeping the input data features. 1% could be considered the optimal noise level for this case of study.

Sicily (Italy) is the geographic area taken into account since the main goal of this procedure is to be able to recognize clouds from satellite images, especially during Etna volcanic activity.

As a consequence, the 189x110 pixels, 398N 118E, 358S 178W was selected from the full disk of 3712x3712 pixels shown in Fig.2.

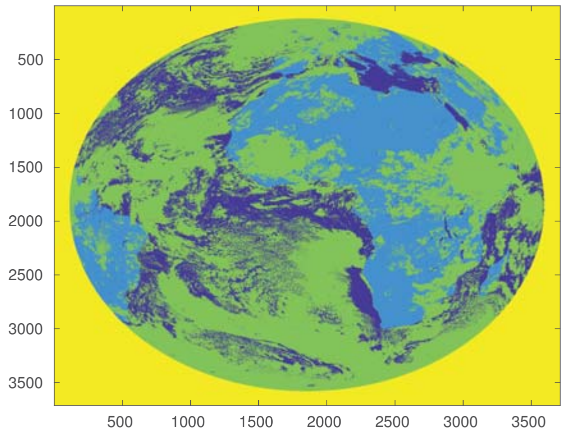

Fig. 2. Full-disk cloud mask

Apart from the daytime and nighttime division, these data sets were further split into two parts: one for the learning step (training set) and the other to test the performance (testing set).

A land mask provided by EUMETSAT is used to process separately land and sea pixels and the ”ground truth” used to train and test the ANN is the cloud mask provided on EUMETCast. In particular, this mask is made by 4 values corresponding to the four classes that a pixel can belong to: (0-clear sky over sea, 1- clear sky over land, 2- cloudy and 3-no data). The class numbered 3 is related to the pixels out of the hemisphere, since we will consider just the selected local area, class 3 won't be taken into account. It is worth to notice that low clouds and dust clouds may be not detected in case of low solar elevation; dust clouds are not well detected if they are too thin.

In the adopted cloud mask, the ”cloudy” class has been split in ”cloudy over sea” and cloudy over land” by appropriately using the land mask. Thus, the adopted cloud mask will be made by four classes, namely, ”0-clear over sea”, ”1-clear over land”, ”2-cloudy over land” and ”3-cloudy over sea” as it is shown in Fig. 3.

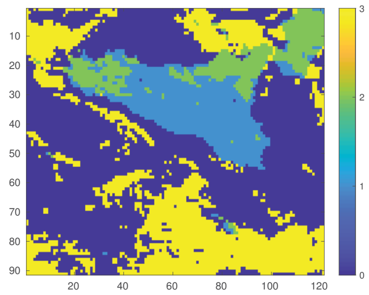

Fig. 3. Post-processed cloud mask of Sicily

Thus, a land-mask will be used to split MSG-Seviri and Cloud mask data in two groups, ”land pixels” and ”sea pixels” that will be separately treated. The ”land pixels” group is made by all the daytime pixels opportunely selected and ”1-clear over land”, ”2-cloudy over land” classes; the ”sea pixels” group is made by all the daytime pixels opportunely selected and ”0-clear over sea” and ”3-cloudy over sea”.

III. METHODS

A supervised classifier based on ANN is investigated in order to develop a cloud detection algorithm able to discriminate clouds over sea and land in satellite images.

An ANN resembles the networked structure of neurons in the brain, with layers of connected nodes whose links are weighted such as the synapses in the brain. These weights are automatically adjusted during training according to a specified learning rule until the neural network performs the desired task correctly. In the proposed ANN, the network training function that updates weight and bias values, follows the scaled conjugate gradient method described in [35].

ANN architecture consists of 3 units: the first layer is the input layer and the number of its nodes is determined by the input parameters; the last layer is the output layer and the number of its nodes is given by the desired output; the layer(s) between the input and output layers are called the hidden layer(s) where non-linear activation functions are used for processing the data.

In particular, each input of the proposed ANN will be an array made of the appropriate satellite channels components as described in the previous section. As a consequence, the ANN input will be an array 5x1. The ANN target and output are made by 4 components with only two feasible values, 0 and 1. If i is the class of a pixel, the ANN output for that pixel will have the component at the *i-th* position equal to 1 and the others set to zero.

The hidden layer is made up by 10 neurons with sigmoid function; the output layer use four softmax output neurons providing as final ANN output an array made by 4 components (one for each class).

The proposed ANN structure will be trained and tested for the following cases:

- Land pixels during daytime
- Sea pixels during daytime

After the training phase, each ANN will be tested and once the final architecture is settled down, the map reconstruction is performed. In fact, the ANN gives as output a matrix of dimension *[number of classes] x [number of pixels]* corresponding to a matrix of inputs of dimension *[number of channels] x [number of pixels]*. Thus, the overall area needs to be rearranged by mean of the provided ANNs outputs.

IV. RESULTS

The dataset for training and testing the ANN is made of MSG images recorded in 2008 as described in Section II. February and August 2008 day-time images have been considered for this preliminary study. In particular, almost 330330 pixels have been taken as training set and almost 440440 pixels as testing set.

The two groups of data, ”land” and ”sea” are separately processed and just during the Map Reconstruction phase, two groups will be opportunely merged again. Thus, after the training phase performed separately on each group, the trained ANNs are tested for both ”land” and ”sea” pixels. In Fig. 4 the ANNs responses are shown after the Map reconstruction phase, showing a good match between the target and the output.

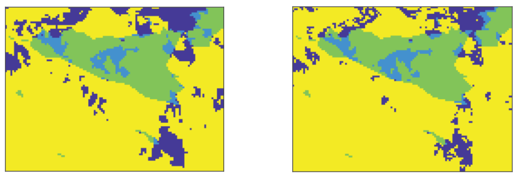

Fig. 4. Left: ANNs output; Right: Cloud mask target

The performance of the ANNs trained and tested with the imperfect satellite images performance are compared with the ANNs trained and tested with the original satellite images in Fig.5 and Fig.6. It is worth to notice that some improvements in terms of performance are obtained when imperfect satellite images are used.

One of the measures able to show ANNs performances is considering whether the algorithm correctly predict a positive result (true positive, tp), correctly specified a negative result (true negative, tn), or got the response wrong, returning a false negative (fn) or false positive (fp). This must be done with respect to a ground truth dataset that contains the desired output. Given these preliminary metrics, we can construct more complex ones, namely accuracy, precision and recall. These are defined as follow:

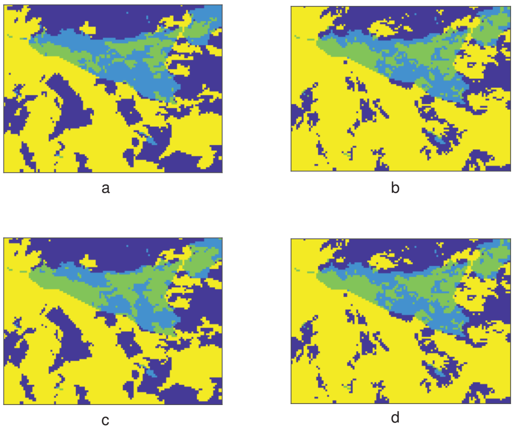

Fig. 5. a) ANNs output: ideal case, b) cloud mask corresponding target, c)ANNs output: imperfect case, d) corresponding target

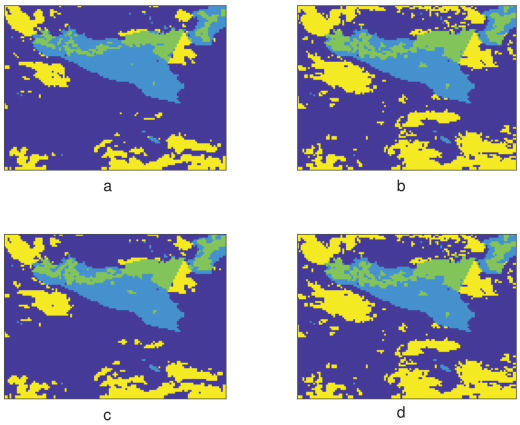

Fig. 6. a) ANNs output: ideal case, b) cloud mask corresponding target, c)ANNs output: imperfect case, d) corresponding target

$$\text{Accuracy} = \frac{tp+tn}{tp+fp+tn+fn} \quad (1)$$

$$\text{Precision} = \frac{tp}{tp+fp} \quad (2)$$

$$\text{Recall} = \frac{tp}{tp+fn} \quad (3)$$

Thus, in Table I, these measures are reported for both ideal and imperfect cases and interesting conclusions can be drawn.

V. CONCLUSIONS

The measures in table I and the results in Fig. 5 show that imperfection enhances ANNs performance in terms of accuracy and recall. Thus, imperfection plays an important role in this ANN-based cloud detection approach that can help improving the existing cloud detection techniques. In particular, these preliminary results show that such approach

TABLE I
IDEAL VS IMPERFECT

	Accuracy	Precision	Recall
Ideal	0.8895	0.9005	0.7411
Imperfect	0.8945	0.8831	0.7776

make the cloud detection tool more robust preventing over-fitting.
Under this perspective, it could be interesting to start from these preliminary results for characterizing the range of noise that should be used. In fact, under a certain level, noise can be useful to improve ANN performance but, on the other hand, over a certain level it degrades its performances.

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