MULTIRESOLUTION WAVELET TRANSFORM AND NEURAL NETWORKS METHODS FOR RAINFALL ESTIMATION FROM METEOROLOGICAL SATELLITE AND RADAR DATA

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Abstract

Rainfall estimation from satellite data have many applications in climatological and meteorological studies. Their calculation requires a rapid processing of large amounts of data in order to achieve the desired result. The Neural Networks (NN) method is one of the several techniques employed to extract meteorologically useful information from remote sensing data. However this method is hardly used by itself to yield quasi-real time rainfall estimates once this demands a large amount of satellite data to generate the input/output data for the NN training. In order to overcome this, we propose to use Multiresolution Wavelet Transform (WT) technique to decompose the images retaining only the key information for the current problem. As a result, the NN training becomes easier and faster. We propose in this study to estimate rainfall over the central part of the São Paulo state, Brazil using both the NN and WT techniques. The analyses were performed using GOES-8 brightness temperature and meteorological radar data from Bauru, SP. The results suggest that NN can successfully estimate rainfall from remote sensing imagery.

1. Introduction

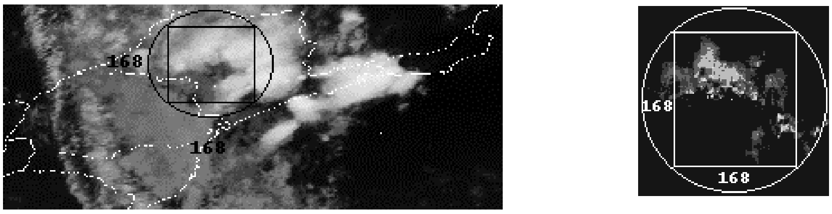
Rainfall estimation from satellite data has a tremendous potential for applications such as nowcasting, climate analysis and hydrological management. However, it demands fast processing of large number of data moreover the resulting information should be available for users in near-real time. Among several procedures currently used for retrieving information from remote sensing data is the Neural Networks (NN) method (Marzban and Stumpf, 1996; Weigang et. al., 1996; Hsu et. al., 1997). The rainfall estimation following this approach involves the processing of large files of meteorological satellite and radar data for training the NN. Consequently, it’s time consuming and requires high performance computers witch is not practical for near-real time meteorological applications. To solve this problem it is proposed the use of multiresolution wavelet transform (WT) to process the data before training the NN. The WT decomposes the original satellite image data in all possible scales by the sampling conditions. Also it permits to choose only the most important physical information for a specific application. Thus, this procedure can reduce drastically the amount of data speeding during the training process. In this paper, it is presented an application of this method for rainfall estimates over São Paulo state, Brazil, during a rain event occurred in March, 1998. The analysis were done using GOES images and radar data.

2. Data

Meteorological radar images, each 30 minutes interval, were obtained through the Internet (http://www.radar. ipmet. unesp.br/). This web site was developed by the Meteorological Research and

Applications Institute (IPMet) located in Bauru City, São Paulo state. IPMet is responsible for the operation and dissemination of all information retrieved from the two Doppler radar (S band, range 240 km). The original radar image has spatial resolution of 1x1 km. The analysis for a rain event were based on 03/02/1998 data.

GOES-8 IR images (resolution of 4x4 km) were provided by the Brazilian Center for Weather Forecasting and Climate Studies (CPTEC). Figure 1 shows the area covered by the radar data (b) and the corresponding satellite image (a).



(a) (b)

Figure 1. a) GOES-8 IR image and b) Radar image at 20:08 GMT, 02/03/1998

The images were named as defined in Table 1, for a helping description. Depending on the radar coverage region (240 km radial circle), the maximum square within the chosen circle (Fig. 1) is 168 km. This region is projected to the IR image such that this image also has 168x168 km. Both IR and RR images are pre-prepared with the 4 x 4 km resolution.

Table 1 - Name definition of IR and RR images on 03/02/1998

Image selected time (GMT)	Image name	
	IR image	Radar image
20:08	TEM1	RA1
20:38	TEM2	RA2
21:08	TEM3	RA3

3. Method

3.1 Multiresolution Signal Decomposition

Mallat (1989) has developed an efficient algorithm to implement Multiresolution Signal Decomposition using filters, Quadrature Mirror Filters (QMF) for processing signals. It allows a hierarchic decomposition of signals into independent frequency channels (Esteban and Galand, 1977; Cohen and Froment, 1990). Thus, one image can be broken down into many lower-resolution components. Since the analysis process is iterative, in theory it can be continued indefinitely or depending on the optimal decomposition criteria and the objective of the application. In case of meteorological satellite and radar images pre-processing, these criteria and objective are to reduce the image domain within the accepted precision and preserve important information of image for further analysis. The original digitized image S has a size of NxN pixels. For all J > 0, it can be represented by 1+3|J| images in the wavelet decomposition (Cohen and Froment, 1990): { A_J , $(D_j^1)_{0\le j\le J}$, $(D_j^2)_{0\le j\le J}$, $(D_j^3)_{0\le j\le J}$}. The image A_J is composed of $2^{-2|J|} N^2$ pixels and it is the same for each detail of the image D_j^d. For example, if the original image is NxN = 168x168 pixels, for J=1 (one level decomposition), the dimensions of the approximation and details $\{A_1, D_1^1, D_1^2, D_1^3\}$ are {84x84, 84x84,84x84,84x84} with the total of 168x168 pixels. In this study, it was used 1 level image decomposition.

3.2 Neural networks for precipitation estimation

It was used the typical three-layer feed-forward neural network. Its structure, with 3x3 inputs/outputs, is illustrated in Figure 2. For updating this kind of network application, usually is used a famous interactive gradient procedure, the so-called *Back-Propagation* algorithm (Rumelhart et al., 1986; Eberhart and Dobbins, 1990).

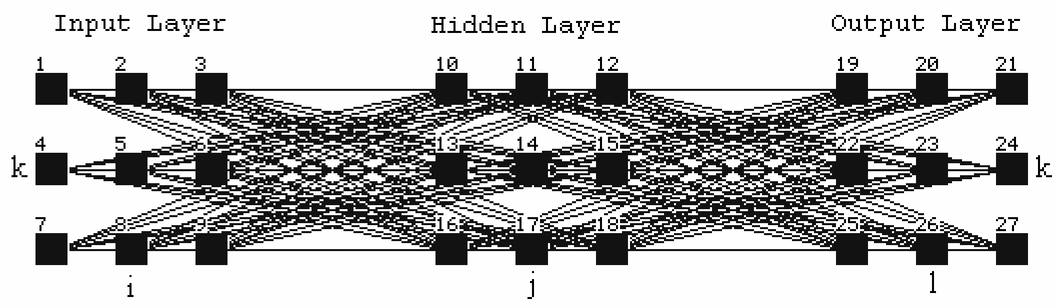


Figure 2. Architecture of a three-layer feed-forward neural network with 3x3 input/output

The *Resilient Propagation* (Rprop) algorithm was used to reduce the computer training time. Rprop is a local adaptive learning scheme, performing supervised batch learning in multi-layer perceptions (Riedmiller and Braun, 1993). The input layer has 84x84 elements, the hidden layer, 28x28 elements and the output layer , 84x84 elements.

3.3 Rain Estimation procedure

The following steps were implemented to obtain an efficient rain estimation:

1- Selection of the satellite and radar images: To select a group of IR temperature and RR rain rates images in sequence, both IR and RR image covering the same region and time. The domain of these images is a parameter defined properly, usually, depending on the radar covered region.
2- Multiple-Level wavelet decomposition and reconstruction: Using multiple-level wavelet analysis method, the original RR rainfall rate images are decomposed to get the 1 level. Then, the image was reconstructed (84x84), half domain of the original image.
3- Neural Network training: Retro-propagation algorithm was used to design the structures of neural network for 1 level reconstructed image, and define the training algorithm and parameters.
4- Precipitation estimation: It was estimated rainfall using trained network for 1 level reconstructed images. For the training, the input pattern was the IR temperature image and the output pattern was the rainfall rates images.
5- Estimated image interpolation: Image interpolation algorithm was used to reconstruct the estimated image in the dimension of the original image. For example, in the case of 84x84 network estimation, it was used *bicubic* interpolation algorithm to convert the estimated radar image to 168x168 pixels.

4. Precipitation Estimation

Some definitions will be used in this section as follows: a) Interpolated image (IP) is the image interpolated from the original image using *bicubic* algorithm; b) WT decomposition is the wavelet decomposed image; c) WT reconstruction is a wavelet reconstruction image; d) NN reconstruction is an image which has been reconstructed through a trained neural network (for example, the input is TEM1 and the reconstructed output is RRA1; the network was trained by TEM1, TEM2 and RA1, RA2); e) NN estimation is an image which was obtained by a trained neural network (for example, the input is TEM3 and the output is a ERA3 estimated image). Initially, it was selected 168x168 pixels images and the approaches of the 1 level (dimension of 84x84 pixels).

4.1 NN reconstruction and estimation

Figure 3 shows the NN reconstructed image (the RRA1 through the TEM1 and RA1) and NN estimated image (the ERA3 through the TEM3 and RA3). Comparing the RA1 with the RRA1, the reconstruction is almost perfect (RMSE is zero). The ERA3 also shows a better estimation compared to the RA3.

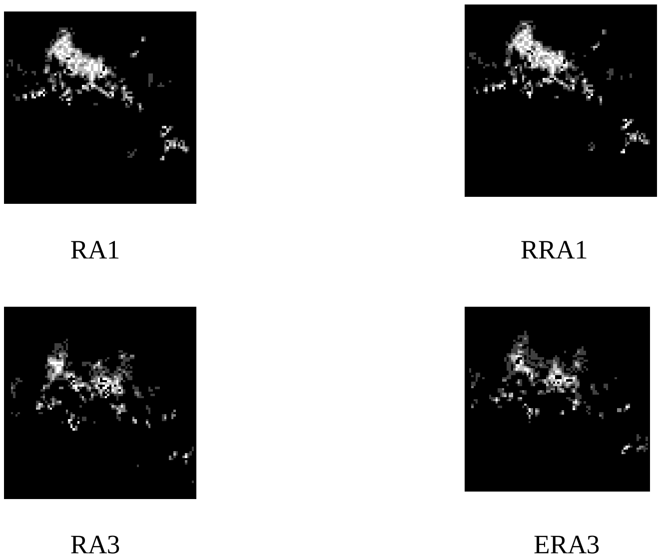


Figure 3. NN reconstruction and estimation

4.2 Estimation error analysis

For evaluating rain estimates from neural networks, the coefficient of correlation (ρ), the Standard Deviation (σ) and Mean Square Error (MSE) data are analyzed. The criteria for evaluating if rainfall estimation error is acceptable, is given by Bitencourt, 1996: $\rho \geq 0{,}6$, $\sigma_e \cong \sigma_v$ and MSE $< \sigma_v$, where σ_e is the Standard Deviation of the estimation image from networks and σ_v is the Standard Deviation of the original radar image. Table 2 shows the resulted statistics. The results show that the error of estimating rainfall from neural network is within the criteria defined by Bitencourt. This suggests that the wavelet decomposition and neural networks methods could be useful for this kind of application.

Table 2. Estimation error analysis

	σ	ρ	MSE
RA3	1.12413 (σ_v)		
ERA3	1.0468 (σ_e)		
RA3 vs. ERA3		0.677598	0.7753

4.3 Interpolated precipitation distribution

To obtain the absolute data of the estimated rainfall, it is needed to return the image from 84x84 to 168x168 pixels. In relation to the wavelet decomposed image, it is also an opened problem because of the no well decomposition coefficients criteria for providing for the output of neural network. Thus, here the interpolation (*bicubic* algorithm) is just simply used to convert the image (output of neural network) to its original domain. At the same time, working with the same sequence of data for rainfall estimation data without using wavelet decomposition but using bicubic interpolation, it was possible to reduce the image domain. Comparing with the results of both sequences, the wavelet decomposition presented better results.

5. Conclusions

This paper shows the implementation procedure of the Multiresolution Wavelet Transform and Neural Networks methods for rainfall estimates using meteorological satellite and radar images. The application of this method is successful to obtain rainfall rates over the São Paulo state, Brazil. The estimated rainfall distribution images matches very well with corresponding radar images. Further research on this topic should involve the suitable wavelet selection to decompose the satellite and radar image, and the analysis of several physically important meteorological features which could influence the images patterns.

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