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Neural Network Application : Rainfall Forecasting System in Hong Kong

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Abstract. At the moment, weather forecasting is still an art - the experience and the intuition of forecasters play an significant role in determining the quality of the forecasting. The "human judgment" is still an indispensable part of a good forecasting. This paper describes the development of a new approach of rainfall forecasting by using neural network. All of these meteorology data are provided by Royal Observatory of Hong Kong (ROHK). The network architecture is based on a recurrent Sigma-Pi network. The results are very promising and this neural based rainfall forecasting system is capable of providing a reliable rain storm warning signal to the Hong Kong public in advance.

1. Introduction

Hong Kong is situated at the southeast coast of China and consists of a group of islands and a peninsula bordered with the Guantung Province of China. The territory covers a total area of about 2,700 square kilometer. It is within the sub-tropical region and is influenced by the monsoon climate dominated by the Asia landmass. Consequently, in each year, during the Spring/Summer transition period, Hong Kong is often affected by heavy rain storm. Since 1992, a heavy rain storm warning signal were introduced by the Royal Observatory of Hong Kong (ROHK) to inform the public about the intensity of the rain storm. This warning signal is the "Green-Amber-Red-Black" colour code. In Table. 1, it shows that the different colour code warning signals are classified in different amount of rainfall. However, these warning signals do not provide an early warning to the public and it is simply a confirmation of the current state of the weather condition. The general feeling is that it would be valuable if the ROHK could issue a warning at least half an hour ahead so that the properties and human lives lost can be minimized. The objective of this work is to develop a neural network based rainfall forecasting supporting tool which is capable of providing the public with a reliable rain storm warning signal in advance. This forecasting will also be less dependent upon the subjective judgment and experience of forecasters.
The rainfall forecasting in Hong Kong is mainly based on weather radar and satellite pictures together with other supplementary factors like the geographical situation, rain gauge past records, cloud pattern, and wind trough. These data are interpreted by the forecaster in accordance with their past experience. Meanwhile, the rainfall forecasting results were aimed at long term forecasting over a synoptic scale accuracy which are not up to the mesoscale (over few hundred kilometer) accuracy

level for a very short term (over few hours) forecasting. In this paper, we describe the development of a neural network approach for rainfall nowcasting (very short term forecasting). The input parameters of the network are the radar echoes, and the rain gauge measurements. And also, because of the geographical situation of Hong Kong, the input parameter pre-processing method is required to be developed The neural network architecture is based on a recurrent Sigma-Pi Network [1].

Rainfall amount per hour (in mm)	Rain Storm colour code warning signal
1 - 20 mm	Green
21 - 49 mm	Amber
50 - 100 mm	Red
over 100 mm	Black

Table. 1 Rain Storm Warning Signal Classification from the rainfall amount.

2. Inputs Pre-processing

In Hong Kong, a computer-based radar system have been implemented at ROHK since 1983. It employs a digital video signal processing and all radar data are stored as a bitmap of 256x256 (=65536) pixels in 16 colours. The methodology of extracting at these data is based on the digitizing and converting the radar echoes into rainfall rate as described in [2]. In Fig. 1, an example shows that the radar image picture around Hong Kong which covers about 190,000 square kilometer at different time frames. The percentages of the amount of water droplets can be represented by the intensity of the gray colour in the radar picture. However, the whole radar image frame is too large for the rainfall nowcasting in Hong Kong and, therefore, the intensity of the water droplets which cover around Hong Kong area are required for analysis. It is understood that their intensity near Hong Kong will have larger effect than those farther from Hong Kong. There is, obviously, a greater probability of rainfall if the radar image with much denser blocks at the Hong Kong region and less denser blocks as going farther from Hong Kong. According to the above strategy, 28 blocks are constructed for a small faction of the radar image as shown on Fig. 1. The bitmap data inside each block are evaluated to the normalized average rainfall rate for the input vector of the network. In addition, logarithm scale weighting factor is introduced to the per-processing of different image blocks. The weighting factor is to adjust the strength of the radar image blocks according to their significance to Hong Kong.

As the rainfall distribution is quite uneven at Hong Kong, the northern part of Hong Kong island in the past always experienced different level of rainfall from the southern part of Hong Kong island, especially in heavy rainfall condition. One of the major reasons contributes to this uneven rainfall distribution is the terrain layout of Hong Kong. The southern part and northern part of Hong Kong Island are separated by mountains. In order to establish an appropriate neural model to deliver a reliable rainfall nowcasting, the whole Hong Kong is then unevenly divided into a number of geographical cells which are based on the terrain characteristic and the distribution of population and rain gauges. Ten geographical cells are then obtained. In Fig. 2, it

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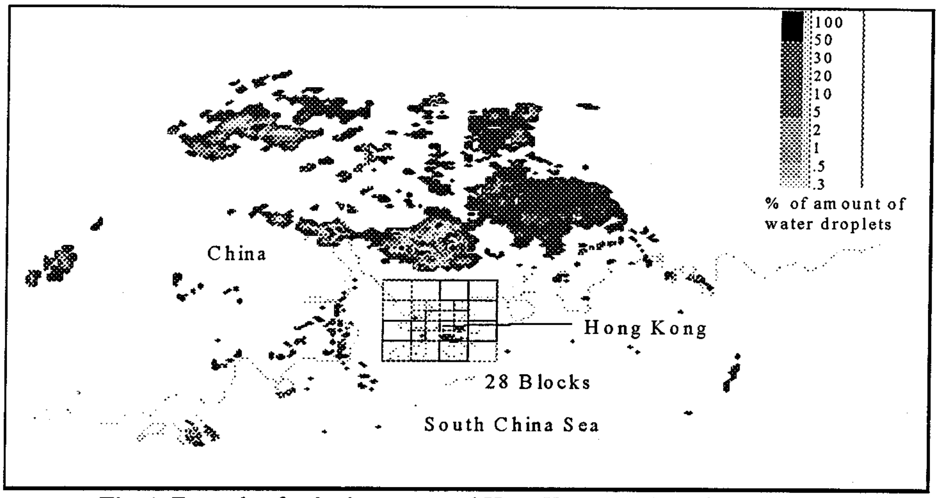

Fig. 1. Example of radar image around Hong Kong together with 28 blocks

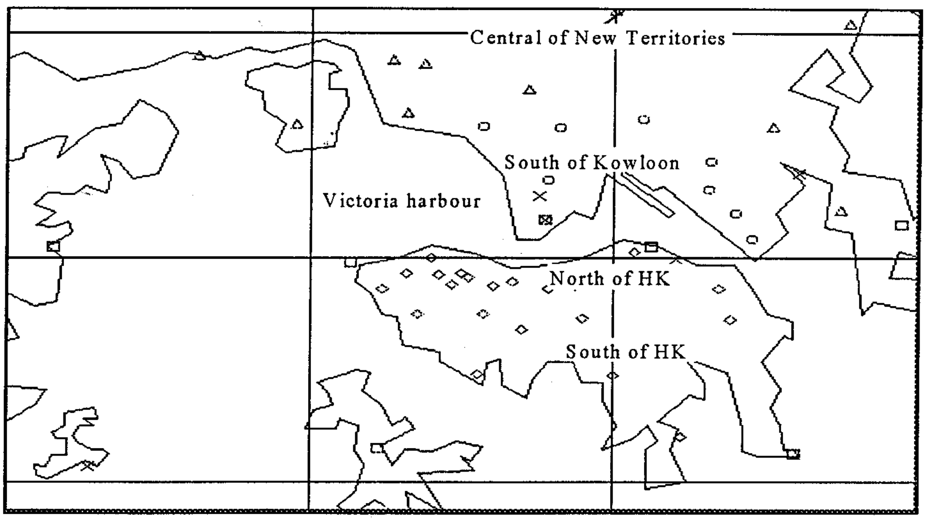

Fig. 2. Rain gauges distribution and layout of Hong Kong

shows that the distribution of different rain gauges superimposed on the Hong Kong map. Because the major part of the urban area are mostly covered by three geographical cells: a) South of Kowloon and North of Hong Kong Island (SKNH), b) South of Hong Kong Island (SHK), and c) Central of New Territories (CNT). In the present study only these three geographical cells are investigated.

3. Network Architecture and Learning Algorithm

In the present development, a recurrent Sigma-Pi Neural Network is selected because its strong dynamical characteristic would significantly enhance this type of

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meteorological time series application [1]. There are 31 input nodes at the input layer which represents 28 radar image blocks data and 3 averaged rain gauge data of the three geographical cells. At the output layer, three output nodes are used to represent the averaged rain gauge value in the corresponding geographical cells at the next half an hour. In the hidden layer, there are 21 hidden neurons and 31 multiplication conjunctions between input layer and hidden layer. All the neurons in the hidden layer and the output layer are with a self-feedback loop. The derive of the dynamic learning algorithm for the Recurrent Sigma-Pi Network is based on steepest descent optimization [3]. The general form of the gradient equation as follow:

Synapses weights:

$$-\frac{\partial E}{\partial w_{kj}} = \delta_k \cdot (o_j + w_{FB} \cdot \frac{D\partial o_k}{\partial w_{kj}}) \tag{1}$$

if we define δ_k as $\delta_k = (t_k - o_k) \cdot \sigma'(net_k)$

where t_k be the desired value

$$\frac{\partial o_k}{\partial w_{kj}} = \sigma'(net_k) \cdot (o_j + w_{FB} \cdot \frac{\partial o_k}{\partial w_{kj}}) \tag{2}$$

Feedback weights:

$$-\frac{\partial E}{\partial w_{FB}} = \delta_k \cdot (Do_k + w_{FB} \cdot \frac{D\partial o_k}{\partial w_{FB}}) \tag{3}$$

$$\frac{\partial o_k}{\partial w_{FB}} = \sigma'(net_k) \cdot (Do_k + w_{FB} \cdot \frac{D\partial o_k}{\partial w_{FB}}) \tag{4}$$

where o_j and o_k are the output of hidden and output neurons respectively; net_k be summing output in k output neurons; w_{kj} be the synapses weights; w_{FB} be the feedback weights; E be the sum squared error function and D be the unity delay operator.

4. Validation of proposed model

The input vector is composed of 28 blocks of radar image data and three averaged rain gauge values. The three output nodes represent the forecast of the averaged rain gauge values of the three different geographical cells. Weights were initialized randomly between -0.5 and 0.5. The learning rate and the momentum factor were selected as 0.1 and 0.01 respectively. The learning procedure was performed on a SUN Sparc Classic platform. In the training phase, 10,000 training iterations were performed and the final convergence RMS error is 0.0355. For the validation of model, the rainfall nowcasting were performed on three different occasions: 8 May 1992, 13 May 1992 and 14 June 1992.

i) 8 May 1992: In Fig. 3, three different histograms represent the rainfall amount on the corresponding geographical cells in Hong Kong. In the actual rainfall record, it indicates that the rain began at 6:30 and became heavy rain at about 15:00. It is also noticed that different rainfall level was recorded in the CNT geographical cell compared to the other two geographical cells. This effect is mainly due to the terrain effect together with the wind convergence effect on different areas. In the network outputs, the amount of rainfall was predicted to be over 100 mm within one hour from 15:00 to 16:00 at the Hong Kong Island, which implies that a "Black" colour rain storm warning signal should be issued before 15:00 in one hour ahead by the ROHK. This forecast results compared to the actual rainfall record is reliable and promising.

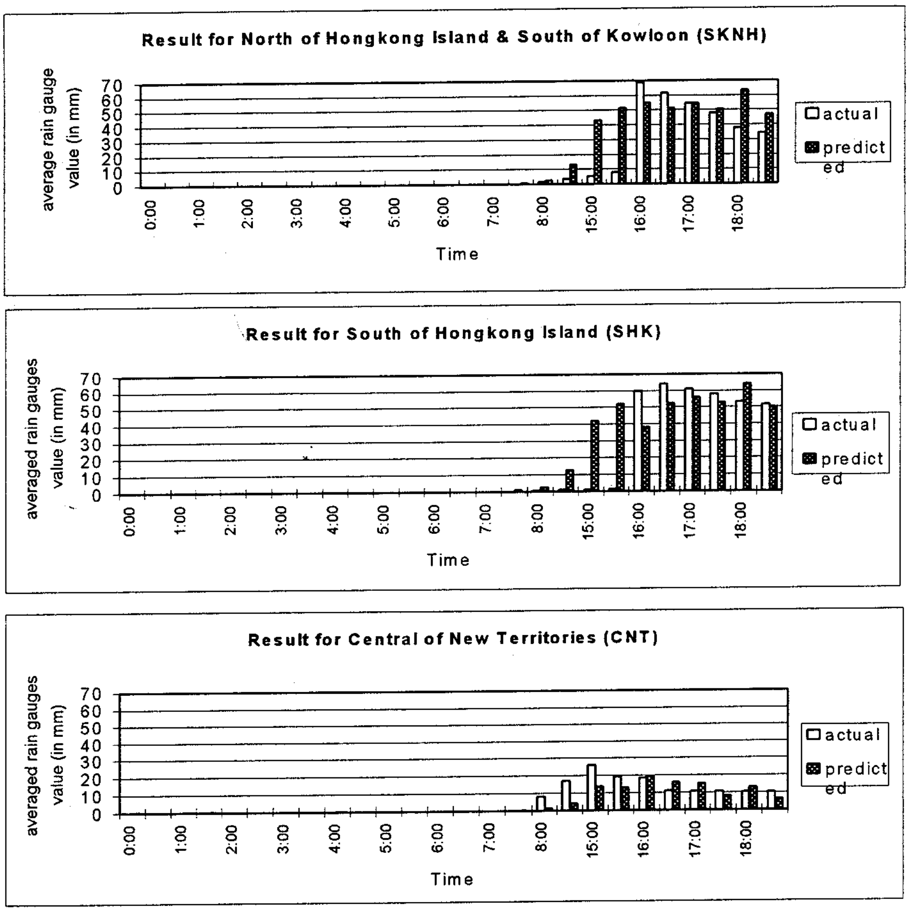

Fig. 3. Result on 8 May 1992

ii) 13 May 1992: Because the network was mainly trained under different types of rainfall conditions, a test to assure that the network is also capable of providing accurate forecast at no rain scenario is essential. On 13 May, no rain was recorded. In this test, the network output predicted an absolutely no rain condition for the three different geographical cells. This result strongly corroborates that the developed system is capable of coping with different weather situations.

iii)14 June 1992: The proposed network can be applied on the whole day forecasting and predicted the rainfall amount level on every half an hour. In Fig. 4, it shows the

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comparison of the rainfall amount between actual and forecast. The forecasting RMS error in terms of amount level is only 0.7645, which is quite accurate for the weather forecasting point of view.

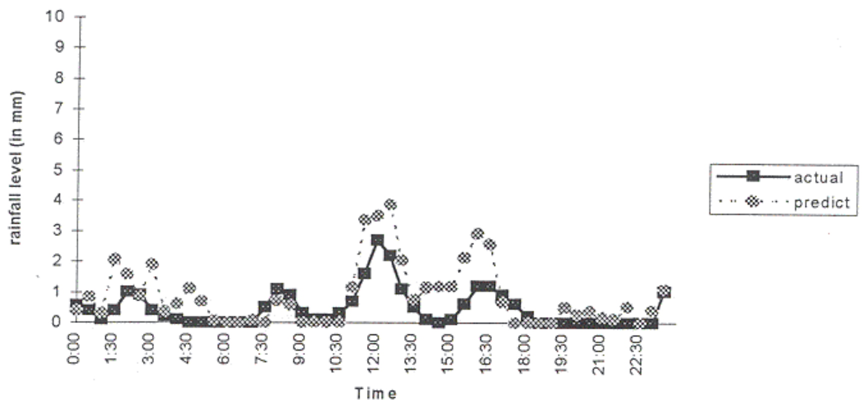

Fig. 4. Result on 14 June 1992

In this study, the above results demonstrated that the developed rainfall nowcasting system is capable of providing a reliable forecast to support the ROHK to issue different reliable rain storm warning signals to the Hong Kong public in one hour ahead. In addition, the system is also capable of coping with the terrain effect at different geographical cells.

5. Conclusion

This paper briefly describes the development of a neural network based rainfall nowcasting supporting system in Hong Kong. In weather forecasting point of view, the obtained results are accurate and reliable although the results cannot up to a millimeter accuracy. The results indicate that our developed neural based nowcasting system is capable of providing a reliable rainfall nowcasting in Hong Kong. The most important is that the system enables the ROHK to issue a reliable rain storm warning signal to the Hong Kong public in one hour ahead.

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