Prediction of Rainfall Rate Based on Weather Radar Measurements

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***Abstract-* Weather radars are used to measure the electromagnetic radiation backscattered by cloud raindrops. Clouds that backscatter more electromagnetic radiation consist of larger droplets of rain and therefore they produce more rain. The idea is to predict rainfall rate by using weather radar instead of rain-gauges measuring rainfall on the ground. In an experiment during two days in June and August 1997 over the Italian-Swiss Alps, data from a weather radar and surrounding rain-gauges were collected at the same time. The neural SOM and the statistical KNN classifier were implemented for the classification task using the radar data as input and the rain-gauge measurements as output. The rainfall rate on the ground was predicted based on the radar reflections with an average error rate of 23%. The results in this work show that the prediction of rainfall rate based on weather radar measurements is possible.**

I. INTRODUCTION

Weather radars were originally (and still are) used by meteorologists in order to forecast very short term weather conditions and issue warnings for hazardous weather phenomena. However, it was soon realized that these instruments can form potential tools in the study of a wide range of hydrological applications. Weather radars measure the electromagnetic radiation backscattered by cloud raindrops and hence their potential to estimate rainfall. Clouds that backscatter more electromagnetic radiation consist of larger droplets of rain and therefore they can potentially produce more rain [1]. The idea is to estimate rainfall rate by using weather radars instead of rain-gauges that measure rainfall on the ground. The wider spatial coverage provided by weather radars, compared that of any dense network of ground based rain-gauges is an obvious advantage. Although the idea sounds quite tempting, experience over the past four decades has revealed a series of problems related to meteorological conditions, ground clutter, shadowing by mountains attenuation etc [2]. Nevertheless, worldwide research underlines the significance of acquisition of good estimates of rain-rate with the use of weather radar [3], [4].

Traditionally, radar reflectivities are converted into instantaneous rainfall intensities by using the power-law $Z= a\cdot R^b$ (where Z is the radar reflectivity and R is the rain rate). In this work, we explore an alternative to this methodology, namely, the use of neural and statistical classifiers for the estimation of rainfall rate based on weather radar reflectivity measurements. The latter approach has recently been used to tackle a number of other meteorological and climatological problems [5]-[8].

II. MATERIAL

In 1977, an experiment was carried out over the Italian-Swiss Alps during which data for two case studies were collected. The first case study refers to two consecutive days in June and the second to two consecutive days in August 1997. The data were simultaneously collected from the Monte Lema C-band Doppler weather radar [3] and surrounding rain-gauges. The available data consist of radar reflectivities recorded every 5 minutes over 44 ground based meteorological stations and rain rates measured at these stations. For each of the above case studies, a total of 576 radar reflectivity values are available at each station (for two consecutive days 2x288 = 576 values). Rain-gauge measurements were taken every 10 minutes (i.e. only 288 values in each two day period). To make them consistent with the above 576 radar values in each case study, each 10 minute rain-gauge measurement was subsequently spread over the corresponding two five-minute period, so a total of 576 rain rate values were derived, for each of the meteorological stations. The first 376 data patterns of June and the first 376 data patterns of August were used for training the system. The remaining 200 data patterns of June and 200 data patterns of August, were used for evaluation. Each data pattern comprises 44 pairs of radar and corresponding rain-gauge measurements.

III. METHOD

For the classification task the neural network self-organizing map (SOM) classifier, and the statistical k-nearest neighbor (KNN) classifier were used.

A. The SOM Classifier

The SOM was chosen because it is an unsupervised learning algorithm where the input patterns are freely distributed over the output node matrix [9], [10]. The weights are adapted without supervision in such a way, so that the density distribution of the input data is preserved and represented on the output nodes. This mapping of similar input patterns to output nodes, which are close to data. The output nodes are usually ordered in a two each other, represents a discretisation of the input space, allowing a visualization of the distribution of the input dimensional grid, and at the end of the training phase, at each output node are assigned similar training patterns. In the evaluation phase, a test pattern is assigned to the output node with the weight vector closest to the vector of the test pattern.

For the rainfall prediction system 752 of the radar data were used for training the SOM classifier, whereas the remaining 400 were used for evaluation. When a test radar pattern was assigned to an output node, the similar training radar patterns assigned to the specific node during training were considered. The average of the corresponding rain patterns was the predicted rainfall rate. The error rate was defined as the absolute difference of the predicted to actual rainfall, divided by the actual rainfall. Figure 1a shows an example of an input radar reflectivity pattern Vs the average of the matching radar patterns. Figure 1b shows the actual rain pattern for the specific input radar pattern Vs the predicted rain pattern. Figure 2 displays the same case for the KNN system.

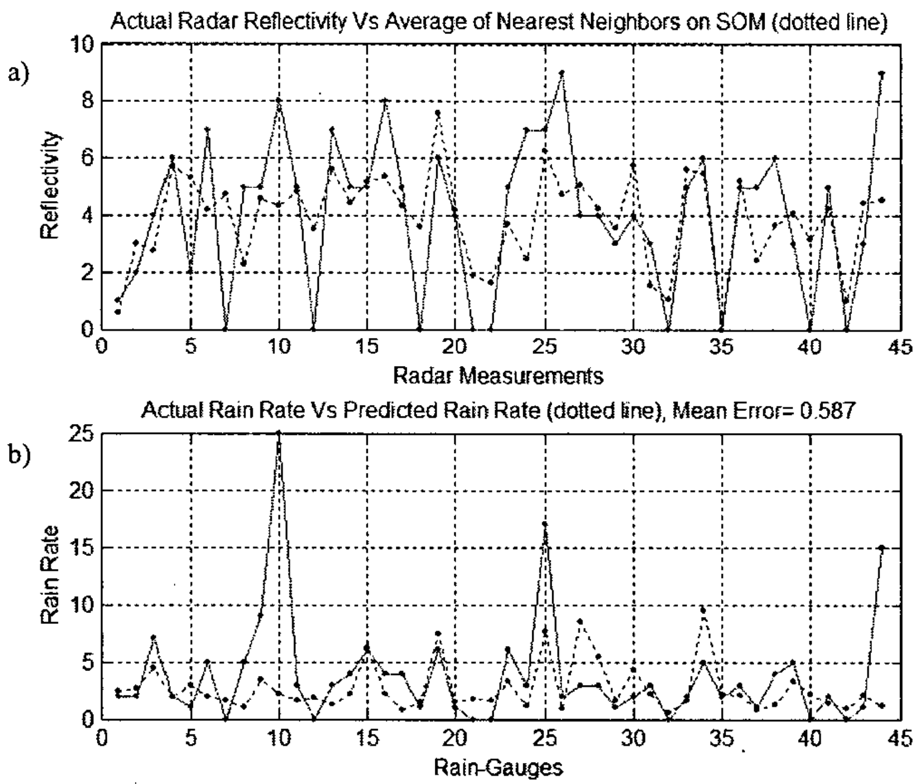

Fig. 1. An example of the input radar reflectivity pattern (red line) with the average of the matching radar patterns (blue dotted line) for the SOM system. Figure 1b shows the average of the corresponding rain patterns (red line) along with the predicted rain pattern (blue dotted line).

B. The KNN Classifier

The statistical KNN classifier was also used for the rainfall prediction system. In the KNN algorithm in order to classify a new pattern, its k nearest neighbors from the training set are identified [11]. The new pattern is classified to the most frequent class among its neighbors based on a similarity measure that is usually the Euclidean distance. In this work the KNN classification system was implemented for values of $k = 1$ to 8.

In a similar manner to the SOM system, for a test radar pattern its k nearest neighbors were found from the 752 training radar patterns. Again, the average of the corresponding rain patterns was the predicted rainfall rate. Figure 2a shows an example of the input radar reflectivity pattern Vs the average of its k (=4) nearest neighbors radar patterns. Figure 2b shows the actual rain pattern for the specific input radar pattern Vs the predicted rain pattern.

IV. Results

Table I tabulates the error rate for the SOM system for different map sizes and table II the error rate for the KNN system for different values of k.

TABLE I
ERROR RATE FOR THE SOM SYSTEM FOR DIFFERENT MAP SIZES. THE ERROR RATE WAS DEFINED AS THE ABSOLUTE DIFFERENCE OF THE PREDICTED TO ACTUAL RAINFALL, DIVIDED BY THE ACTUAL RAINFALL

SOM	8x8	9x9	10x10	11x11	12x12	13x13	14x14
Error Rate	29.1	28.8	28.2	28.1	28.6	23.6	27.3

TABLE II
ERROR RATE FOR THE KNN SYSTEM FOR DIFFERENT VALUES OF k

K	1	2	3	4	5	6	7
Error Rate	23.2	22.8	22.9	22.9	23.1	23.3	23.7

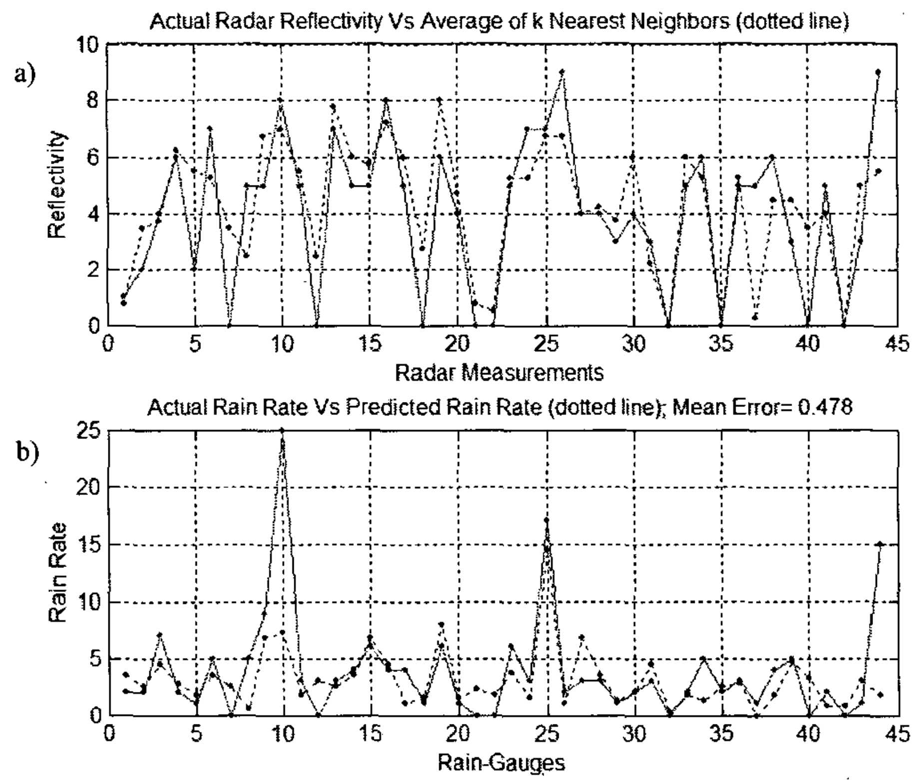

Fig. 2. An example of the input radar reflectivity pattern (red line) with the average of the matching radar patterns (blue dotted line) for the KNN system. Figure 2b shows the average of the corresponding rain patterns (red line) along with the predicted rain pattern (blue dotted line).

For the SOM best results were obtained when using the 13x13 map size and it was comparable to the results of the KNN. The fact that the error rate falls abruptly at a specific SOM architecture shows that there is a balance when an adequate number of similar patterns are assigned to a winning node in order to provide a good matching with the rain data. The SOM classifier was trained for 10000 epochs and the results for the SOM system are the average of three different runs. Test cases, when the test radar pattern was assigned to an output node where no similar training radar patterns were assigned during training, were ignored. Such cases are attributed to the limited number of training data (data only for four days were available), which didn't cover all the possible combinations of radar reflection Vs rain among the 44 stations. It is anticipated that more data will lead to better results.

The KNN gave in general better results than the SOM classifier. This is understandable since the problem was rather tailor-made for the KNN since it required the identification of the nearest neighbors from the pool of patterns. The average error rate was significantly improved due to a number of pattern cases where no or little rain was available and which both systems predicted correctly.

Using the power-law $Z= a \cdot R^b$ (where Z is the radar reflectivity and R is the rain rate) for converting radar reflectivities into instantaneous rainfall intensities, with a=316 and b=1.5 [12], [4], yielded an error rate of 27.3% for the same evaluation set of 400 cases. This error rate was higher than the error rates of 23.6% obtained by the SOM system and 22.8% obtained by the KNN system.

V. CONCLUSIONS

A novel system was presented for the estimation of rainfall rate based on weather radar measurements. The system exploits the five-decade-old notion that there is a relationship between the radar measurements (reflectivities) and the rain rate (as this is measured by rain-gauges at ground level). The results of the present research suggest that the estimation of rain rate based on weather radar records and a methodology based on KNN and SOM classifiers is possible. Even though the data used covered only two rain events covering a total of just four days, representative pattern waveforms were identified and the system yielded a satisfactory success rate, which outperformed the traditional power-law relationship. It is anticipated that more data, representing a variety of possible meteorological conditions, will lead to better results.

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