PROMOTING AN ACCURACY OF RAINFALL FORECASTING BY RADAR DATA USING NEURAL NETWORK

Xianyun CHENG, S.MJSCE, Graduate School of Marine Science & Engineering
Masato NOGUCHI, MJSCE, Department of Civil Engineering
Nagasaki University, 1-14, Bunkyo-cho, Nagasaki 852

1. INTRODUCTION

One of the major responsibilities in flood hydrology is to make efficient forecasts of the occurrence of flood events. For practically achieving this goal, besides well understanding the transformation of rainfall to runoff, i.e. rainfall-runoff modelling, rainfall forecasting becomes significant and urgent owing to a fact that rainfall is the most important and direct agent to cause flood and the flood forecasting therefore essentially depends on forecasting of rainfall. With radar rainfall information remotely observed by the Foundation of River & Basin Integrated Communications, i.e. FRICS, it becomes possible to forecast spatial and temporal distribution of rainfall with an interest lead time over a catchment. Because the neural network (NN) has great potential to handle complex and nonlinear phenomena in nature, while uncertain questions can be treated well with the Fuzzy rule, a new methodology is accordingly developed, wherein two main components are included: (1) computation of rainfall movement with modified correlation method and Fuzzy rule, and (2) determination of rainfall intensity distribution using the NN approach. Reasonable results have been derived with a high accuracy through using data on a real time basis.

2. RADAR RAIN GAUGE DATA FROM FRICS

The radar rain data with a 30-minute interval received from a FRICS terminal, dated on June 30, 1995, have been used for conducting research in this paper. Fig.1 shows an example of a rain field, where the domain covers whole area of Nagasaki prefecture as well as the nearby sea. The area is divided into 58×30 grids, where each grid size is 6 km in longitudinal direction and 9 km in latitudinal direction. The rainfall intensity in each grid is categorized into 1 to 9 degrees represented by: 1: 1~5, 2: 5~10, 3: 10~20, 4: 20~30, 5: 30~40, 6: 40~50, 7: 50~70, 8: 70~100 and 9: 100~ (unit: mm/hr), respectively.

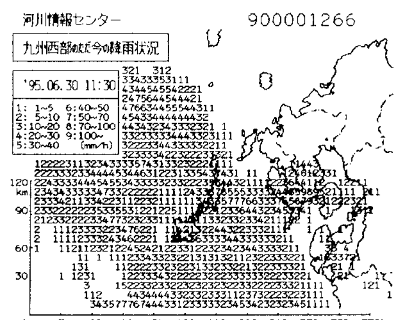

Fig. 1 Rainfall field example served by FRICS

3. DETERMINATION OF RAINFALL MOVEMENT

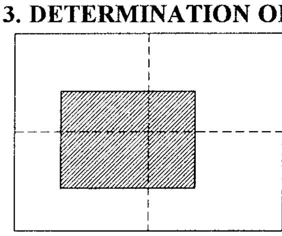

Fig.2 Geometry definition of overlapped grids

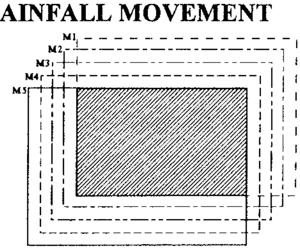

Fig.3 Illustration of determining overlapped rain fields

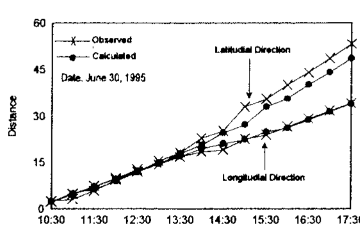

Fig.4. Comparisons Between Observed and Calculated Movement

Components of a movement consist of two aspects: velocity and direction. It is very difficult to determine these two elements accurately based only on the information of known rainfall data owing to numerous influential factors such as wind speed and air pressure. Consequently, a modified correlation method is introduced here, which is mainly based on the consideration that heavy rainfall will play a dominant role in flood formation, thus requiring more attention. Mathematically, a series rainfall value-depended weights are served when applying successive moving match comparisons judged with the normal correlation method. The rainfall in overlapped grids can then be easily re-computed referring to Fig.2. The results are demonstrated in Fig.4.

4. DETERMINATION OF RAINFALL INTENSITY

The variations of rainfall over a specific area can be systematized into two classes: one is external change in the horizontal direction, mainly governed by rainfall movement, and the other is comparatively called internal change in the vertical direction, corresponding to the four stages of rainfall formation: production, growth, decrease and disappearance. The first class can be decided with the procedure described in the previous section, while the succeeding connections within the second class can be simulated through the performance of a NN since its special attributes. As illustrated in Fig.5, if the NN is taken as a "black box", then a pair of adjacent rainfall vectors (as one pattern) is its input and output, respectively. A number of such patterns are used to train the NN for identifying their internal nonlinear relationships. For study here, three successive rainfall vectors from FRICS are used to predict the fourth vector, over the common parts as shown in Fig.3. The procedures associated with a simple Fuzzy rule are developed, where rain fields *M1*, *M2*, *M3* and *M4* are used to predict the rain field *M5*.

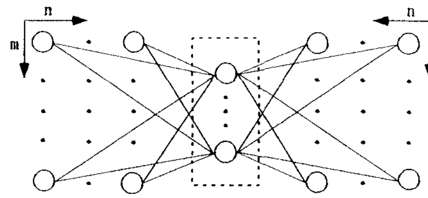

Fig.5 Neural Network for rainfall forecasting

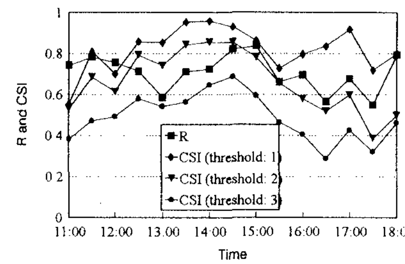

Fig 6. Temporal variations of R and CSI

5. PERFORMANCE OF THE MODEL

The results are graphically demonstrated in Fig.6. It can clearly be seen that *CSI* varied as the different threshold value selected. This is due to a fact that its value decreases if spatial distribution of rainfall intensity is not exactly anticipated, and also that a proportionality of rainfall field to a whole area interested is not so large. This things suggest that appropriate parameter should be programmed for estimating an accuracy of the goodness of prediction. Considering above-mentioned matter, present short-term rainfall forecasting seems to be done fairly well. A calculated rainfall field and its original one from FRICS are displayed in Fig.7 and Fig.8, respectively.

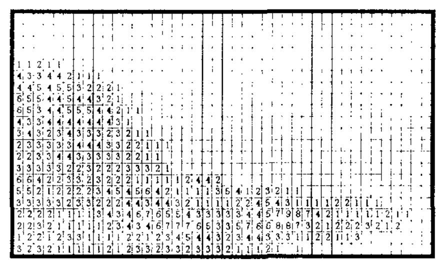

Fig.7 Observed rain field at 11:30

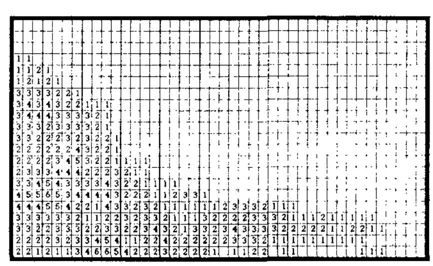

Fig.8 Calculated rain field at 11:30

6. CONCLUSIONS

Since rainfall is one of the most difficult elements to be determined, the outcomes obtained up to now show potential for short-term rainfall prediction. If the four stages of rainfall formation (production, growth, decrease and disappearance) can be distinguished when applying the NN in the second phase of the study, better yields can be expected.

REFERENCES

Cheng, X. and M. Noguchi (1996): Rainfall-runoff Modelling by Neural Network Approach, Proceeding of International Conference on Water Resources & Environmental Research: Towards the 21st Century, Vol. 2, pp.143-150, Kyoto, Japan.

French, M. N., W. F. Krajewski and R. R. Cuykendall (1992): Rainfall Forecasting in Space and Time Using a Neural Network, J. Hydrology, 137, pp. 1-31.

Haykin, S. (1994): Neural Network - A Comprehensive Foundation, Macmillan College Publishing Company, New York.