Fifth IFSA World Congress (1993), 1222-1225

Prediction System on Chance of Rain by Fuzzy Relational Model

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The purpose of this paper is to construct a prediction system on the chance of rain in a local region using a fuzzy relational model. The prediction system consists of two parts. One is a prediction part on the chance of rain. The compositional law of fuzzy inference, proposed by Zadeh, is applied to predict the chance of rain. The other is a learning part of a fuzzy relational model using input-output data. A simple and fast learning algorithm is used in this part. Simulations are carried out by the actual weather data in our city and their results show the validity of prediction by the fuzzy relational approach.

1. Introduction

In modern meterological weather forecast, forecasting techniques have been developed remarkably due to the extraordinary progress of the computer simulation techniques. Prediction rate of weather forecasting has been coming up over 80 percent. Using the simulation results by the super computer based on the fluid dynamics and some visual informations sending from artificial satellite and so on, weather casters have been forecasting synthetically. However, we can predict the personal weather forecast empirically, for example, if the sky becomes darkened, it'll rain soon.

In this study, we propose a prediction system on the chance of rain in a day after by the fuzzy relational model on the basis of the weather data at a local region on the earth. If we try to apply the ordinary fuzzy inference to the problem, such as the chance of rain, which many factors are related to the phenomenon, it is unable to generate fuzzy production rules. While, using the fuzzy relational model by the compositional law of fuzzy relations, we can expect to realize a simple and fast prediction system [1].

2. Fuzzy relational model

Input-output relation in this system is shown in Fig.1.In this figure, input variables $x_1 \sim x_5$ are weather data as follows : x_1: averaged humidity in a day [%], x_2: averaged atmospheric pressure in a day[mb], x_3: averaged temparature in a day [° C], x_4: pressure difference between a day and a day before [mb], x_5: averaged chance of rain in a day [%]. Output variable y is only one : y: averaged chance of rain in a day after [%] ,where $x_1 \in X_1, x_2 \in X_2, \cdots, x_5 \in X_5, y \in Y$. $X_1 \sim X_5$, Y are universal sets to each parameters.

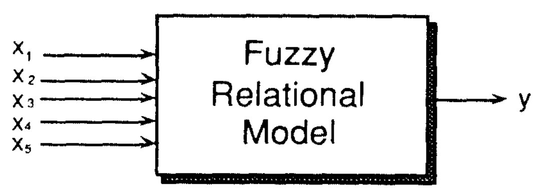

Fig.1 Fuzzy relational model

We select these parameters as input-output variables which have great influences to the chance of rain in a day after among various ones.

In this system, we use a fuzzy relational model based on Pedrycz's idea [2]. At first, we construct fuzzy relations from input data. Then, fuzzy inference is carried out by the composition between those fuzzy relations and the refrence fuzzy relation and the chance of rain at a point is calculated. At the same time, the refrence fuzzy relation R(k-1) is also renewed to R(k). (learning) Detailed algorithm of this fuzzy relational model is expressed in the next section.

3. Algorithm of prediction system

The algorithm of fuzzy relational model is shown in Fig.2.

① Initial set of reference fuzzy relation R(k-1) : At first, we must set initial values R(0) of reference fuzzy relation:

$$\mu_{R(0)}(n_{A1},n_{A2},n_{A3},n_{A4},n_{A5},n_B)=0$$

where $n_{A1} \sim n_B$ are integers to satisfy next conditions.

$$1 \leqq n_{A1} \leqq 3,\ 1 \leqq n_{A2} \leqq 4,\ 1 \leqq n_{A3} \leqq 2,$$
$$1 \leqq n_{A4} \leqq 2,\ 1 \leqq n_{A5} \leqq 4,\ 1 \leqq n_B \leqq 11$$

② Input of weather data

For example, we use the input data of k-times in the following.

$$(x_1^k, x_2^k, x_3^k, x_4^k, x_5^k, y^k)$$

③ Learning

We renew the reference fuzzy rela-

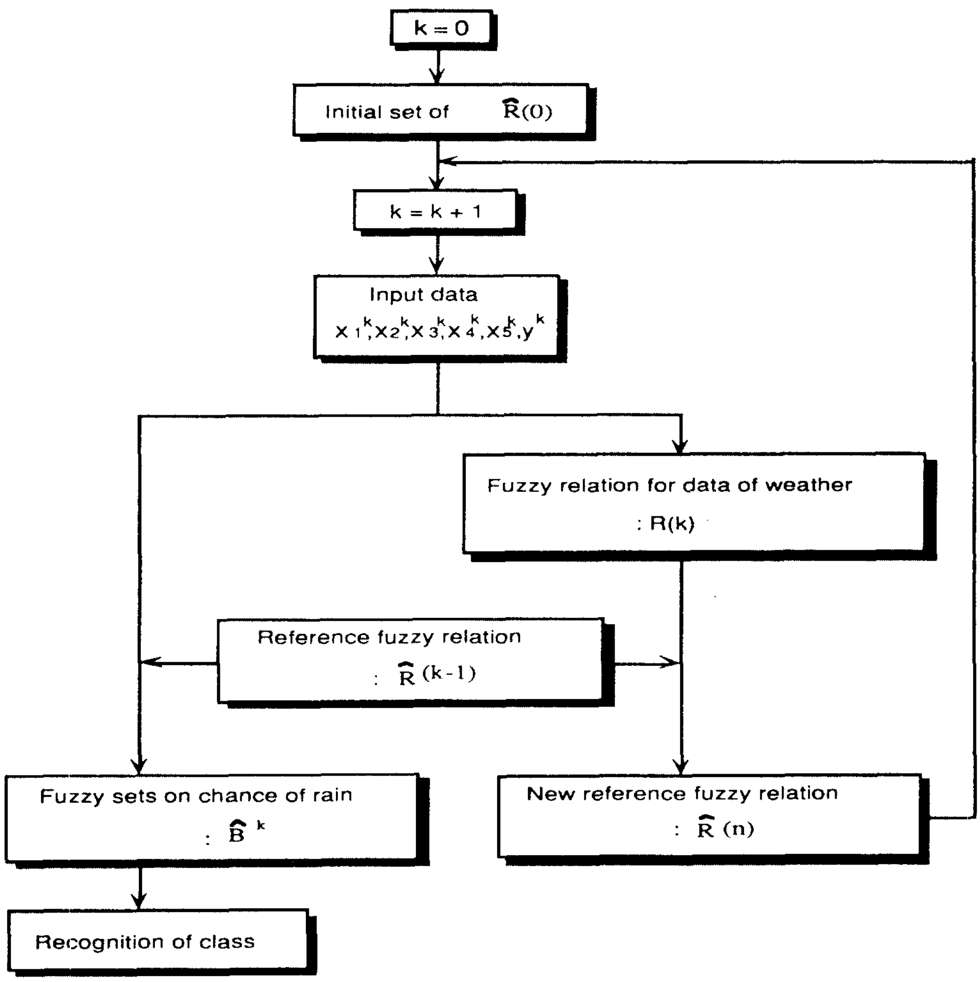

Fig.2 Prediction and learning algorithm on chance of rain

tion in each calculating cycles. The reference fuzzy relation is indispensable to the prediction. Threfore, we need to learn this reference fuzzy relation. Fuzzy sets to input-output parameters are defined in the following. Membership functions of these fuzzy sets are also shown in Fig.3, respectively.

$$A_1^1, A_1^2, A_1^3 \subset X_1$$
$$A_2^1, A_2^2, A_2^3, A_2^4 \subset X_2$$
$$A_3^1, A_3^2 \subset X_3$$
$$A_4^1, A_4^2 \subset X_4$$
$$A_5^1, A_5^2, A_5^3, A_5^4 \subset X_5$$
$$B_1, B_2, \cdots, B_{11} \subset Y$$

We can express these fuzzy sets using the k-times input data as follows :

$$\tilde{A}_1{}^k = \sum_{i=1}^{3} \mu_{A1}{}^i(x_1{}^k) / i$$

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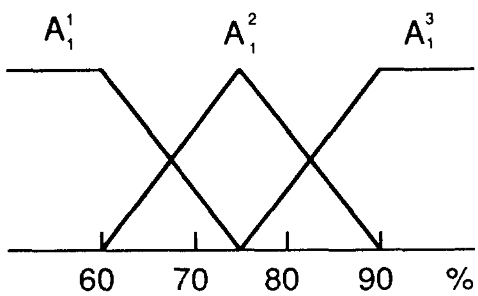
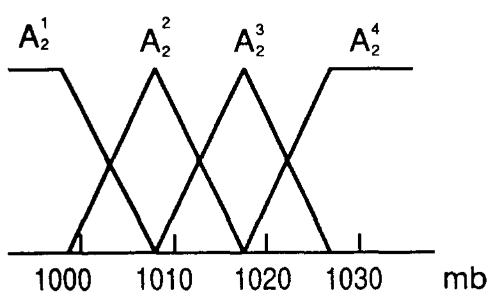
$$\tilde{A}_5{}^k = \sum_{i=1}^{4} \mu_{A5}{}^i(x_5{}^k) / i$$

$$\tilde{B}^k = \sum_{i=1}^{11} \mu_B{}^i(y^k) / i$$



(a) Averaged humidity in a day



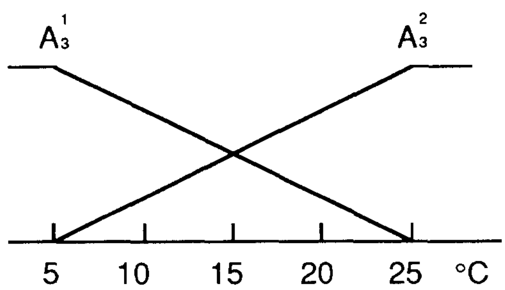
(b) Averaged atmospheric pressure in a day

Next, R(k) is calculated by the fuzzy sets as follows :

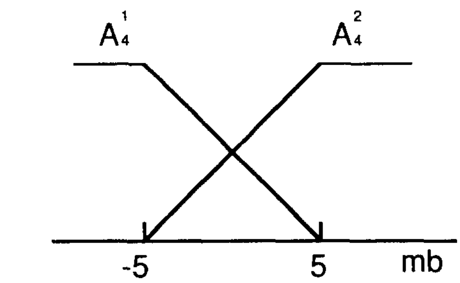
$$R(k) = \tilde{A}_1{}^k \times \tilde{A}_2{}^k \times \tilde{A}_3{}^k \times \tilde{A}_4{}^k \times \tilde{A}_5{}^k \times \tilde{B}^k$$

where notation $\times$ denotes the cartesian product, and an element of R(k) is expressed by

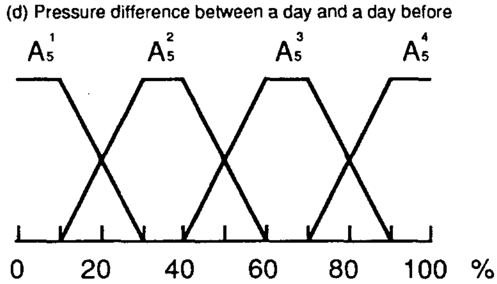
$$\mu_R(n_{A1}, n_{A2}, n_{A3}, n_{A4}, n_{A5}, n_B) = \mu_{\tilde{A}_1}{}^k(n_{A1}) * \mu_{\tilde{A}_2}{}^k(n_{A2}) * \mu_{\tilde{A}_3}{}^k(n_{A3}) * \mu_{\tilde{A}_4}{}^k(n_{A4}) * \mu_{\tilde{A}_5}{}^k(n_{A5}) * \mu_{\tilde{B}}{}^k(n_B)$$



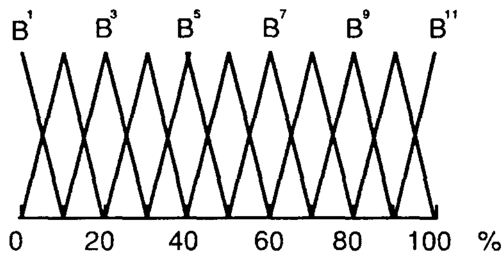
(c) Averaged temparature in a day



(d) Pressure difference between a day and a day before



(e) Averaged chance of rain in a day



(f) Averaged chance of rain in a day after

Fig.3 Membership functions

where notation $*$ expresses t-norm, in actual, the algebraic product.

Using the fuzzy relation R(k), the reference fuzzy relation $\hat{R}(k-1)$ is renewed (learned) by the next equation

$$\hat{R}(k) = \hat{R}(k-1) \boxplus R(k)$$

where notation $\boxplus$ denotes the algebraic sum, t-conorm. Therefore, an element of $\hat{R}(k)$ is expressed as follows :

$$\mu_{\hat{R}(k)}(n_{A1},n_{A2},n_{A3},n_{A4},n_{A5},n_B)$$
$$= \mu_{R(k)}(n_{A1},\cdots,n_B)+\mu_{\hat{R}(k-1)}(n_{A1},\cdots,n_B)$$
$$-\mu_{R(k)}(n_{A1},\cdots,n_B)\cdot \mu_{\hat{R}(k-1)}(n_{A1},\cdots,n_B)$$

④ Prediction of chance of rain

Grades to the chance of rain are calculated by the following composition.

$$\hat{B}^k = (\tilde{A}_1^k \times \cdots \times \tilde{A}_5^k) \circ \hat{R}(k-1)$$

in which $\hat{B}^k$ corresponds to the prediction result and it is different from $\tilde{B}^k$ in the above section. $\hat{R}(k-1)$ denotes the reference fuzzy relation which has been already learned by input data up to (k-1)-times, that is, data of one times before. While, notation $\circ$ means the max-product composition. A class of maximum grade in fuzzy sets $\hat{B}^k$ is recognized as the prediction result of the chance of rain. If one would like to predict and learn the other input data, processes ②～④ should be recurred in the above algorithm after setting k=k+1.

4. Simulation

In our simulation, the reference fuzzy relation is learned by weather data from December 1990 to May 1991 at Kanazawa City in Japan. Using this reference fuzzy relation, we predict the chance of rain and compare it with the one forecasted by the meterological observatory (reported on the newspaper). An example of comparison is shown in Fig.4.

5. Conclusion

Our predition results are lesser than those forecasted by the meterological agency. However, we will be able to construct a better prediction system if the more dynamic data and the global scientific informations will be added in future .

References

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2) W.Pedrycz: An Identification Algorithm in Fuzzy Relational System, Fuzzy Sets and Systems, Vol.13(1984), pp.153-167.

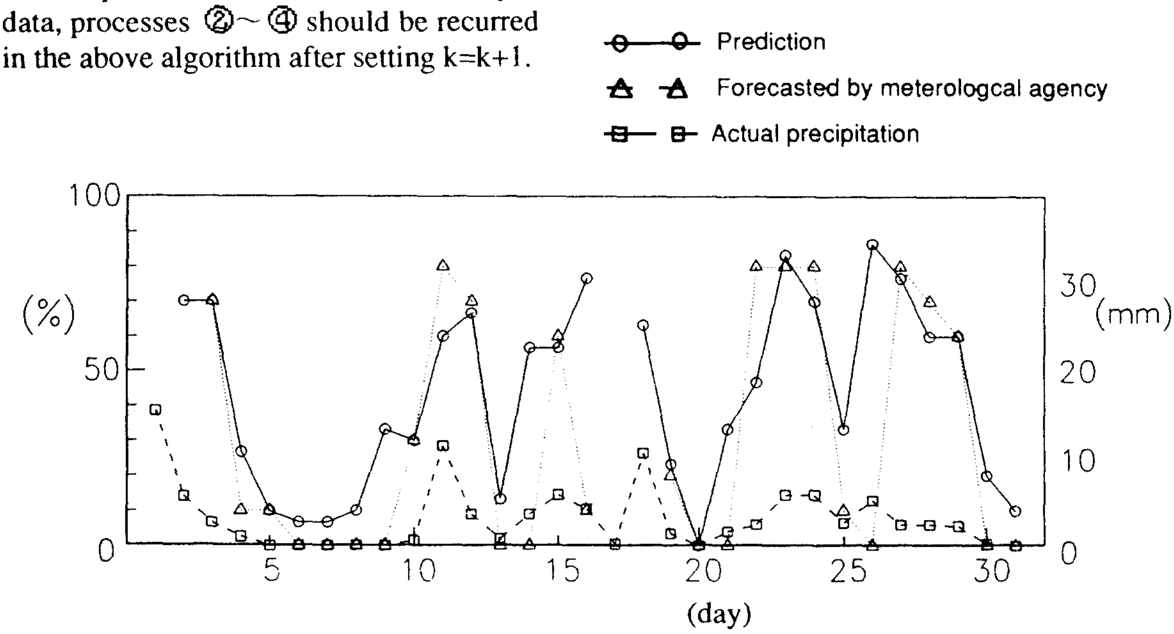

Fig.4 An example of simulation results