Sensor Integration System and Learning System for Automatic Reusable Manufacturing System

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1

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Contents

1. Introduction

We have developed many technologies in various industries to increase productivity. These technologies can improve the productivity, but they have led to environmental deterioration and made many environmental problems. Environmental problems are environmental pollution, industrial waste, desertification, global warming, depletion of resources, etc.

In order to solve these serious problems and protect our environment, we must develop the recycle technologies in various industry fields, such as aircraft, automobile, electronics, factory machine, ship, spacecraft, and so on.

The recycle technologies can realize to use resources and products effectively, then saves resources and energy that is used in production. It will be also one solution to break the industrial waste problem (See Fig. 1.1). There are three major recycle technologies:

One is to change the industrial waste into raw materials. Figure 1.2 shows the recycling process of materials. This technology can save resources and reduce the waste. Recycled materials will apply to all industries with conventional manufacturing systems. The technology concentrates development of a new recyclable material with low cost. A recycled paper is an example of the recycling of materials.

One is recycling technology of system. This technology has been studied in factory machine and plants. Recently the manufacturing is changing from mass production to various kinds and small amount production. The system which utilized this technology called the flexible manufacturing system and consists of various function modules. Functions of the system can be changed by adding or changing one or more new function modules. Therefore, we do not need a new machine for a new product. Besides, it is very easy to repair the breakdown system, it is only to change the

Fig. 1.1 Recycle technology for various industries

breakdown modules. Then we can save resources which will be used for a new machine and do not dispose the old or breakdown machine. This technology has been utilized in a robotic system [Fukuda 1987]. Figure 1.3 shows the recycling process of the module.

One is reusable manufacturing technology. This technology extends the lifetime of the product or the module by repair or fix the malfunction or breakdown part. By repairing or fixing, the breakdown product is not disposed as an industrial waste, then resources are saved. However a malfunction or breakdown part on a product is always different and the cause of breakdown is various and different, so that human experts repair or fix most malfunction or breakdown products

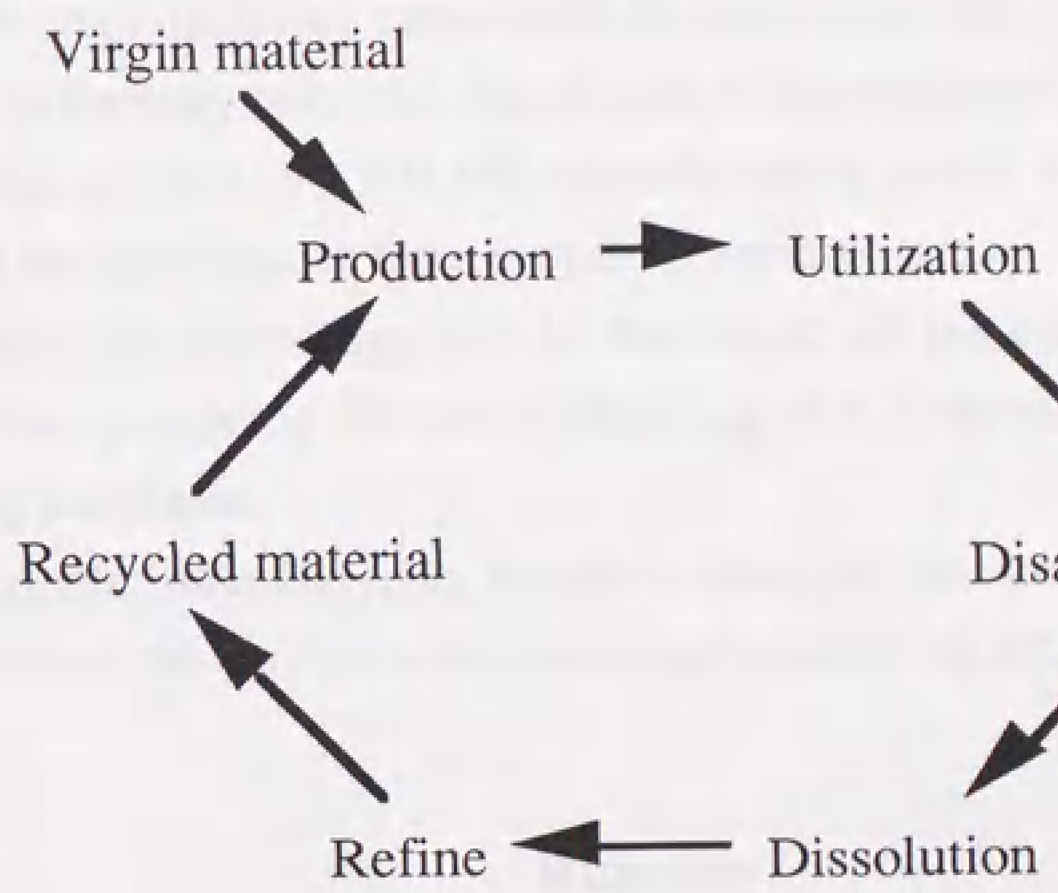


Fig. 1.2 Recycling process of materials.

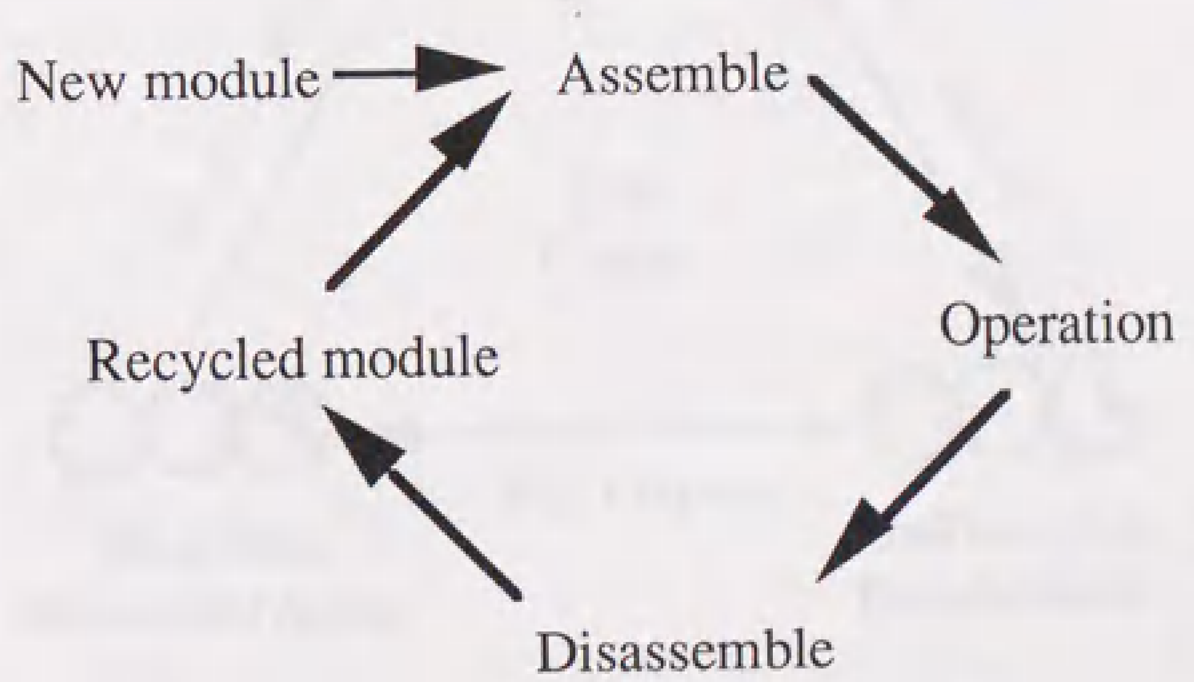


Fig. 1.3 Recycling process of module

In order to realize automated reusable manufacturing, this some intelligent technologies are desired: one is the inspection of the product or the module, one is the recognition of the malfunction or breakdown part, one is the planning of reusable manufacturing, how to repair or fix the part.

Follow sections, we present how to realize the reusable manufacturing system with the robotic technologies, then show the example of reusable manufacturing system that is applied for aircraft industry.

1.1 Intelligent robotic technology for reusable manufacturing system

Reusable manufacturing can extend the lifetime of the product till it would be disused. This technology only uses the amount of resources and energy that are enough to repair/fix the product. So that this manufacturing needs the smallest amount of resources and energy of above three recycling technologies.

Therefore, this technology will be the key of saving our environment, saving resources and not producing industrial waste. Figure 1.4 shows the outline of reusable manufacturing processes.

The reusable manufacturing has been done by human experts in long time. Recently, however, the number of human expert is reducing. Besides it needs long time

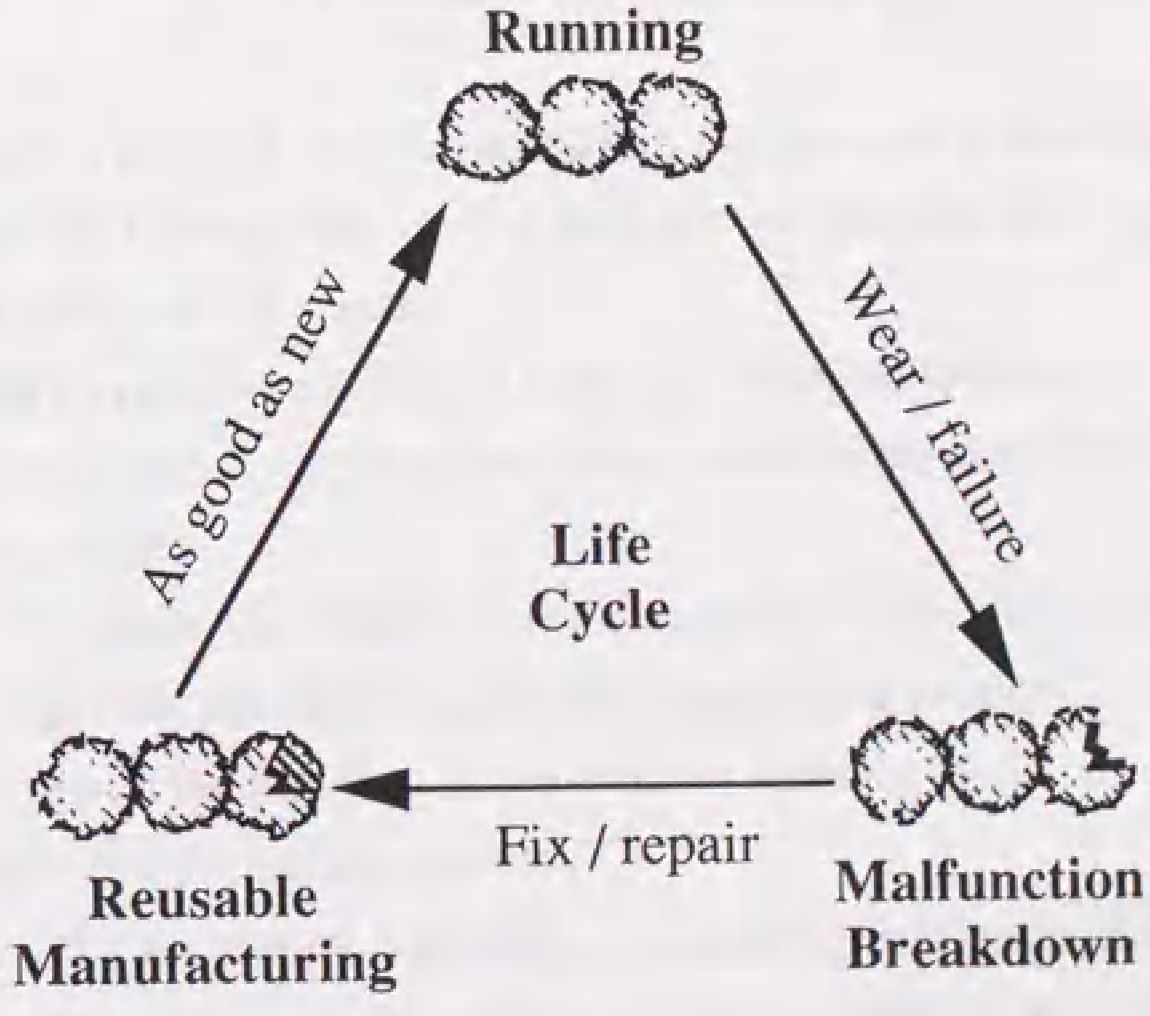


Fig. 1.4 Extended lifetime by the reusable manufacturing

to train a person as an expert, then the automatic reusable manufacturing system is desired.

However, there are some problems that prevent the automatic reusable manufacturing from realizing as follows:

(1) It is difficult to predict when the breakdown is occurred.

(2) It is difficult to predict where the breakdown or malfunction is occurred.

(3) It is difficult to recognize what is cause of breakdown.

(4) It is difficult to plan how to fix or repair the breakdown or malfunction part.

(5) The shapes of the product would be changed with using.

To realize the automatic reusable manufacturing, we must apply some robotic technologies to solve these problems as follows:

(1) Sensory system with various sensors and multi-sensor integration / fusion system.

(2) Artificial intelligence technology for fault diagnosis in the running process and repairing/fixing way in the repairing/fixing process.

(3) Manipulator system with some intelligent control methods.

These technologies are now studying individually, and they would be concentrated into the reusable manufacturing technology.

1.1.1 Sensory system technology

The sensory system is very important in the automatic reusable manufacturing system, because all information of the products is obtained into the manufacturing system through this sensory system.

The sensory system is utilized in three processes as follows:

1) To detect the occurrence and location of the breakdown/malfunction in the running process.

2) To measure the shape of the product in case the product's shapes are changing with utilization in the repairing/fixing process.

3) To inspect the function of the product whether it will be used as possible as before in the inspection process.

Improving the accuracy of detecting, measuring, and inspecting the product, the sensory system would have multi various sensors, as well as realizing the measuring the complicated product that cannot be measured by the single sensor.

In order to manage multi various sensory data, the sensor integration/fusion system [Luo 1989, 1992], [Hackett 1990] has been studied. Multiple sensory systems have a major problem: how to integrate/fuse sensory data to produce the more reliable and accurate information. Various sensor integration/fusion methods have been reported so far: hypothesis testing by sensor models and Bayesian approach [Durrant-Whyte 1988], multiple hypothesis approach [Cox 1991], confidence distance matrix [Luo 1988], estimation by performance and cost criteria [Zheng 1989], estimation of cost by Bayesian method [Richardson 1988], probabilistic approach [Sabater 1990], Bayes-maximum entropy method, energy-minimize curve method [Beckman 1992], using multi-input hidden Markov model [Aono 1992], using Kalman filter [Dessen 1989], [Duriev 1989], [Nakamura 1989], [Durrant-Whyte 1990], [Olivier 1991], [Kosaka 1992], [Hager 1993], [D'Orazio 1993], [Hughes 1993], Kalman filter with dummy parameters [Kawashima 1992], intentional observation with information criterion [Sakaguchi 1992], multi-agent approach with logical sensor [Berge-Cherfaoui 1991], [Gasparovic 1992], using recursive term utility function [Basir 1992], using maximum likelihood method [Xu 1991], weighting scheme based on the information theory [Basir 1993 a], using neural networks [Matsumoto 1992], [Moriizumi 1992], [Moriwaki 1992], [Song 1993], using mappings between sensor [Mukai 1993], using fault tolerance network and the Subsumption Architecture [Ferrell 1993], using knowledge database [Ramparany 1992], using hierarchical structure [Oomichi 1992], using the physical network [Takahashi 1993], a multicriteria approach [Basir 1993b], the state-based sensor [Murphy 1993], using the tree data-structure [Hong 1993], and a fuzzy logic [Abidi, 1991], [Abdlghafour 1993].

To apply the reusable manufacturing for the more complicated products, the sensory system has the more various sensors. Then the management of the sensors is very difficult. Therefore, the integration/fusion methods, such as the hierarchical sensor integration/fusion method, utilizing some kind of neural networks, and so on, must be studied hard to realize the wider application of the reusable technology.

1.1.2 Artificial intelligence technology for fault diagnosis and repairing/fixing way.

In order to detect the occurrence and location of malfunction/breakdown in the running process and make the repairing/fixing schedule automatically, artificial intelligent technologies, such as an expert system, a neural network [Rumelhart 1986], a fuzzy set theory, and so on, would be applied for these processes.

The fault detection in dynamically system has been studied so far [Frank 1992], [Graham 1993]. Almost of the fault detection systems are based on an expert system. The essential components are a knowledge base that acquires both analytical and heuristic knowledge, a database that carries information about the current state of the process from the measuring system, and an inference engine with forward or backward reasoning.

The expert system for the repairing/fixing schedule also consists of a database that contents are relation between the cause of malfunction/breakdown and the way of repairing/fixing, and a knowledge base of the skill that acquires by human experts.

These technologies are the more important in the reusable manufacturing system, the product is the more complicated and large. And management technology of knowledge base , such as the integration of the knowledge base, the automatic analysis for a unknown data set, the classification of the data set, the addition of the new knowledge base for a new failure and a new repairing way, and so on, will be the key issue to realize these expert systems for the complicated and large system.

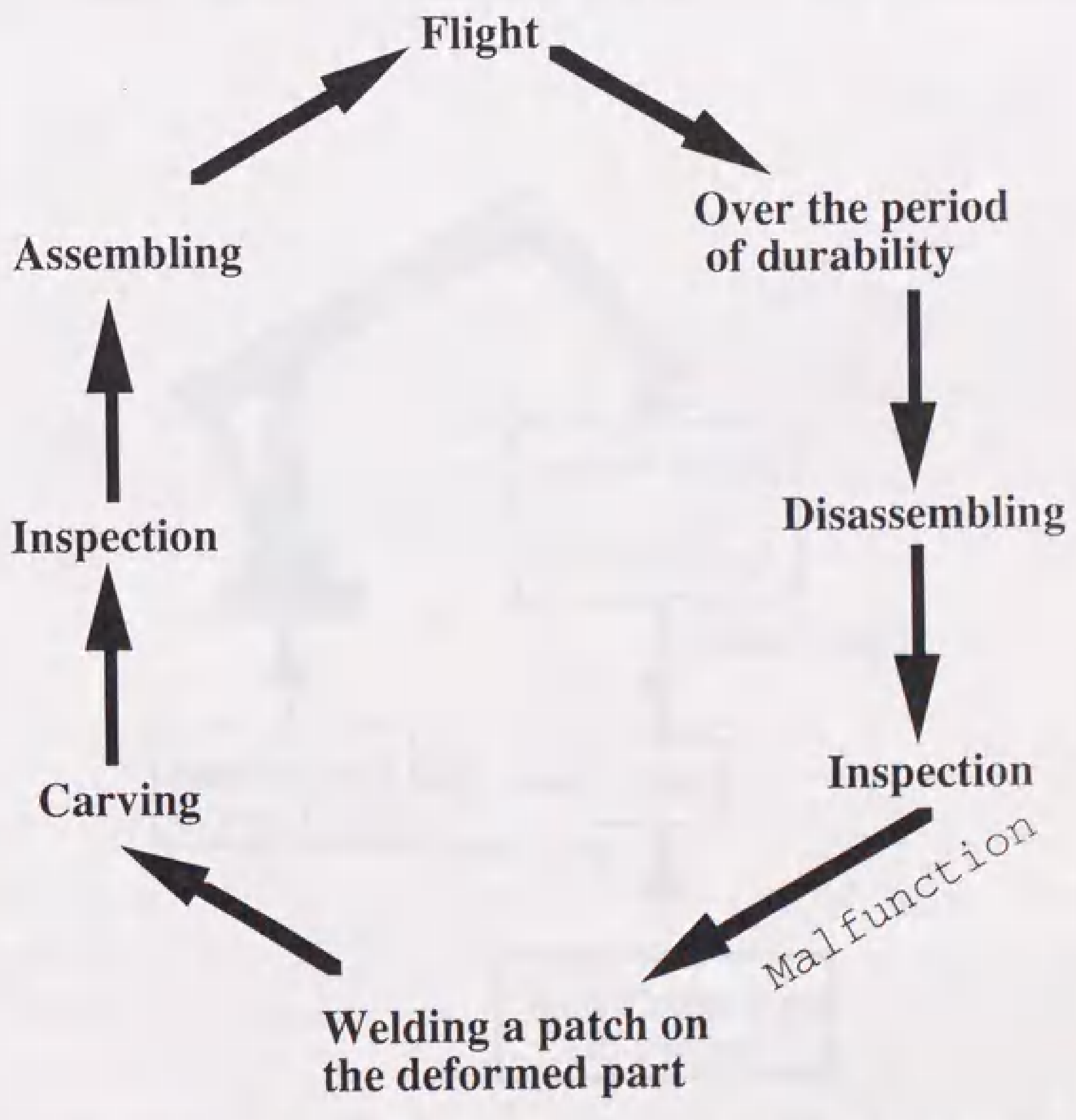


Fig. 1.5 Reusable manufacturing process of a jet engine's parts

1.1.3 Manipulation system

A reusable manufacturing is very difficult than the conventional manufacturing. Because the repair/fix will take place on only the malfunction/breakdown part of the product. The repairing/fixing works are various, such as welding, bonding, cutting, carving, assembling, disassembling, and so on. Besides the shape of the breakdown product would be different from a new one.

Therefore the manipulator system would be required flexibility and dexterousness of moving that is controlled by the force control method [Kawasaki 1990], the impedance control method [Hogan 13], etc. The high accurate calibration and compensation method for the manipulator system would be necessity for the accurate repairing/fixing, Multiple manipulators system would be required in order to realize more complicated repairing/fixing products that requires handling the product.

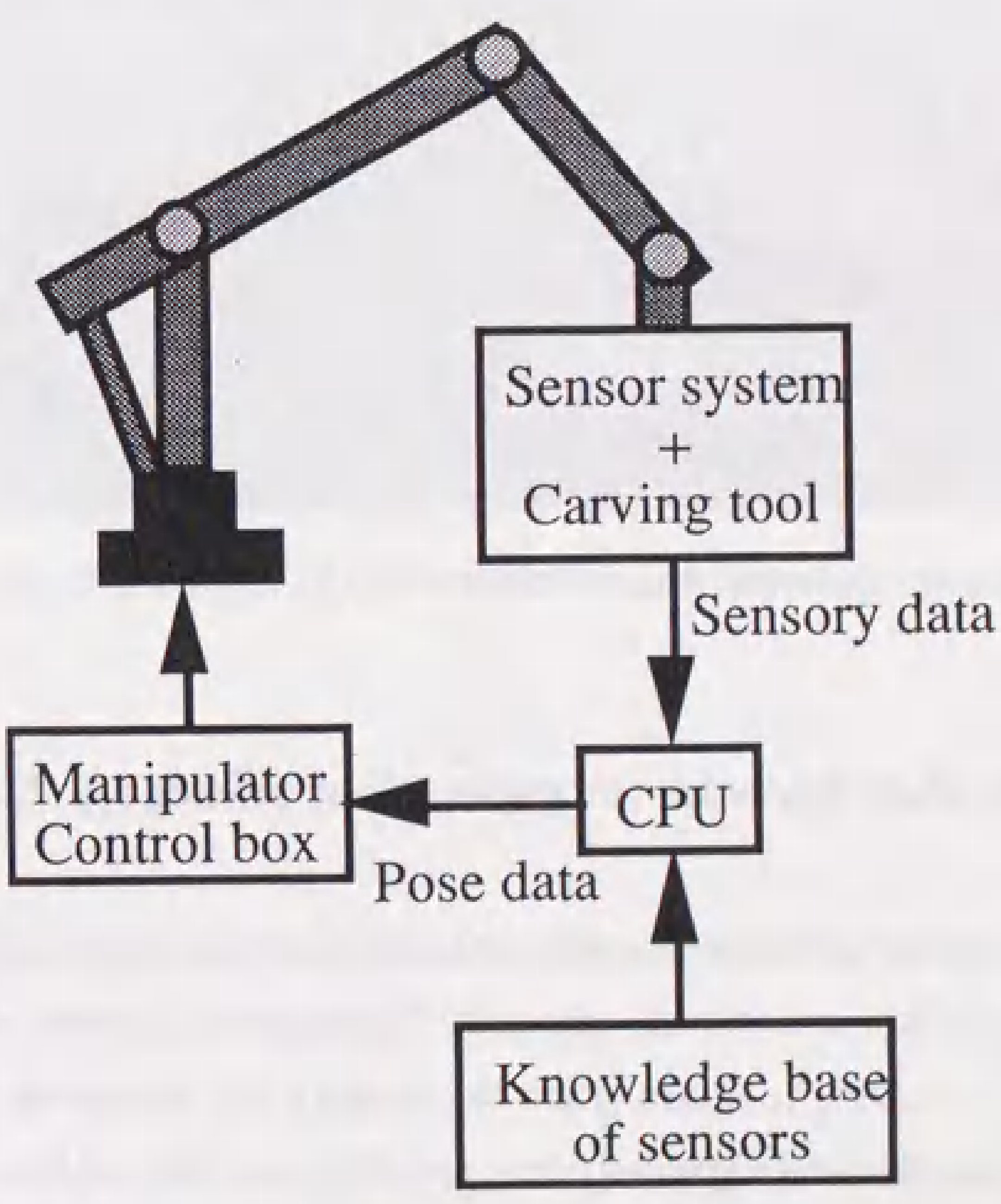


Fig. 1.6 Reusable manufacturing system

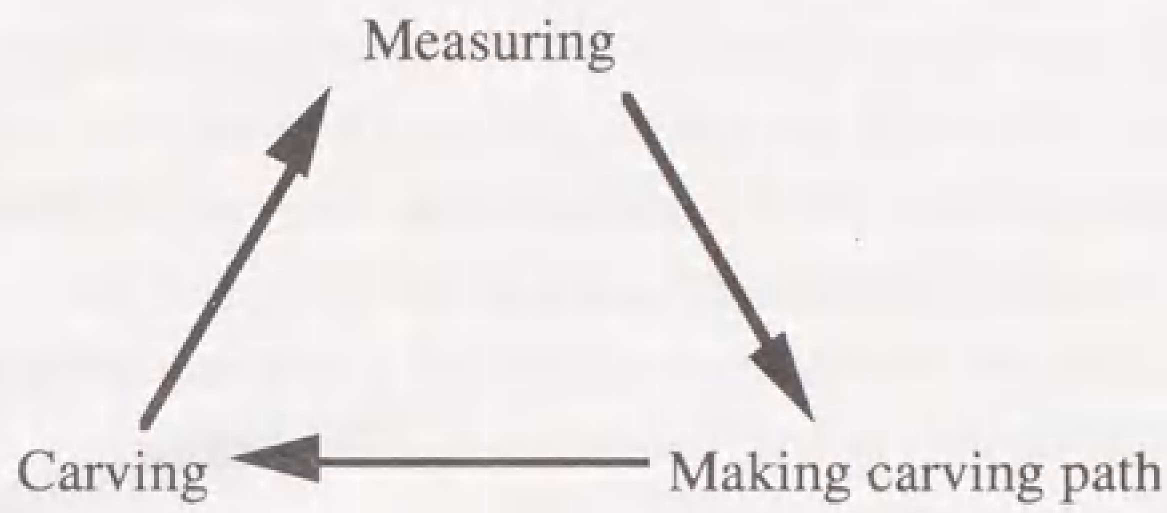


Fig. 1.7 Automatic reusable manufacturing process

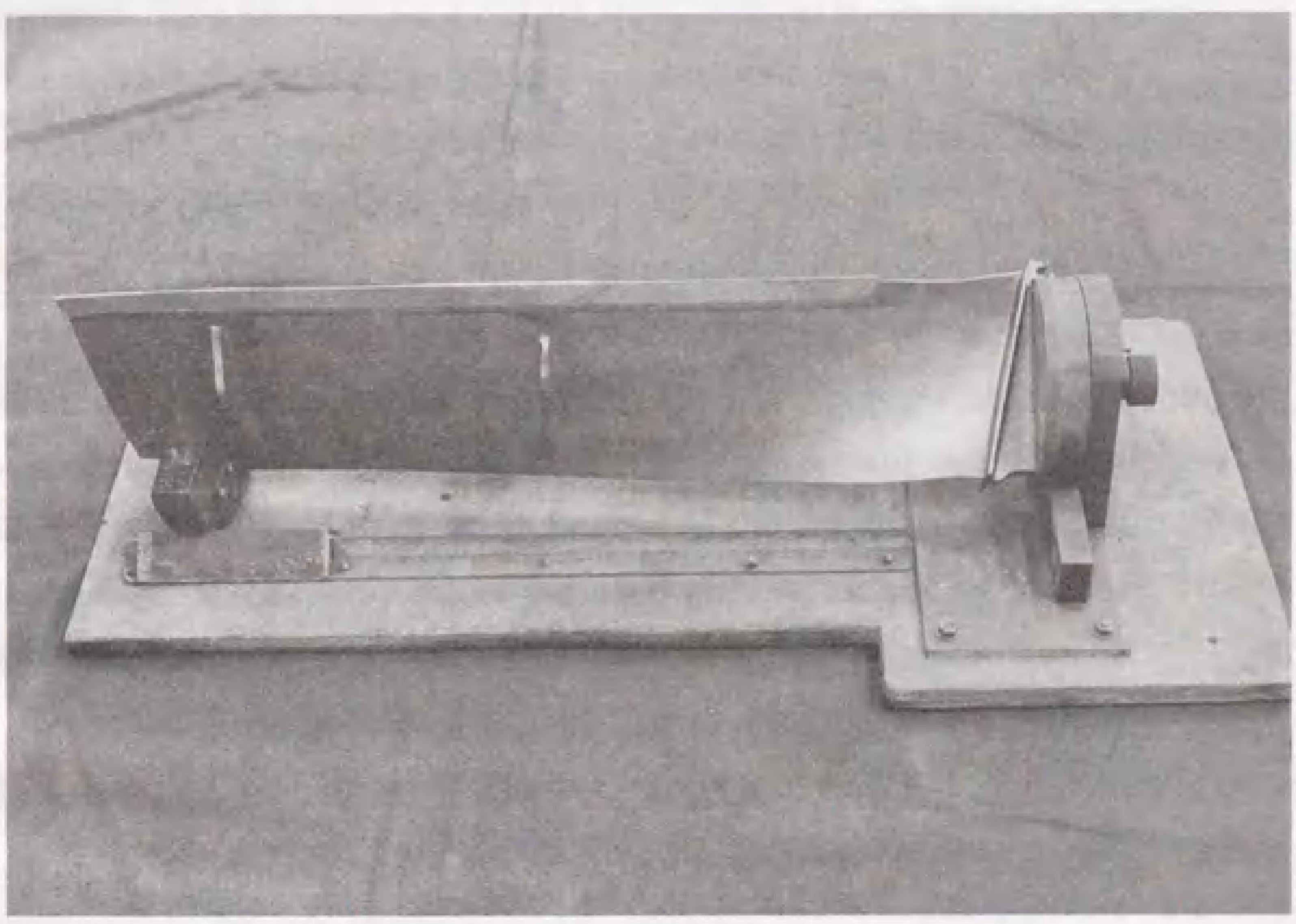


Fig. 1.8 Object of the reusable manufacturing system.

1.2 Reusable technology for aircraft industry

We have been studying the automatic reusable manufacturing system for aircraft industry [Fukuda 1993], [Shimojima 1993]. An aircraft consists of various and many parts, especially an engine has a lot of and many kinds of parts.

In order to reduce the cost of flying, safety margin of each part is low, since they are controlled strictly. When there are malfunction parts, they are not disposed but repaired, because most of them are made from rare materials in precise and very expensive.

Figure 1.5 shows the reusable manufacturing process of the jet engine's parts. When the engine finishes the period of durability, it is disassembled. Then, each part is inspected. If there is a malfunction part, a patch is welded on the part. The welded part is carved to the suitable shapes for reusing. At last, the part is inspected whether the part can be reused. If the part pass the inspection, it will be assembled into the engine.

In this study, the first try of the realizing the automatic reusable manufacturing system is automatizing the carving and inspection processes, because these processes are the key of reusable manufacturing. Automated carving systems with robots are not widely applied to make a repaired and reusable work from a used one that has distortion and defects. Because the works' surface's shapes are complicated and different from new one, and it requires more skillful experiences, therefore most of these works have been carried out by human experts. In recent years, however, the number of the experts is decreasing, even it takes a long time to become an expert.

Therefore, automated manufacturing systems for repair and reusable products have been desired so far from these industrial sectors.

Most of the present automated manufacturing systems need the CAD data of works [Proctor 1989] or sensory data of a force-torque sensor to carve works. For the manufacturing of the reusable products that have complicated surfaces and profile different from the original, the present systems are not suitable. Because the CAD data do not express the profile of used works but the original one, therefore the systems using the CAD data cannot carve the used one. While the systems with force-torque sensor cannot recognize the desirable shape from the sensory data.

To solve these problems, an intelligent manufacturing system [Fukuda 1993], [Shimojima 1993] which consists of cutting tool and a 3-D measuring system are proposed. Figure 1.6 shows the outline of the manufacturing system. The manufacturing system measures each target's surface shapes with this measuring system and make the carving path from the measurement data. Figure 1.7 shows the manufacturing process in this system.

Figure 1.8 shows the object of our reusable manufacturing system which is a part of the turbine jet engine.

Following chapters, we denote the sensor integration method, the multi-sensor system with fuzzy inference and neural networks, the 3-D measuring system with the LED displacement sensor and the vision system with sensor integration method based on fuzzy inference, the adaptive sensing strategy for the LED displacement sensor and the vision system, and the learnable fuzzy inference based on spline function which is an approach for the artificial intelligence technology.

Figure 1.9 shows the outline of this dissertation.

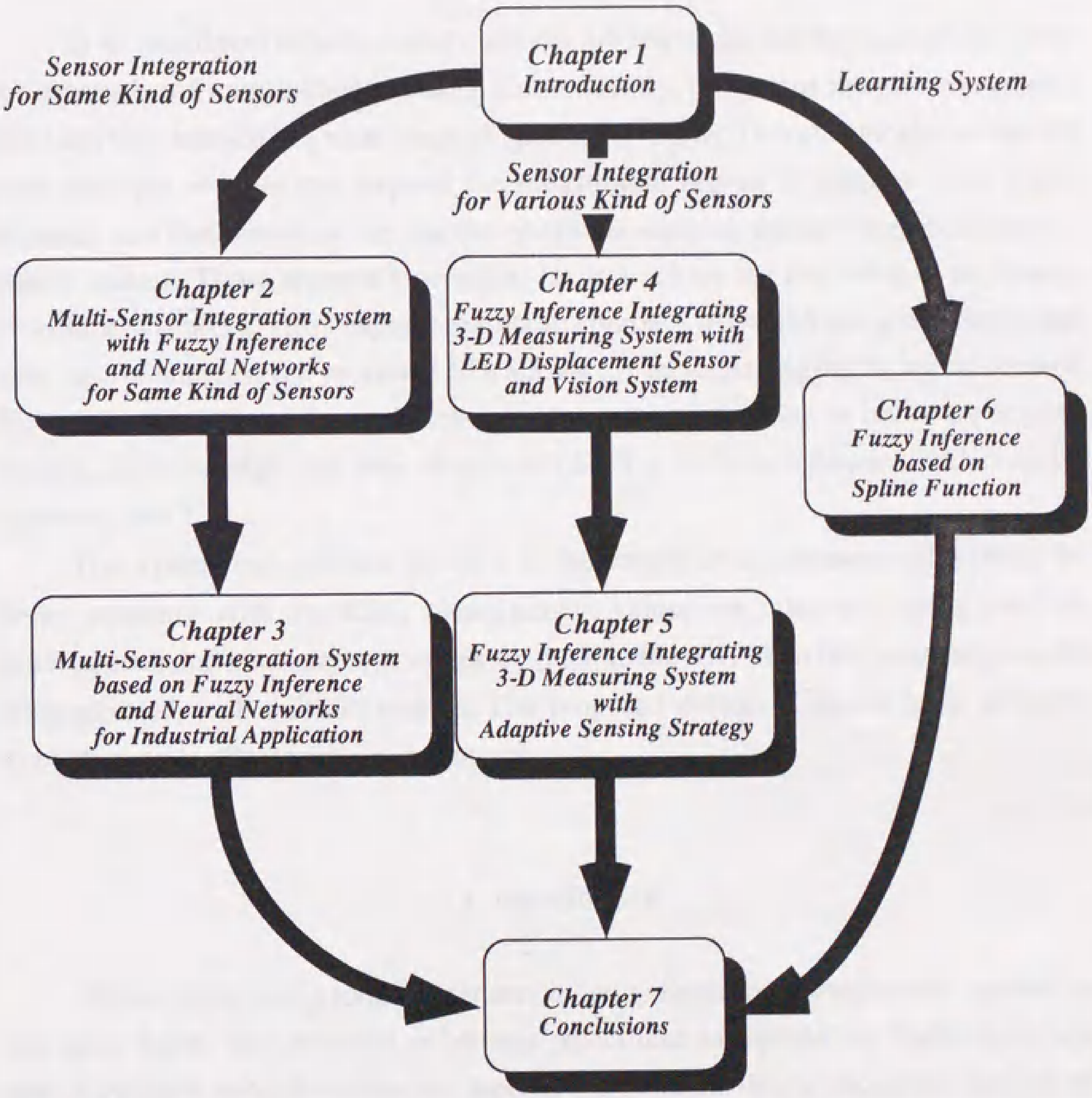


Fig. 1.9 Contents of this dissertation

2. Multi-Sensor Integration System with Fuzzy Inference and Neural Networks for Same Kind of Sensors

In an intelligent robotic system, sensors are important for the recognition of the system state and environmental status. Consequently, the sensor integration system (SIS) has been studied in a wide range of application fields. This chapter shows that SIS with multiple sensors can expand the measurable region of sensors with higher accuracy and that operators can use the system as easily as a single high performance sensor system. Those systems reported so far do not have the flexibility to the change or replace of sensors. This chapter presents an approach to the SIS using the knowledge data base of sensors; the proposed SIS allows for the changing/replacing of sensors. The system consists of four subsystems: 1) sensors performing as hardware sensing devices, 2) knowledge data base of sensors (KBS), 3) fuzzy inference, and 4) neural network (NN).

This system can estimate the error in the sensor's measurement value using the fuzzy inference with the KBS. Measurement values are integrated using the NN. Inferred error and measurement values are put into the NN. Then NN's output gives the integrated value of multiple sensors. The proposed system is shown to be effective through a series of extensive experiments.

2.1 Introduction

We are using many kinds of sensors in many fields, and they can be applied to any other fields. The demands of sensors' specifications spread out higher accuracy and wider application. For example, used for the robot moving/approaching must be an extensive range and stability of environment sensors, and the measurement in production at super high precision processing needs sensors for the wider range and higher accuracy. It is too difficult for a single sensors to satisfy these demands. Even if it could fill these requirements, it would be very expensive. For these demands, the sensor integration system (SIS)[Luo and Kay 1989] has been studied. The SIS uses a combination of multiple sensors and operators can use this system as easily as a single high performance sensor system. Using multiple sensors, the SIS must select the closest and most accurate one.

In this chapter, we present the SIS which has the flexibility against the changing/replacing of sensors. This system has the knowledge data base of sensors' specification (KBS) and estimates the error of each sensor's measurement value by the fuzzy logical inference with the KBS. The estimated errors and measurement values are put into the Neural Network (NN). Then the NN gives the integrated value of multiple sensors.

2.2 *System configuration*

2.2.1 *Outline of system architecture*

Proposed system consists of four subsystems : 1) sensors as hardware sensing devices, 2) knowledge data base of sensors (KBS), 3) fuzzy inference, and 4) neural network (NN). The total system is shown in Fig. 2.1. In this block diagram, "Meas. Val.", "Env. Data" and "Inf. Err." implies the measurement value of the sensor, the states of environment and the inferred error of the sensor by fuzzy inference, respectively.

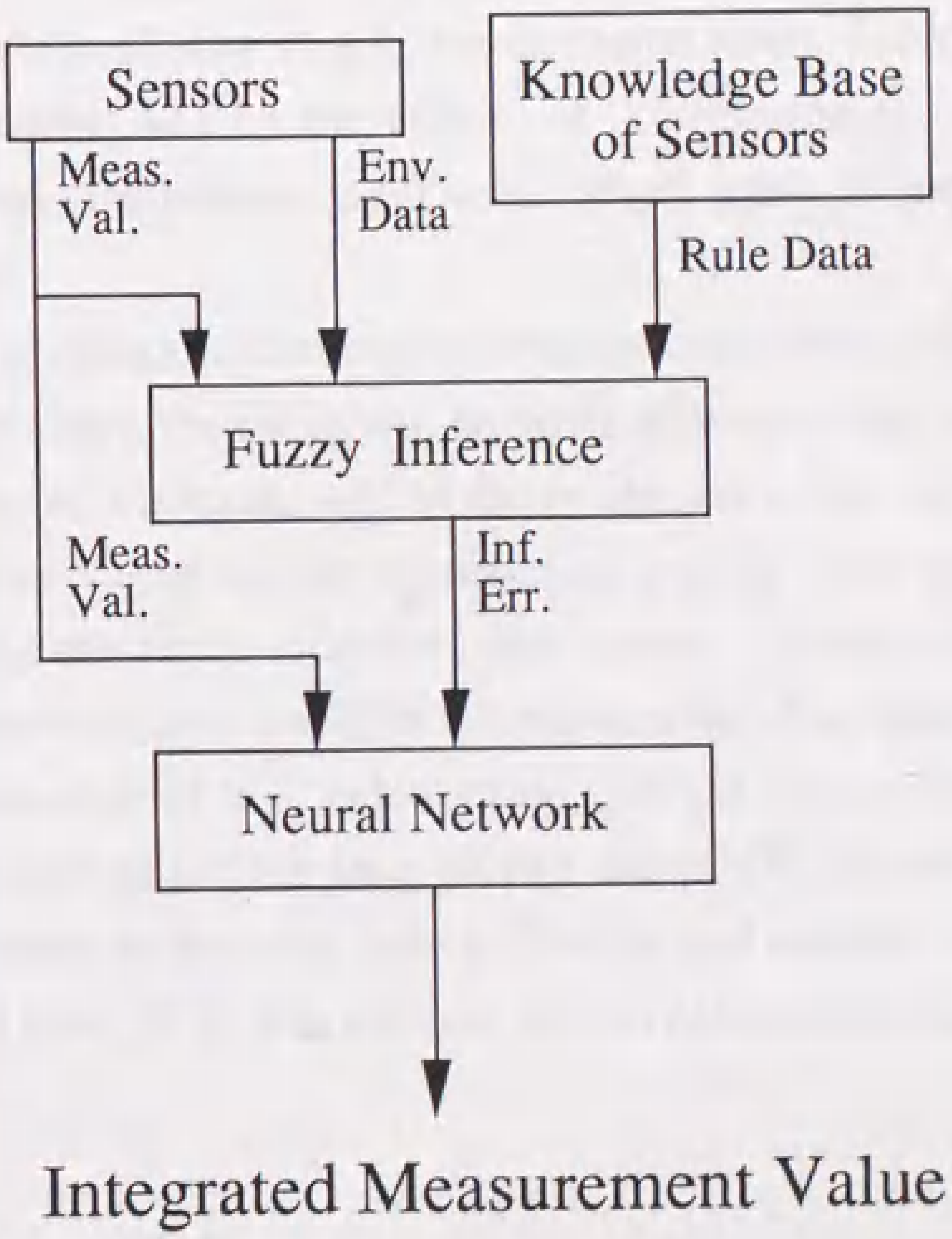


Fig. 2.1 Sensor Integration System

2.2.2 Knowledge data base of sensors

Sensors' specifications are written in the knowledge data base of sensors. They are, 1) measurement region, 2) measurement precision, 3) resolution of sensor, 4) environmental restrictions to use sensor such as condition of temperature, brightness and so on, and 5) error affected by environments. For 4) and 5), every factor affecting measurement values of each sensor is written in this data base. The followings are data examples of the non-contact gap sensor, which is used in the experiments:

Measurement range:	0 - 2 mm
error rate	0.5 %
Recommended temperature range:	0 - 100 Degree.
Temperature drift:	0.06 %

2.2.3 Fuzzy inference

Measurement value of sensors may contain some errors. Error is caused by the principle of measurement and by the effect of environments. If error can be estimated, we can obtain the measurement value which is the closest to the true value and the most accurate.

Possible cause of sensor measurement error are considered as followings: If the sensor uses semiconductors, the cause will be drifts of temperature, and in the case of using optical techniques, the cause will be the brightness of the environment. These physical phenomena are vague and the influence on sensors is not clear either.

Therefore, using the fuzzy inference, this system estimates these values and infers considerable maximum errors. This system uses the simplified fuzzy inference, which has characteristics of less calculation, and the defuzzificated values are continuous. The followings are the case of two inputs (X, Y) and one output (Z). Equation (2.1) represents the i-th rule, where Ci is the real number, and the fitness for each rule is described in eq. (2.2). The inferred error is defuzzificated value given in eq. (2.3).

The Rule of Fuzzy Inference:

Ri : If X is Ai Y is Bi then Z is Ci $(i=1,\cdots,n)$ (2.1)

The Fitness of the i-th Rule:

Fi=FAi(X)•FBi(Y) (2.2)

Defuzzification:

$$Z = \frac{\sum_{i=1}^{n} F_i \bullet C_i}{\sum_{i=1}^{n} F_i} \tag{2.3}$$

Membership function and the deduced action clause of each rule are determined automatically based on the sensor measurement region, sensor precision, usable sensor region for each environment and effect from each environment to the measurement value. In this way, the system can estimate the maximum measurement error easily when the sensor is replaced. The membership function has the shape of trapezoid in this chapter. Representation of the membership function for the i-th sensor measurement region is shown as Fig. 2.2. Figure 2.3 shows the system outline of error estimation fuzzy inference.

mem[0]=r[0][i]
mem[1]=r[0][i]+p[i]•(r[1][i]-r[0][i])
mem[2]=r[1][i]-p[i]•(r[1][i]-r[0][i])
mem[3]=r[1][i]

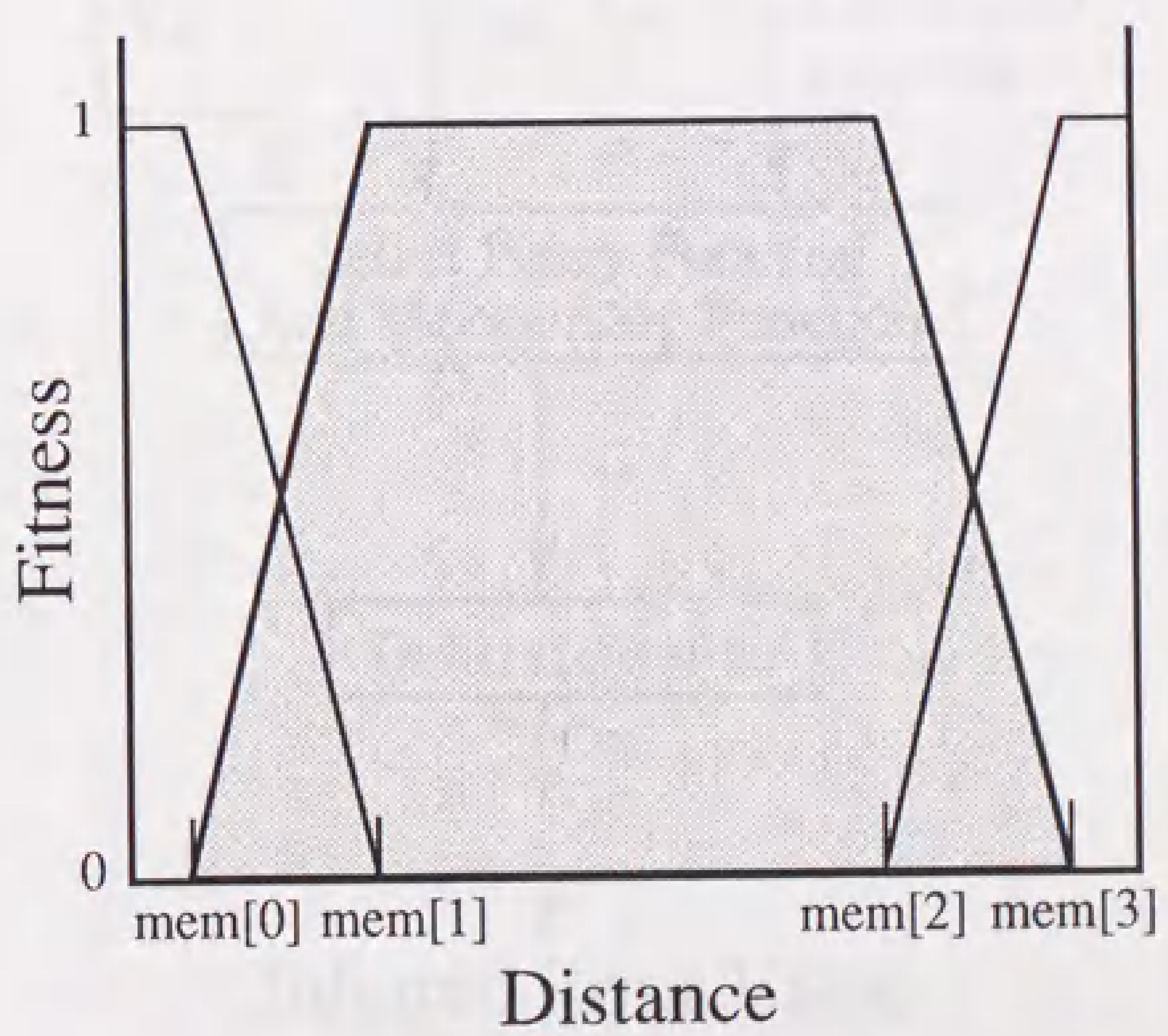


Fig. 2.2 Membership Function

r[0][i] : Lower limit of the i-th sensor measurement region
r[1][i] : Upper limit of the i-th sensor measurement region
p[i] : Measurement precision of the i-th sensor.

2.2.4 Neural networks

The neural networks (NN) is expressed as an artificial mathematical model. Characteristics of NN are : 1) A large and varied quantity of inputs can be processed quickly by parallel distributed processing, 2) NN gives expected outputs based on learning, 3) NN gives almost the expected outputs against inputs without learning experience, if learning patterns are optimized. 4) NN can change the processing pattern not by changing the NN's program but by changing NN's learning pattern.

The NN's learning method adopted here is the back propagation method [Rumelhart et al., 1986]. The NN is used for the integration of measurement values from multi-sensors. According to the NN's 4th characteristics, by changing the learning data patterns, we can integrate a new multi-sensor system. The input/output relationship is represented as follows:

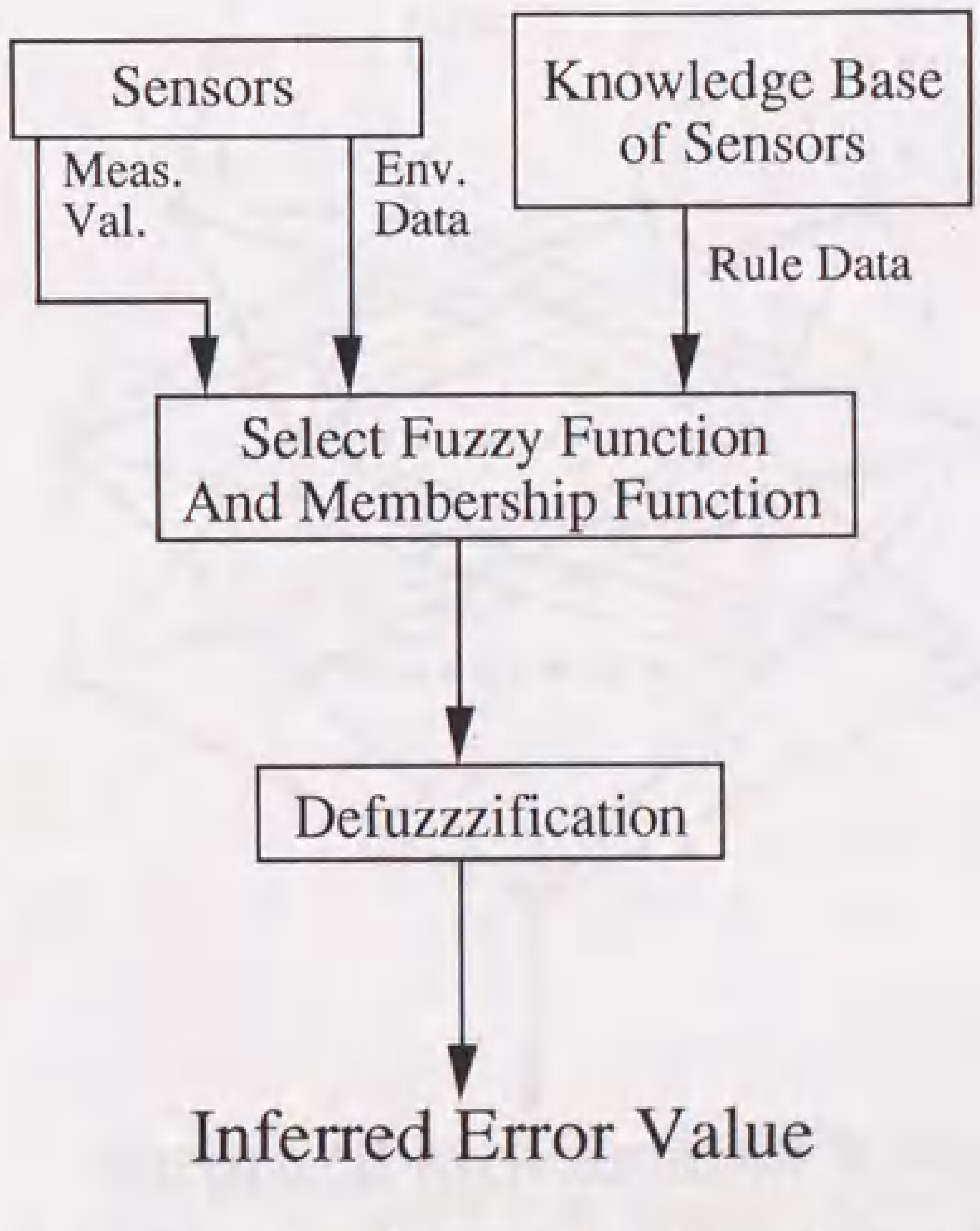


Fig 2.3 System outline of error estimation with fuzzy inference

$$\mathrm{Unit}i=\sum_{j=1}^{J} \mathrm{W}ij \bullet \mathrm{O}j+\mathrm{B}i \qquad (2.4)$$

$$\mathrm{O}j = f(\mathrm{Umit}j)$$

$$f(X) = 1/(1+\exp(-X))$$

Unit i : Input value of the i-th Unit

Oj : Output value of the j-th Unit in the previous layer (j=1,,,,J)

Wij : Weight connecting the j-th Unit with the i-th Unit

Bi : Bias of the i-th Unit

f(X) : Sigmoid function.

Learning is carried out by changing connection weights. When an input pattern is p, the output of the i-th unit is Opi, and the expected output of the i-th unit is Dpi. The error function E is defined by eq.(2.5). Connection weights are changed in order to reduce the value of E. Connection weights change is given by eq.(2.6), where h is the coefficient of learning:

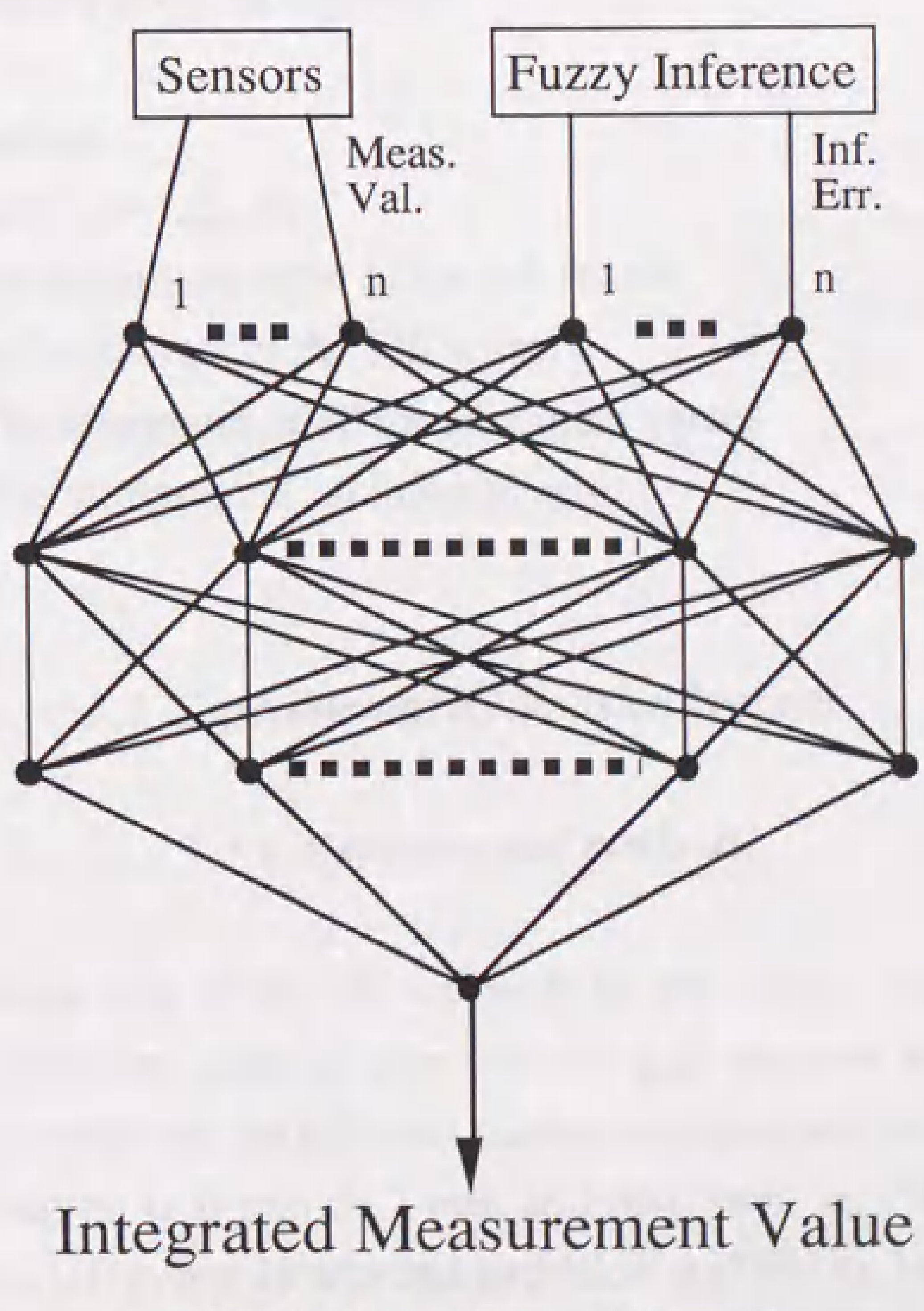


Fig. 2.4 Outline of Neural Networks

Error function:

$$E = \sum_{i=1}^{I} \frac{\left(D_{pi} - O_{pi}\right)^2}{2} \tag{2.5}$$

Value of changing connection weight:

$$\Delta W_{ij} = \eta \frac{\partial E}{\partial W_{ij}} \tag{2.6}$$

In this chapter, we use 4-layered NN employing 2 hidden layers and one input/ output layers. It is true 3-layered NN are adequate to express the nonlinear function. But 4- layered NN can express the nonlinear function by less number of hidden layer's units than 3-layered NN. In the case of applying to complicated sensor system, learning time will increase, but learning time problem will be solved by using the hardware system.

Figure 2.4 shows the outline of NN used in this chapter. NN's inputs are the normalized measurement values and the normalized inferred error values of each sensor. These values are given as follows:

Mi*=Mi/Mmax
Ei*=Emin/Ei (i=1,2,,,,n)
Mi : Measurement value of the i-th sensor
Ei : Inferred error of the i-th sensor
Mmax : The maximum of all measurement values
Emin : The minimum of all inferred errors.

2.3 Experimental methods and results

2.3.1 Experimental methods

Learning pattern data of the NN are made by the sensor simulator. Simulated sensors are two different type of non-contact gap sensors which are used in experiments. Each sensor has the different measurement region and precision. Sensor 1's measurement region is 0 mm to 2 mm and precision is $1*10^{-6}$ m. Sensor 2's measurement region is 0 mm to 10 mm and precision is $1*10^{-5}$ m. The sensor simulator is designed considering the following matters: 1) measurement region, 2) resolution of

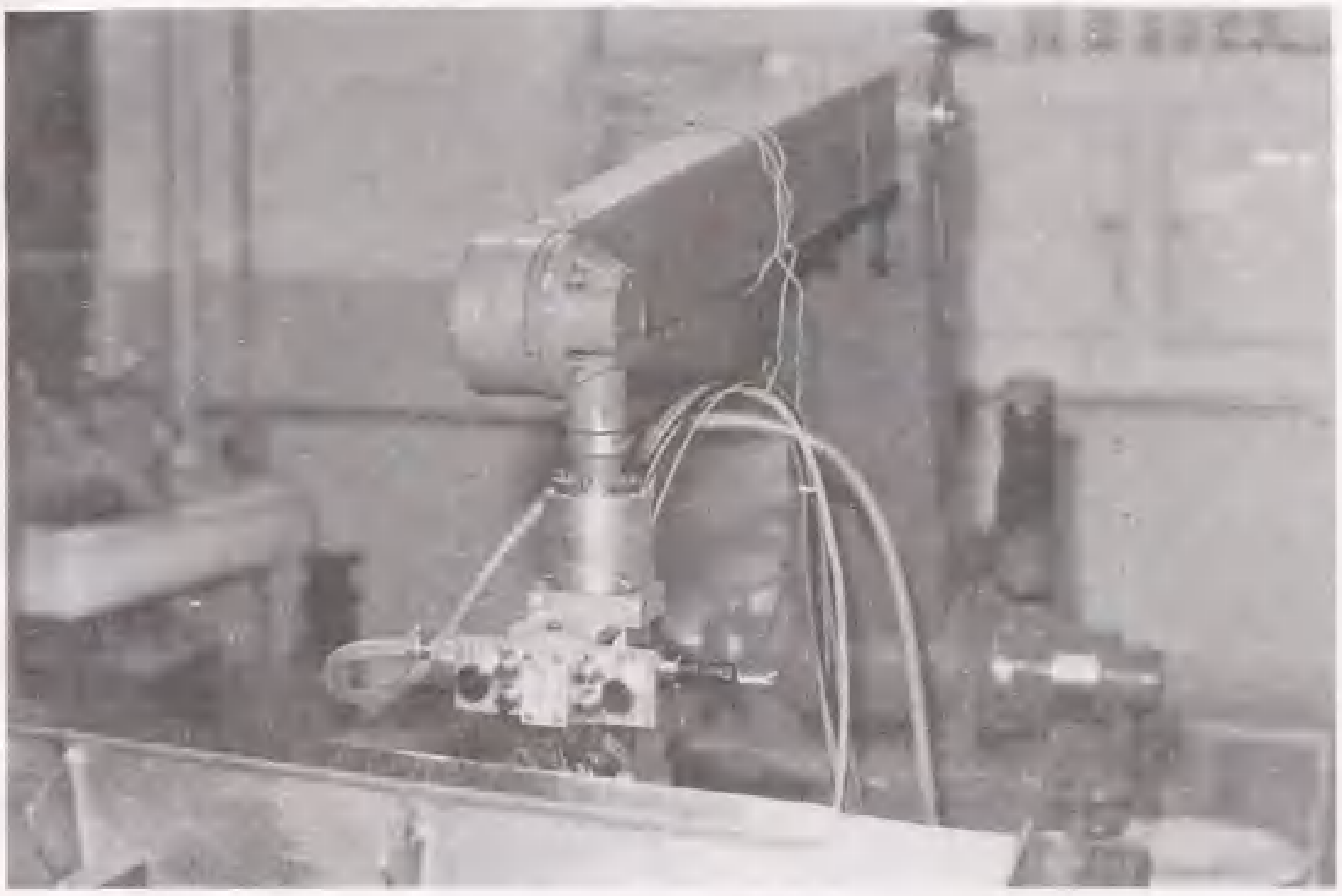


Fig. 2.5 Experimental system

the A/D board and 3) setting position of two sensors.

The experiments are carried out by changing distance between sensors and the measurement object. Each sensor is set at the tip of 5 axis industrial robot shown in Fig. 2.5. As the robot moves, the distance between the sensors and the object, which is the surface of metal materials, changes. These changes are measured by all sensors at the same time. The measurement unit of sensors is voltage, and each data is got into the memory by the A/D board. Then it is transferred into the computer.

When we use multiple distance measurement sensors, the offset caused by the difference in each sensor's setting position is the most important. It is very difficult to cancel this offset because the offset value cannot be obtained. Based on the offset values, the selection of best sensor is changed. In this experiment, when sensor 1 is closer to the object than sensor 2, we define the offset as "plus", and when sensor 2 is closer to the object than sensor 1, the offset is "minus".

Experiments are carried out 3 times. At first, sensors are installed so that the offset is nearly equal to 0 m. Secondly, sensors are set so that the offset is to be "plus" by adjusting the sensor 1's position. Finally, sensors are set so that the offset becomes "minus" by adjusting the sensor 1's position.

In these experiments, three methods of SIS are used:

1) If Clause : When measurement value of sensor 2 is within the measurement region of sensor 1, sensor 1's measurement value is selected. (See Fig 2.6)

2) Fuzzy Inference : The sensor having the minimum inferred error which is

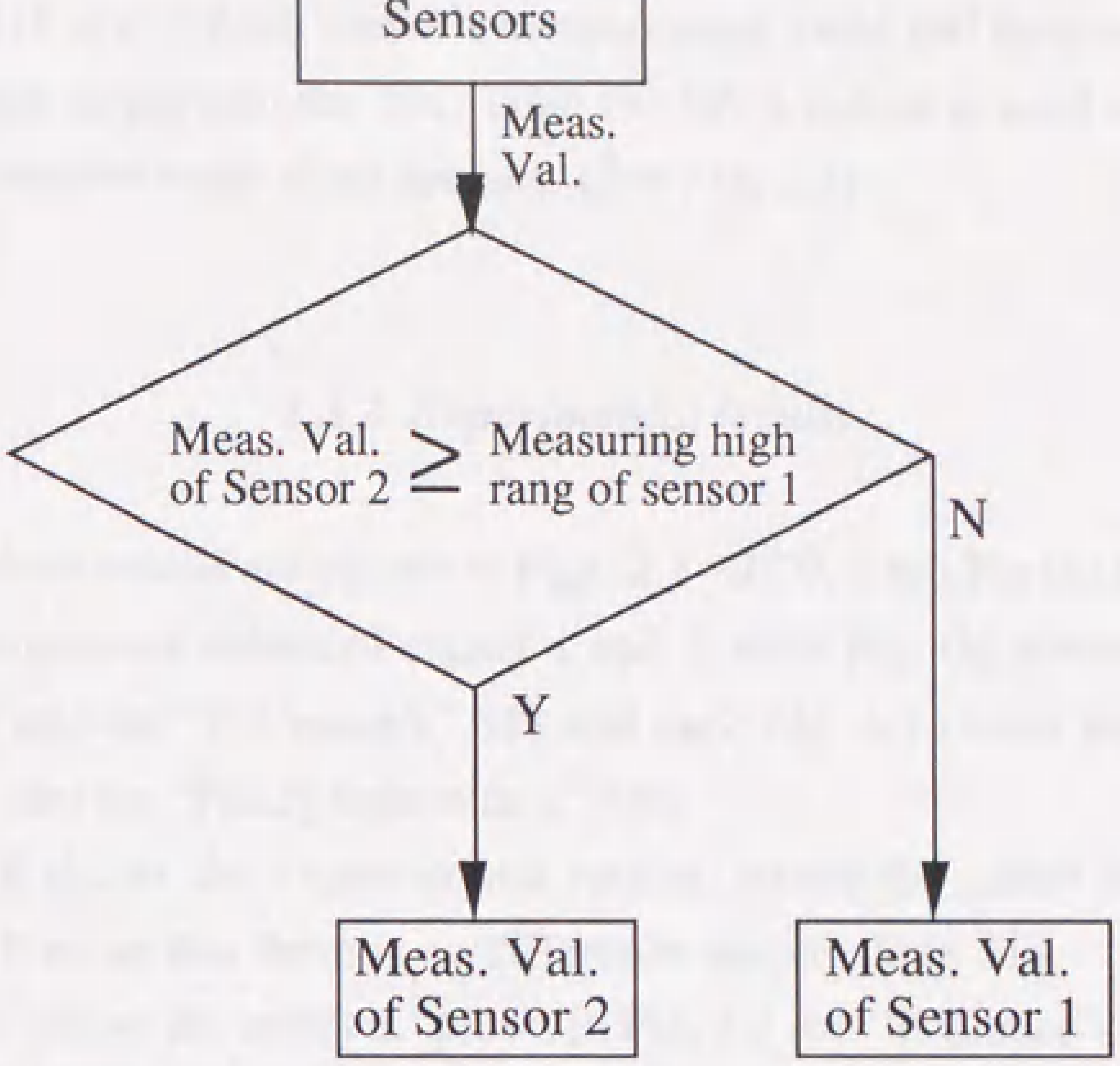


Fig. 2.6 "If Clause's" SIS block diagram

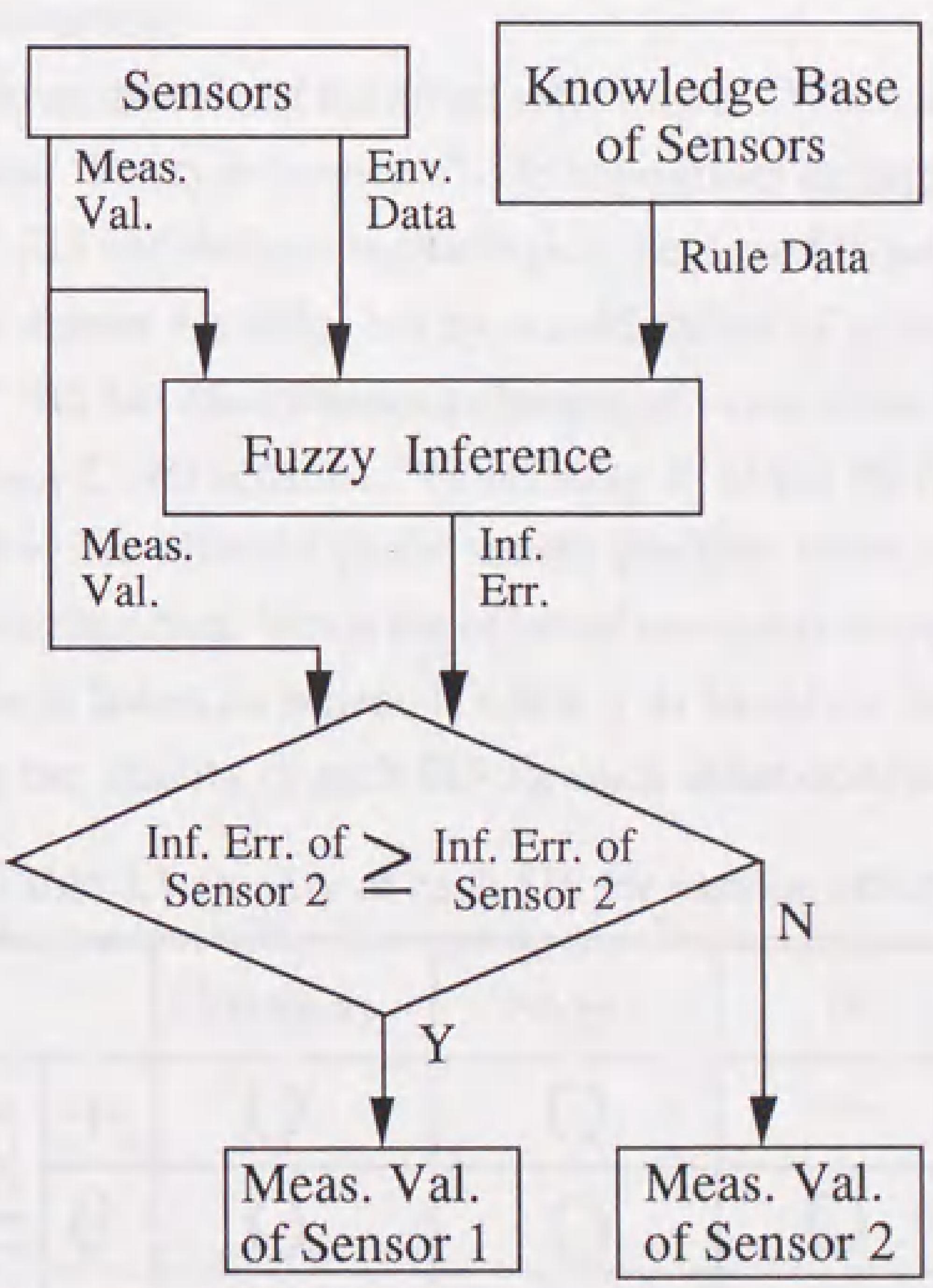


Fig. 2.7 "Fuzzy's" SIS block diagram

estimated by the fuzzy inference of all sensors is selected. (See Fig. 2.7)

3) NN+Fuzzy : Each sensor's measurement value and inferred error by fuzzy inference is put into the NN. Then the NN's output is used as the integrated measurement value of all sensors. (See Fig. 2.1)

2.3.2 Experimental results

Experimental results are shown in Figs. 2.8 - 2.10. Each Fig (a) in Figs. 2.8-2.10 shows the measurement values of sensor 1 and 2, each Fig. (b) shows outputs of the "NN+Fuzzy's" and the "If Clause's" SIS and each Fig. (c) shows the outputs of the "NN+Fuzzy's" and the "Fuzzy Inference's" SIS.

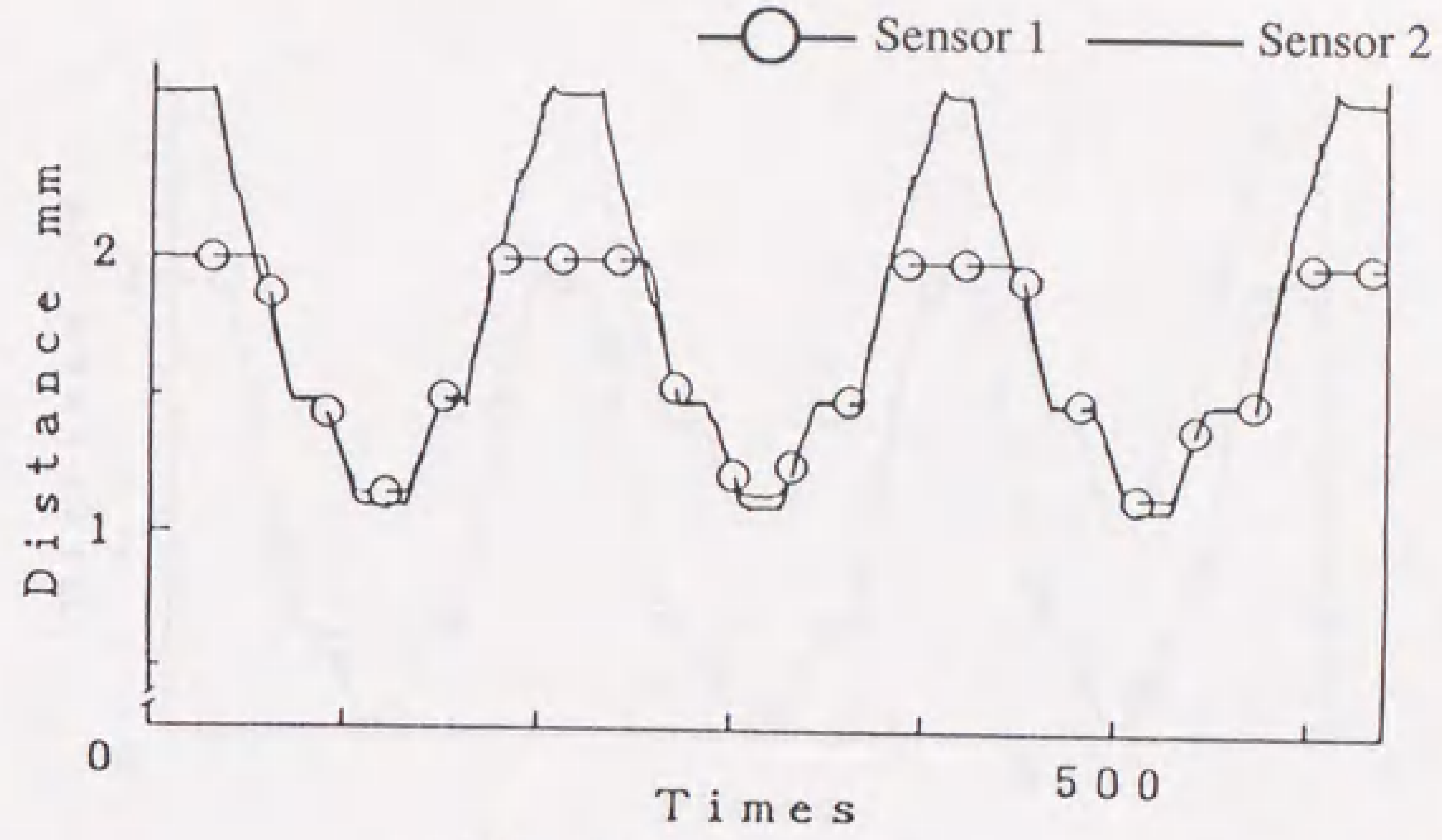
Figure 2.8 shows the experimental results, where the offset of sensor sets is nearly equal to 0 m, so that there is no difference among three SIS.

Figure 2.9 shows the offset is "plus". In Fig. 2.9 (b), "If Clause's" SIS cannot use the sensor 1 efficiently, because sensor 1 is only selected when the measurement value of sensor 2 is in the measurement region of sensor 1. Other systems can use sensor 1 when sensor 1 is measurable.

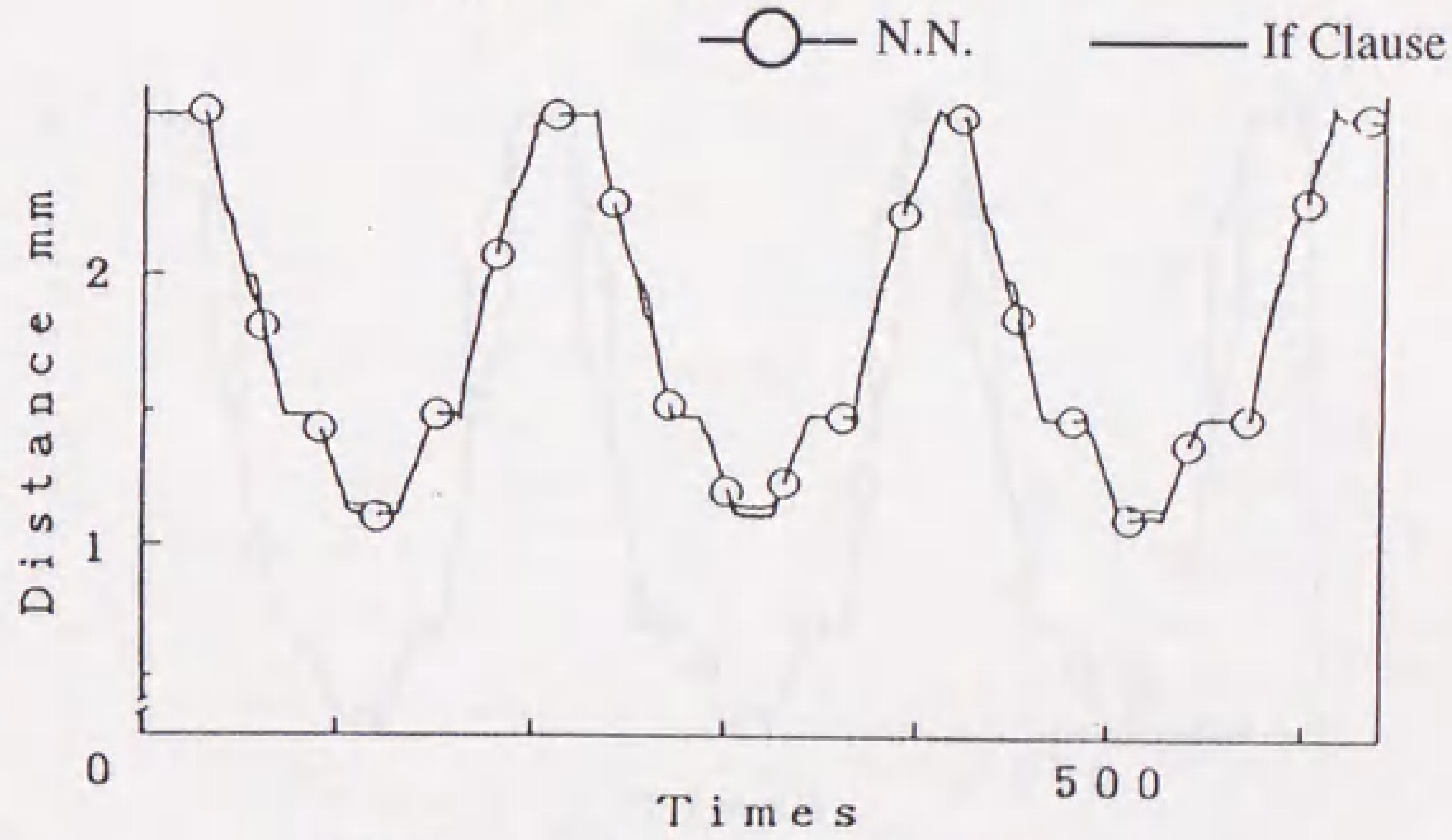
Figure 2.10 shows the case of the offset sets "minus". When SIS selects sensor 1, both "If Clause's" and "Fuzzy Inference's" SIS have errors as large as the value of the offset. "If Clause's" SIS had the insensitive region, because SIS selects sensors not by consideration of the sensor 1's state, but by consideration of sensor 2's. As well, the "Fuzzy Inference's" SIS has discontinuous changes of value when SIS selects sensor 1 over sensor 2 or sensor 2 over sensor 1. "NN+Fuzzy's" SIS is the least error system of all, because this SIS is not affected by the sensor position offset. This is achieved by considering NN's learning data. When the offset of sensors is larger than 0 m, then the NN's expected value is based on sensor 1, while it is based on sensor 2 for the other case. Table 1 shows the quality of each SIS for each offset condition.

Table 2.1 Quality of each SIS for various offset

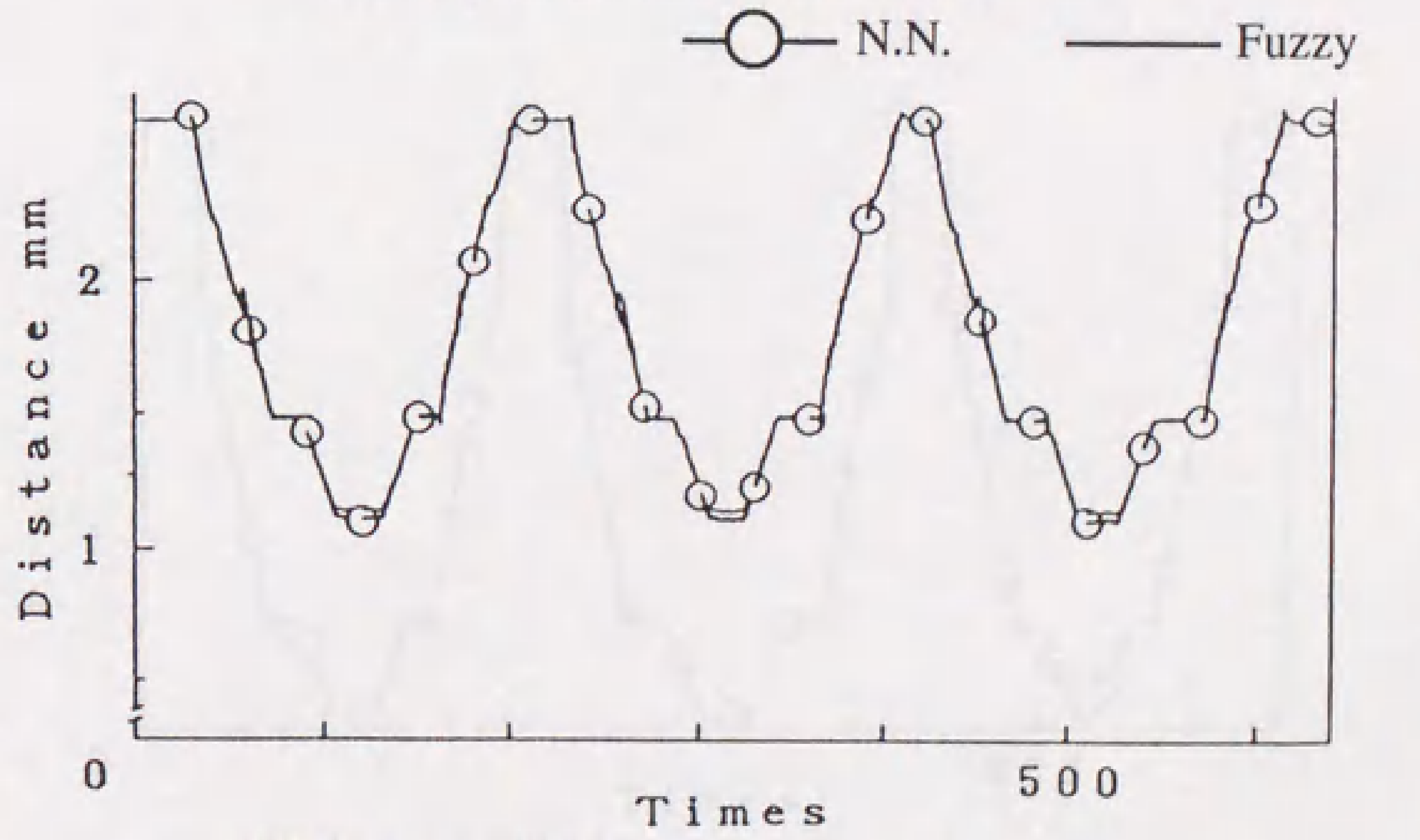
		NN+Fuzzy	Fuzzy	IF
offset	+	O	O	—
	0	O	O	O
	-	O	—	—



(a) Sensor Data 1 and 2.

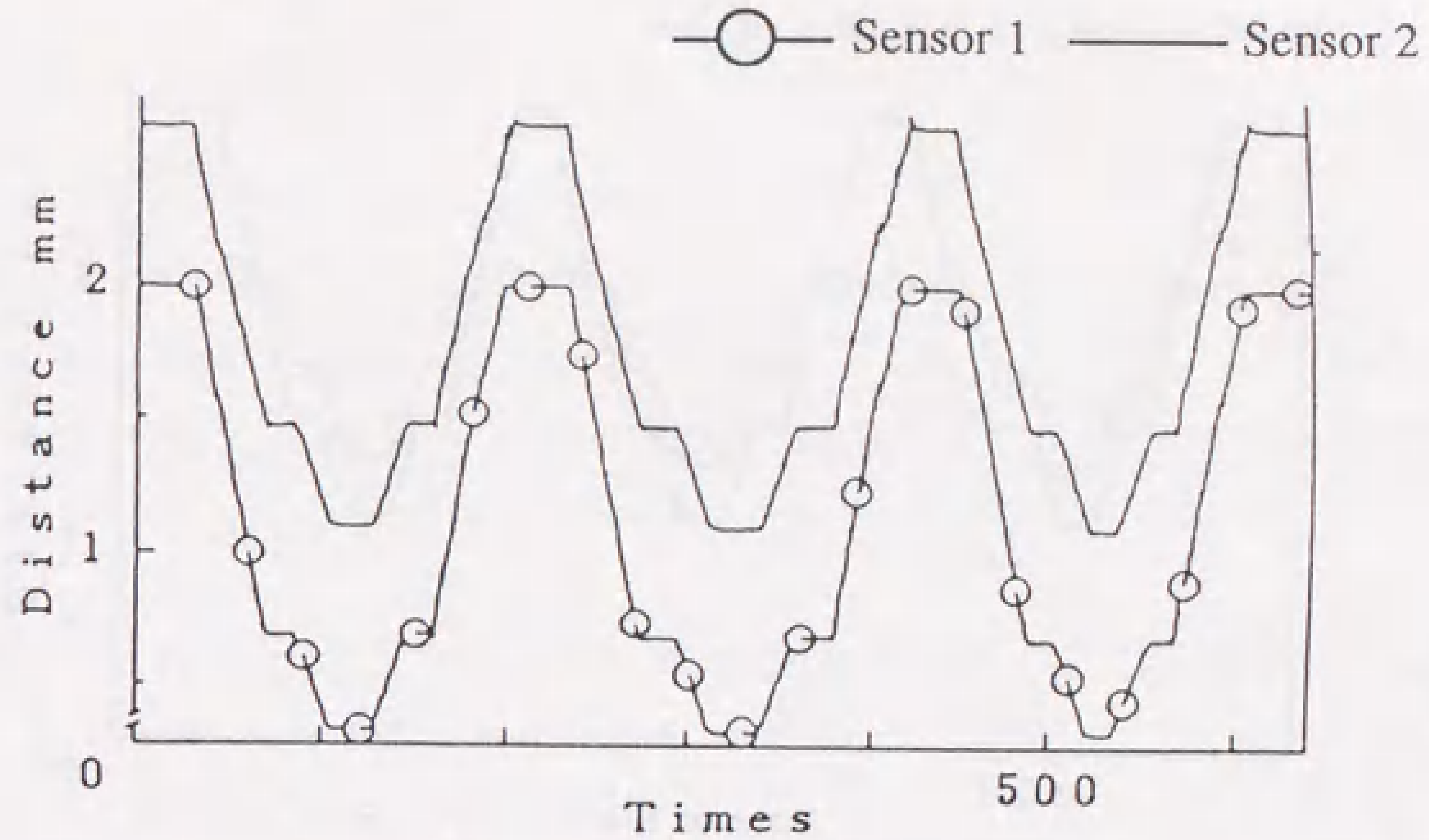


(b) Outputs of N.N. and If Clause

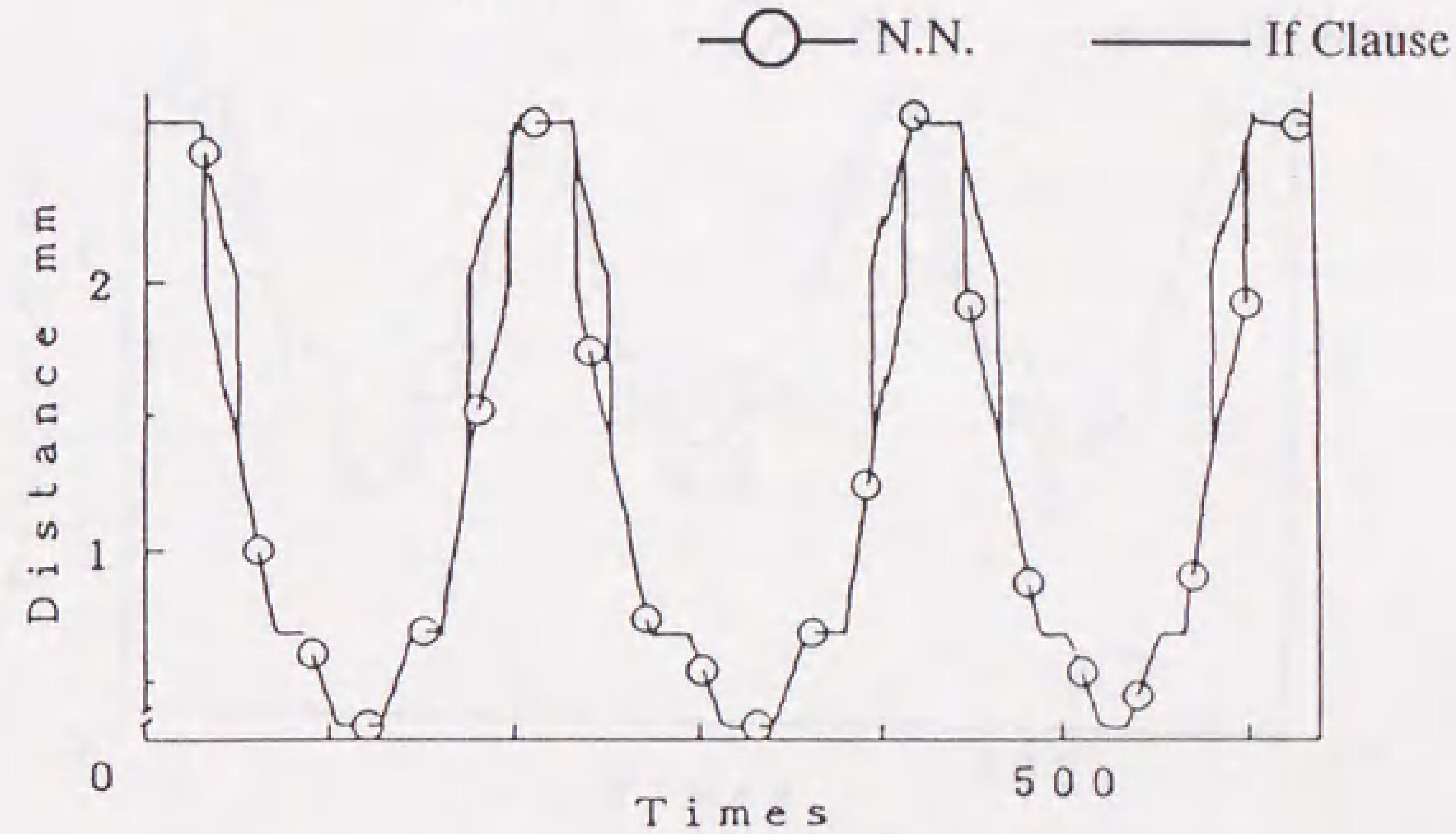


(c) Outputs of N.N. and Fuzzy Inference

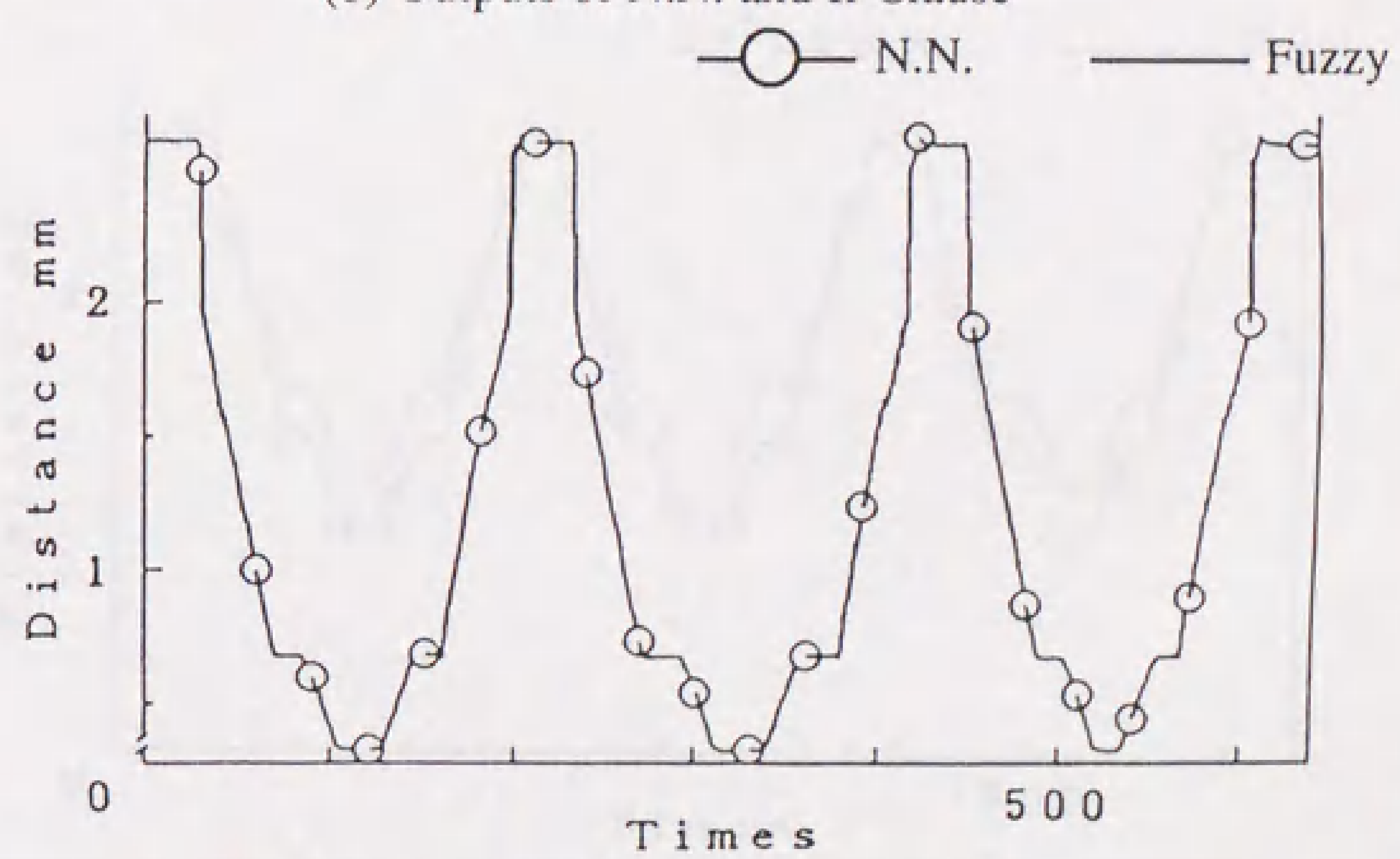
Fig 2.8 Experimental result (Offset=0).



(a) Sensor Data 1 and 2.

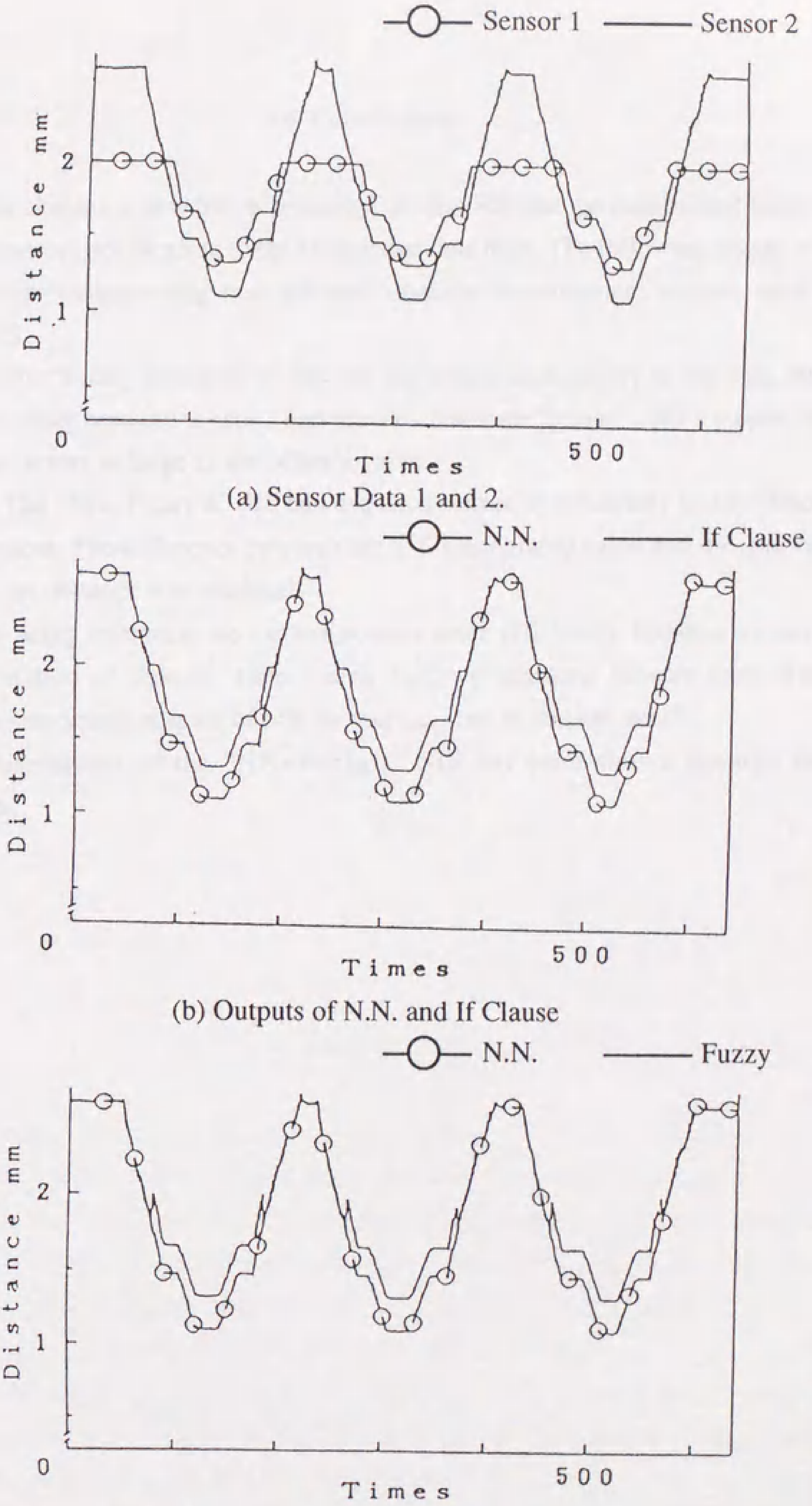


(b) Outputs of N.N. and If Clause



(c) Outputs of N.N. and Fuzzy Inference

Fig 2.9 Experimental result (Offset +).



(a) Sensor Data 1 and 2.

(b) Outputs of N.N. and If Clause

(c) Outputs of N.N. and Fuzzy Inference

Fig 2.10 Experimental result (Offset -).

2.4 Conclusions

In this chapter, a new SIS is proposed, so that SIS can be constructed easily by linking the sensor specification to the knowledge data base. The following results were shown by experiments using two different distance measurement sensors with the proposed SIS:

1) The "Fuzzy Inference's" SIS can use sensor 1 efficiently all the time. But if the offset between sensor 1 and sensor 2 becomes "minus", SIS's output value has errors as large as the offset's value.

2) The "NN+Fuzzy's" SIS can use each sensor as efficiently as any states of sensors. The difference between the SIS's integrated value and the true value of the distance was minimal.

Using fuzzy inference, we can use sensors more efficiently, because we can get more information of sensors' state. Using NN, we can treat sensors more freely, because we can design outputs of NN for various state of sensors easily.

The usefulness of the "NN+Fuzzy's" SIS has been shown through these experiments.

3. *Multi-Sensor Integration System based on Fuzzy Inference and Neural Networks for Industrial application*

This chapter deals with a multi-sensor system applied to unknown curved metal surface cutting robot system. This system cuts products using the data of works' surface shape which are obtained by the measurement. Measurement is done by sensors set on array at the tip of the five axis manipulator. Sensor array is carried to the target surface by moving the manipulator. The manipulator approaches to the surface using sensors' outputs.

For precise cutting, measurement of work's surface is done by high accurate sensors. However these sensors do not have long measurement range. On the other hand, in order to approach to the work fast, the system should use long measurement range sensors. For precise cutting and fast approaching, the system should use both high accurate sensors and long measurement range sensors. In order to use these sensors effectively, we use the multi-sensor integration system based on the **neural network** and **fuzzy inference** techniques. Then the system can consider the angle between sensors and the object. With consideration of the angle, approaching time is improved. The proposed system is shown to be effective through extensive experiments.

3.1 Introduction

To remake a metal product from a warp-old-product, automated manufacturing systems with robots are not applied widely. The shape of target product is complicated and different from new one, therefore most of these manufacturing are executed by experts. But the number of experts is reducing in recent years and it takes a long time to become an expert. So automated manufacturing systems are desired to be applied to remake these unknown and complex surface profile products.

For the automatic operation, the present robotic systems are not suitable. Because some of these systems need CAD data of target product or force-torque sensor data in order to make a cutting path. The former systems need many CAD data for cutting objects which are different from a standard one [Proctor 1989]. The latter systems cannot cut the object precisely because these systems cannot analyze force or torque in accuracy and they do not have any information of the final shape of object [Yoshida 1989].

To solve the problems of automatic operation, we proposed an automated cutting system [Fukuda 1990] which makes the cutting path by measuring and recognizing each surface of the target's object. A series of action of this system is classified into three processes. The first process is approaching. The start, center and end positions of the scanning path of the target's surface are decided in this process. At first, the sensor system is set at a short distance from the target's surface. Then the sensor system approaches to the surface using measurement values of the sensor system. Next process is scanning of the surface. The system gets surface data of the target in this process. The final process is cutting with the surface data of the second process.

The system is classified two parts. One is the sensor system which has some and different specific sensors and is used to measure a distance and angles between sensor array and the object in the approaching and scanning process. Other part is a cutting tool and a six axis force-torque sensor used in the final process.

We can improve the efficiency of total system by reducing time of the approaching process. Only this process has the ability to reduce the time. For quick approaching, the system has some different specific sensors. But the use of multi-sensor makes two great problems. One problem is how to use the suitable sensors for sensing situation and quick approaching. Another problem is how to reduce the effect of the failed sensors. Failed sensor sometimes does harm to the sensor system such as crash with the target object.

To solve these problems, we used the multi-sensor integration system (SIS) based on the neural network (NN) and fuzzy inference. Considering the condition of sensing from fuzzy inference, this SIS can use the sensor system efficiently and finish the approaching process in short time. Also we use NN to detect sensor conditions, by which the system can go on working the task even if sensors are failed.

In our experimental system, we consider the angle between sensors and target the object. The effect of this SIS is shown through extensive experiments.

3.2 Multi-sensor integration system based on neural networks and fuzzy inference.

For precise cutting, we must use the high accurate sensor. But this sensor is not suitable for approaching, because the measurement range is narrow and the sensor system cannot move long distance nor change its orientation very much. If we use the long measurement range sensor, the system can move long distance or change its orientation widely. But it is not good for the planning of scanning path because the accuracy of sensor is low and the decided path is not appropriate. The suitable sensor system is the combination use of high accurate sensors and long measurement range sensors.

Multi-sensor system has some problems. One is how to use the most suitable sensor for the measuring the object. It is difficult to use some different specific sensors together. Because the most suitable sensor will be changed by the situation of sensing. If the system does not use the suitable sensor data, the efficiency of the system will be degraded. For example, so long as the system uses the highest accurate sensor in most of the approaching process, it takes more time in approaching than in case that the system uses the most suitable sensor according to the measuring situation. Another problem is that failed sensors data sometimes cause accident or damage to the system.

In this system, sensors are controlled by multi-sensor integration system based on the neural network and fuzzy inference. This SIS computes the suitability of each sensors for sensing the object based on the fuzzy inference and uses the most suitable

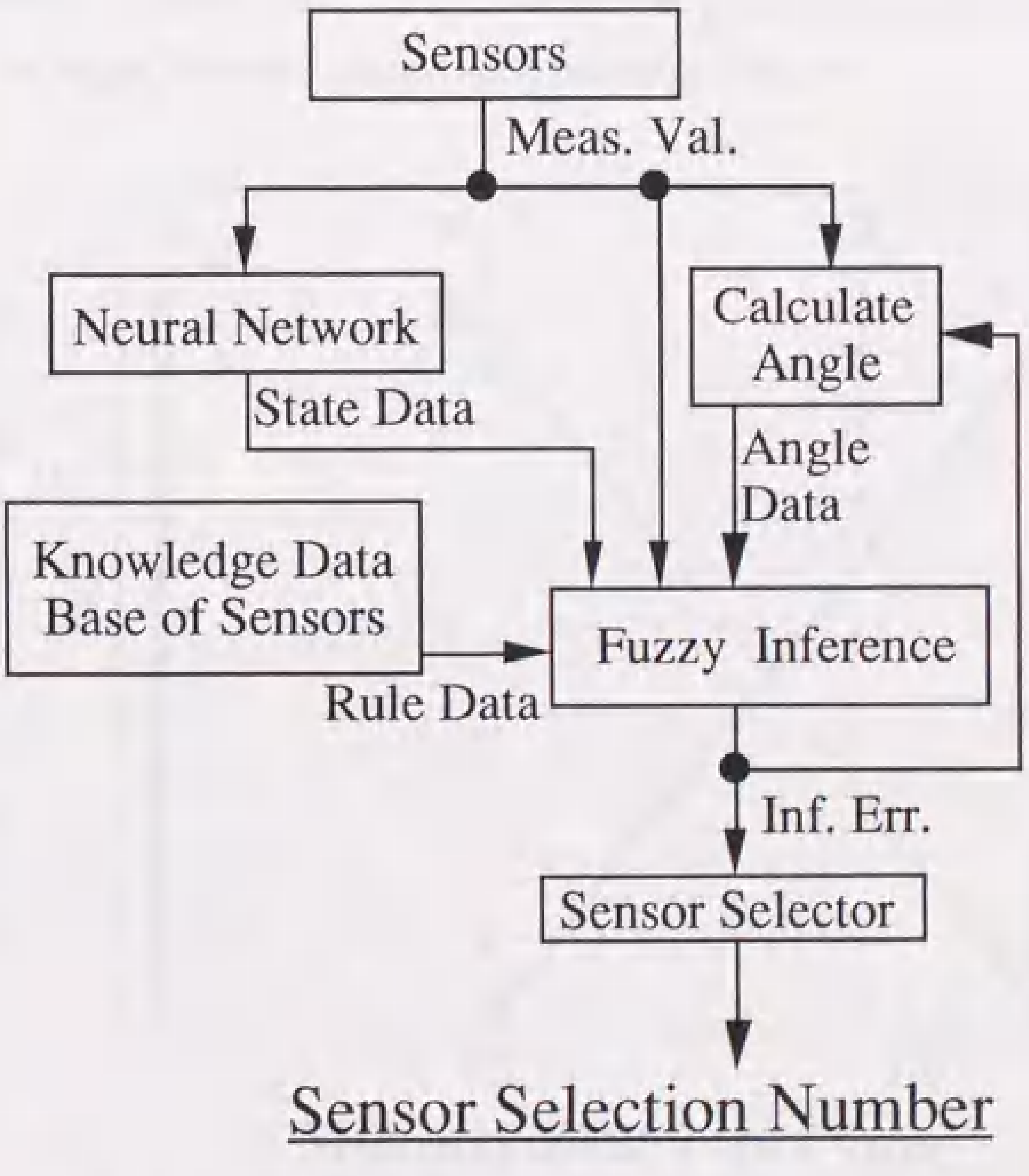


Fig. 3.1 Multi-sensor integration system

sensor. Also it can recognize and eliminate the failed sensor data by NN.

SIS consists of five parts as follows.

(1) Sensing devices

(2) Knowledge data base of sensor

(3) Fuzzy inference

(4) Neural network

(5) Calculator of angle

Figure 3.1 shows SIS's outline. In Fig. 3.1, Meas. Val. refers to sensor outputs, Inf. Err. means the inferred errors by fuzzy inference, Angle Data refers to the information of angle, State Data refers to the state of the sensors, that is, sensor is normal or not, which is estimated by the neural network.

3.2.1 Knowledge data base of sensor

Knowledge database of sensor (KBS) is written about specifications of sensors in the system. KBS consists of measurement range, measurement accuracy, sensor's environments and the grades of its influence. In our experiments, sensor's environment is an angle between a sensor and a target object, because sensors in our system are influenced by the angle between sensors and the target object.

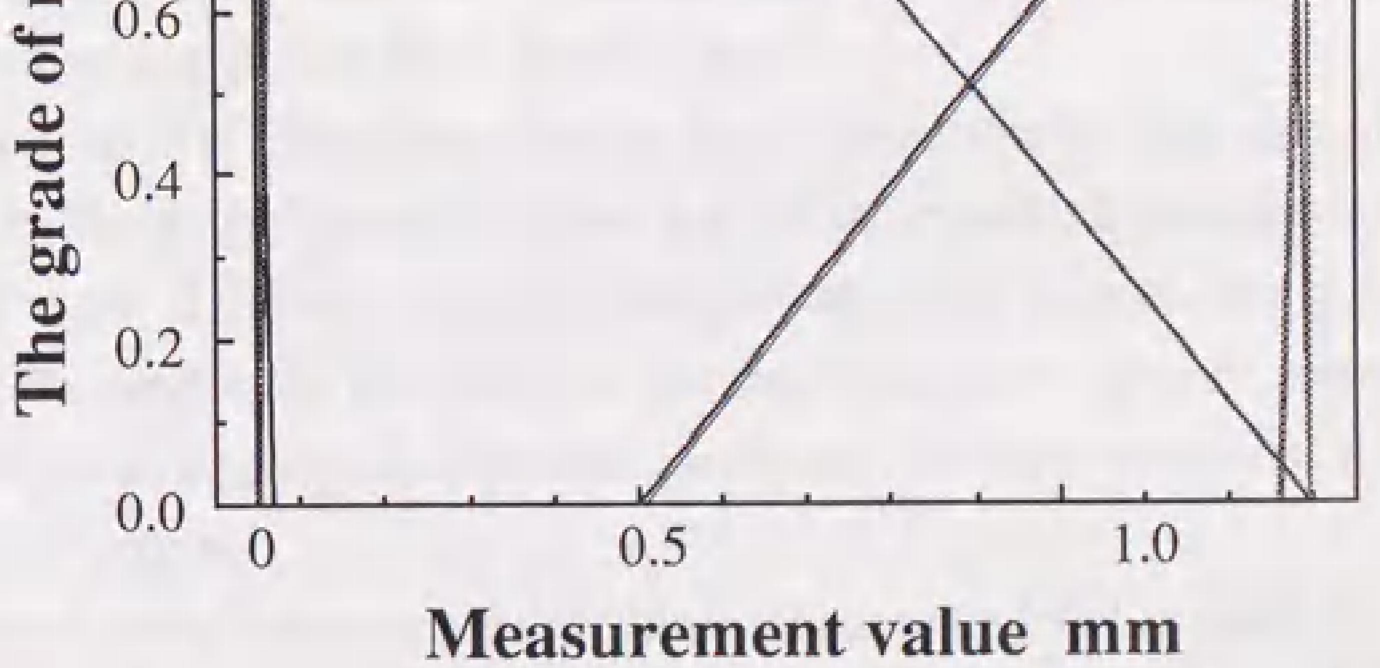


Fig. 3.2(a) Membership function of measurement range (Sensor 7 - 10)

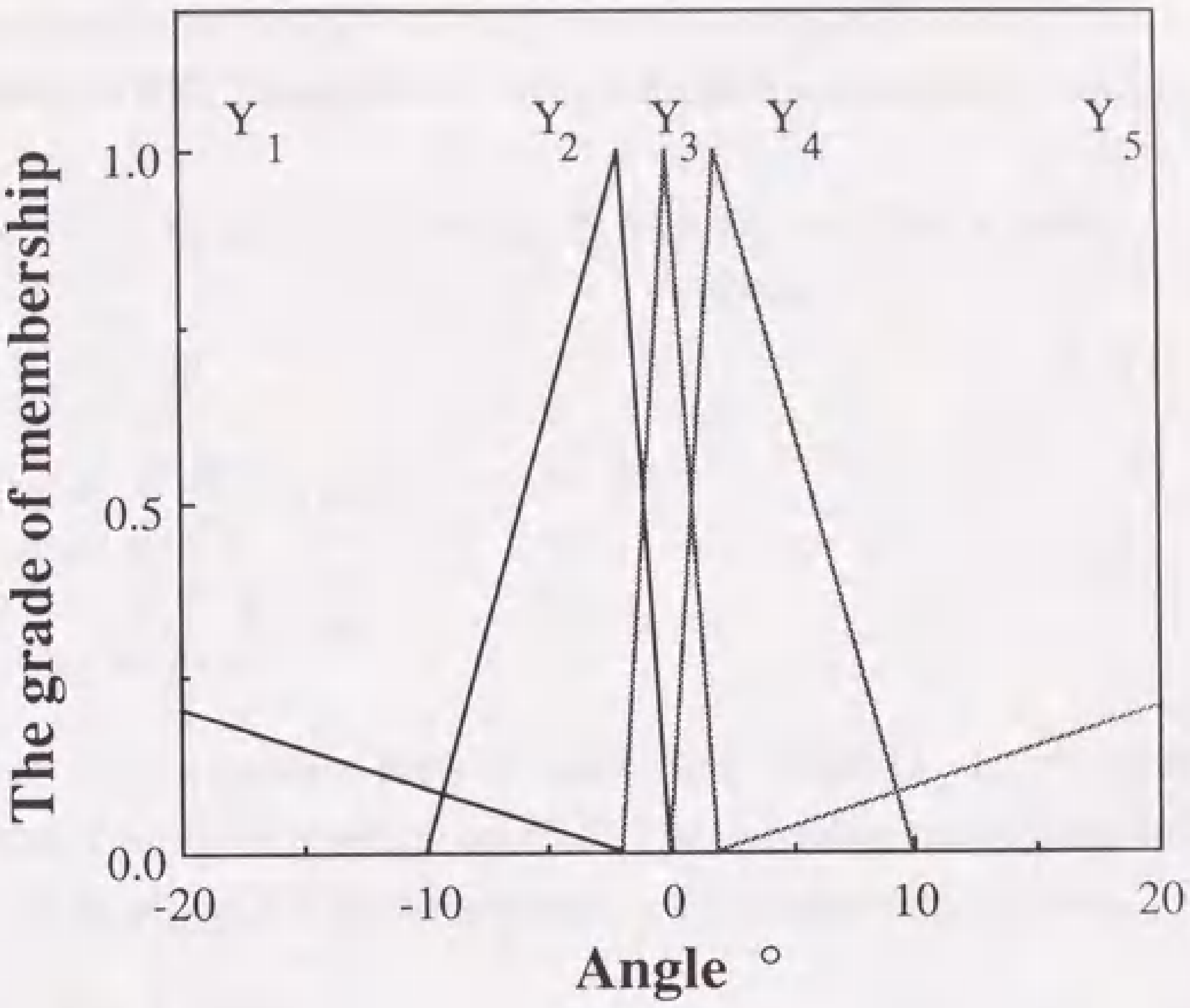


Fig. 3.2(b) Membership function of angle between the sensor and the target object. (Sensor 7 - 10)

3.2.2 Fuzzy inference

Measurement error of sensor is caused by sensor environments such as temperature, humility and so on. Fuzzy inference can treat some vague values. Most of the environmental data of sensor are vague. Therefore we use fuzzy inference to estimate the suitability of sensor for measuring. Inputs of fuzzy inference are a sensor output and information of sensor's environments. The output of fuzzy inference is a measurement error included in the sensor's output.

We use ten non-contact gap sensors in our experiments. This type of sensor is influenced by the angle between sensors and the target object. Measurement error is changed by angle. If the angle is large, measurement error is large. The high accurate sensor is influenced more than the low accurate sensors by sensor's environmental condition. Recommended environmental condition of the highest accurate sensor is the severest of all sensors.

Inputs of fuzzy inference are individual sensor output and an angle around y and z axis between the target object and the sensors. Output of fuzzy inference is an estimated measurement error. The fuzzy rules are made from the data of sensor specifics written in KBS. Equations of fuzzy inference are written as follows.

$$\text{Rijk: If x is } X_i \text{ and y is } Y_j \text{ and z is } Z_k \text{ then } O_{ijk} \text{ is } AX_i + AY_j + AZ_k \quad (i,j,k=1,\bullet\bullet\bullet,5) \qquad (3.1)$$

$$\mu_{ijk} = \mu_i . \mu_j . \mu_k \qquad (3.2)$$

$$O = \frac{\sum_{i=1}^{5} \sum_{j=1}^{5} \sum_{k=1}^{5} \mu_{ijk} \bullet o_{ijk}}{\sum_{i=1}^{5} \sum_{j=1}^{5} \sum_{k=1}^{5} \mu_{ijk}} \qquad (3.3)$$

Equation (3.1) expresses the i-th fuzzy rule, where O_{ijk} is real number. The individual rules' results are given by eq. (3.2). The over-all result of fuzzy inference is given by eq. (3.3). Figure 3.2 shows an example of membership function.

3.2.3 Neural networks

Artificial neural network (NN) is one of the mathematical models of neuron. We use three layered NN as judgment of sensor state. The number of units of the input layer is ten, the hidden layer is thirty and the output layer is ten.

Inputs of NN are all of sensor outputs and each NN's output is reliability of the individual sensors' outputs.

Learning data set consists of two cases, one means all sensor is normal and another means some sensors are failed. We decide the training data as follows,

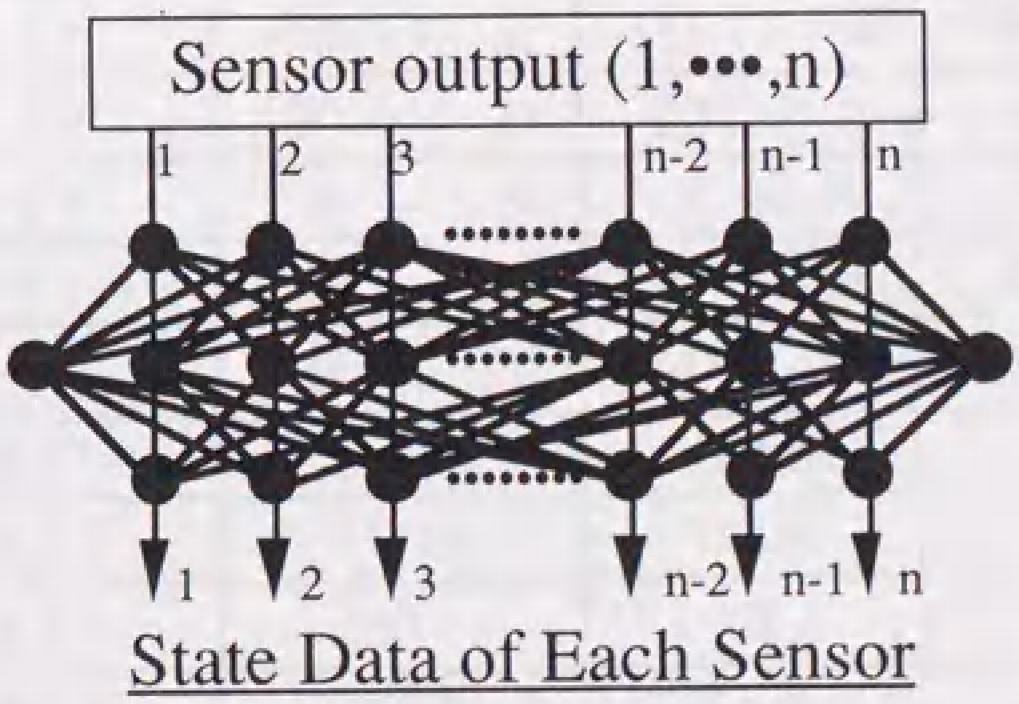


Fig. 3.3 Estimation of sensor state by neural network

(1) When the sensor is failed and the sensor's output is obviously different from other sensors' outputs, the training signal is set as 0.

(2) When the sensor is normal, or the failed sensor's output is obviously same as others, training signal is set as 1.

In the system, if NN's output O_i is,

(1) Oi>0.5, SIS recognizes the i-th sensor as normal.

(2) Otherwise, SIS recognizes the i-th sensor as a failed sensor.

Learning method is back propagation algorithm [Rumelhart 1986]. Figure 3.3 shows the outline of NN.

Table 3.1 Sensor specifics

		Sensor 1,2	Sensor 3~6	Sensor 7~10
Range (mm)		-3.15 ~ 6.85	-0.02 ~ 1.98	0 ~ 1.25
Accuracy (%)		1.0	0.5	0.3 ~ 1.2
Membership	X1	-3.15 ~ -2.95	-0.02 ~ 0.0	0 ~ 0.0075
	X2	-3.15 ~ -2.95	-0.02 ~ 0.0	0 ~ 0.0075
	X3	-3.15 ~ 6.85	-0.02 ~ 1.98	0 ~ 0.50
	X4	6.65 ~ 6.85	1.96 ~ 1.98	0.45 ~ 1.25
	X5	6.65 ~ 6.85	1.96 ~ 1.98	1.235 ~ 1.25
Error mm	AX1	0.15	0.24	0.250
	AX2	0.10	0.01	0.015
	AX3	0.10	0.01	0.00375
	AX4	0.10	0.01	0.015
	AX5	0.15	0.24	0.250
Membership	Y1	-90 ~ -6	-90 ~ -4	-90 ~ -2
	Y2	-30 ~ 0	-20 ~ 0	-8 ~ 0
	Y3	-6 ~ 6	-4 ~ 4	-2 ~ 2
	Y4	0 ~ 30	0 ~ 20	0 ~ 8
	Y5	6 ~ 90	4 ~ 90	2 ~ 90
Error mm	AY1	0.15	0.24	0.250
	AY2	0.001	0.10	0.15
	AY3	0	0	0
	AY4	0.001	0.10	0.15
	AY5	0.15	0.24	0.250

3.2.4 Calculator of angle

In this part, two directional angles between sensors and the target object are calculated from sensors' outputs. Each angle is calculated from all of same directional combinations of sensors' outputs as follows.

$$q_i=\tan^{-1}\{(y_{i1}-y_{i2})/d_1\} \qquad (3.4)$$
$$E_i=e_{i1}+e_{i2} \qquad (3.5)$$

where i is the sensor combination number, y_{i1},y_{i2} are sensors' outputs of the i-th combination, ei1, ei2 are measurement errors of the i-th combination, d_i is a distance between combination sensors. The combination of sensors which has the minimum measurement error of all combinations is used as angle data.

3.3 Experiments and results

3.3.1 Experiments

We made experiments with five axis industrial robot manipulator and the sensor system (see. Fig. 3.4 and 3.5) mounted at the tip of the manipulator. Sensor system

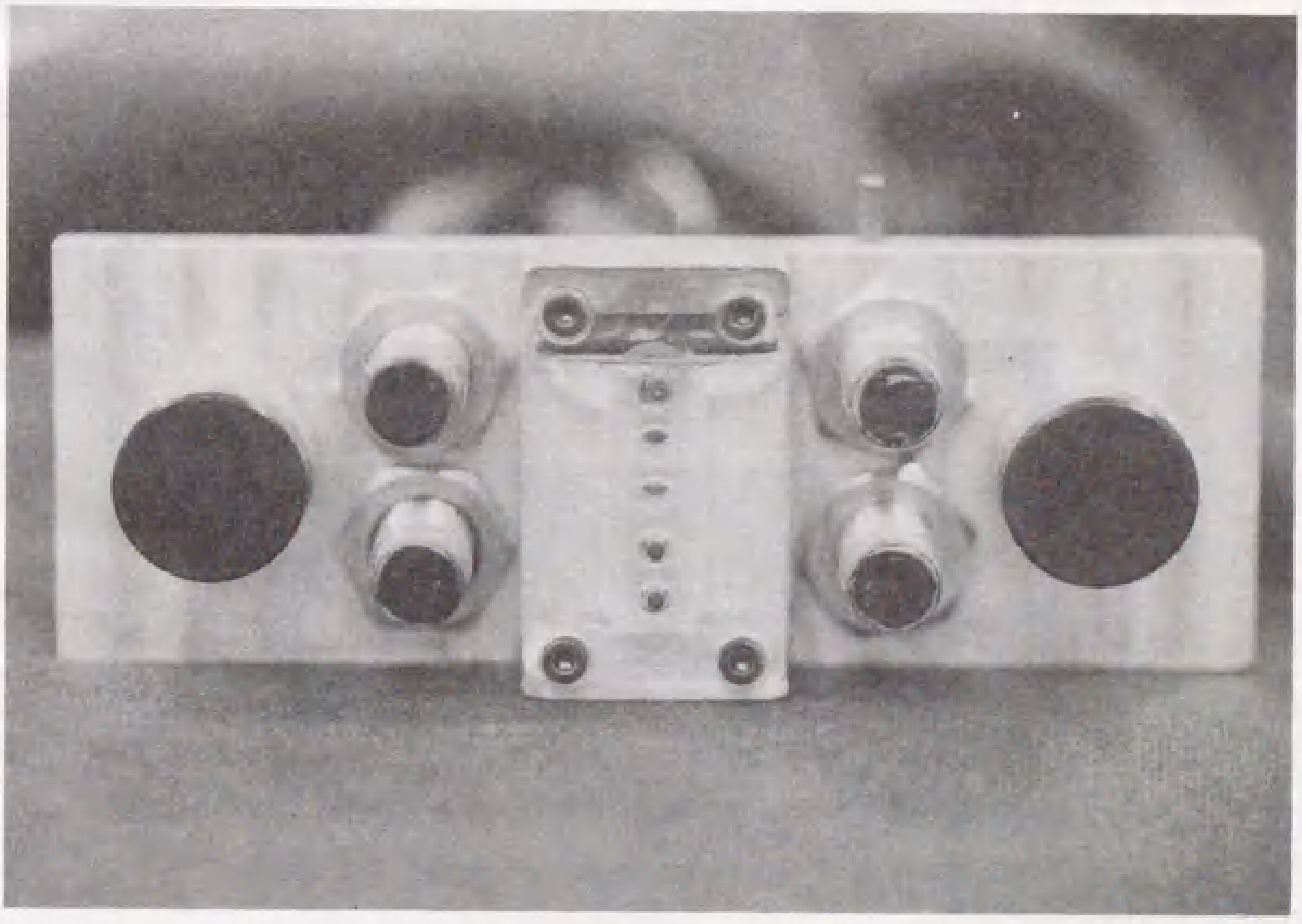
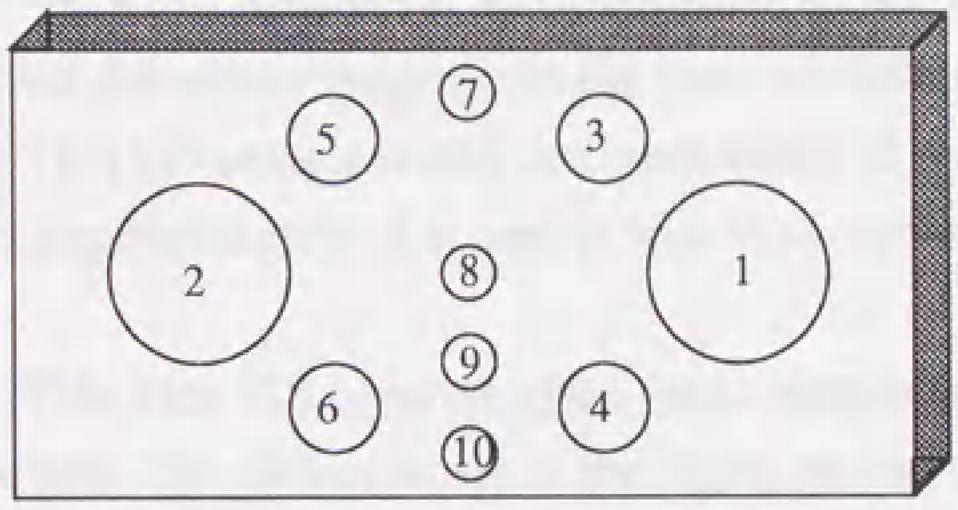
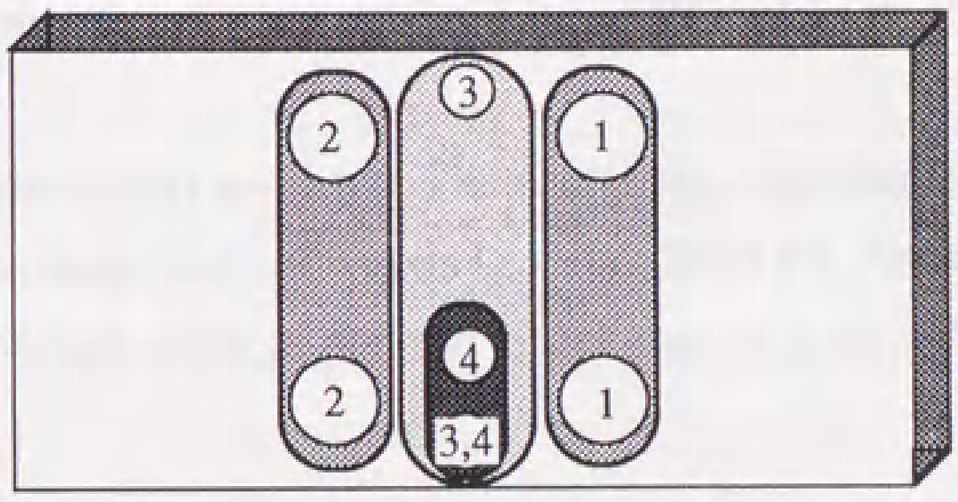


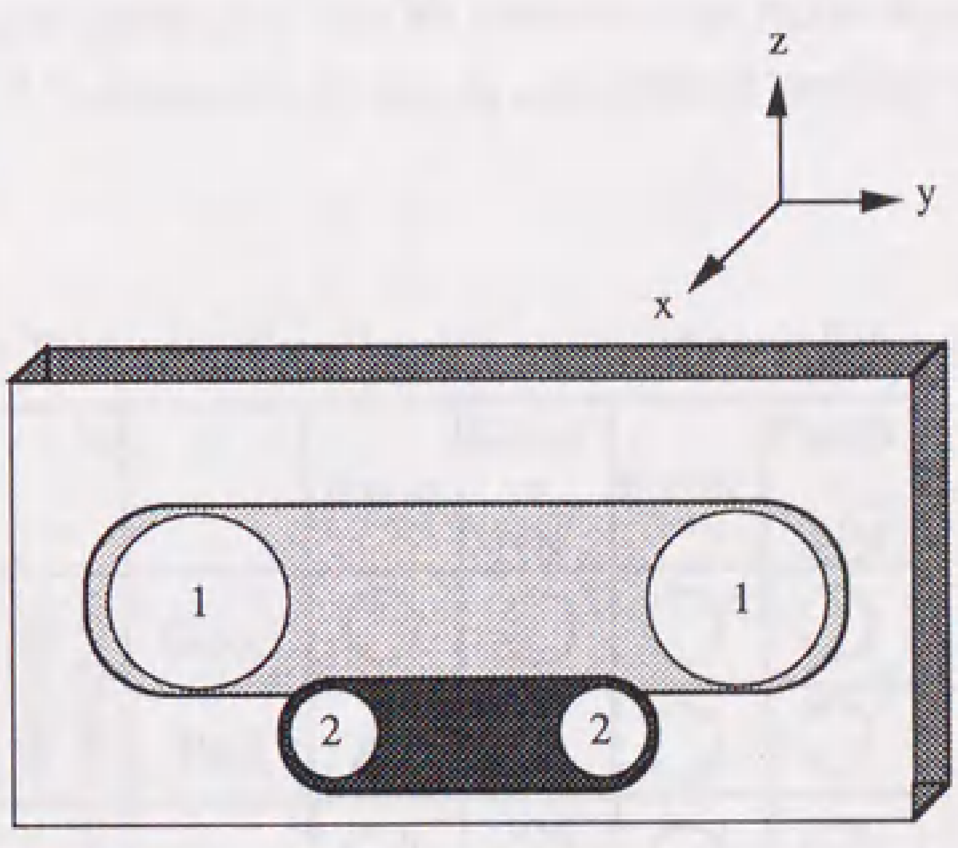
Fig. 3.4 Sensor array



X direction and sensor number



Sensor combination number for measure the angle around y axis



Sensor combination number for measure the angle around z axis

Fig. 3.5 Sensor system and sensor combination.

consists of ten sensors. Sensor's measurement range and accuracy are shown in Table 3.1.

We experimented on the approaching process about each four SISs as follows.

(1) Basic SIS: This SIS selects the high accurate sensor or combination of sensors whenever the sensor output is in the measurement range.

(2) Fuzzy SIS: This SIS selects sensor or combination of sensors according to the value of measurement error. The sensor with minimum measurement error is used.

(3) Basic+NN SIS: This SIS consists of the basic system and NN.

(4) Fuzzy+NN SIS: This SIS consists of the fuzzy system and NN.

In the approaching process, the manipulator is controlled to x direction, angle around y axis and angle around z axis while approaching to the target object. We limited the maximum angle of change at each step in order to approach in safety. The limitation of angle of higher accurate sensors is smaller than that of lower accurate sensors.

We make experiments in two cases. The one is the case that the angle difference between sensors and the target around y axis l exists a little bit. Another is the case that the angle difference between sensors and the target around y axis exists.

3.3.2 Experimental results

Experimental results of approaching process are shown in Fig. 3.6(a) - 3.9(f). Figure 3.6 shows the results in case that all sensors were normal and the angle around y axis was small, Fig. 3.7 shows the results in case that all sensors were normal and the

Table 3.2 The characteristics of each SIS

		Basic	Basic + NN	Fuzzy	Fuzzy + NN
Setting condition	Good	○	○	○	○
	Bad	△	△	○	○
Sensor condition	Normal	○	○	○	○
	Failure	×	○	×	○

angle around y axis was large. Figure 3.8 shows the results in case that sensor 1,2 were failed and the angle around y axis was small and Fig. 3.9 shows the results in case that the angle around y axis was large. Figure (a), (b) and (c) of all Fig. 3.6-3.9 show the sensing process of each direction. Figure (d), (e) and (f) show the approaching process. When all sensors were normal (Fig. 3.6 and 3.7), the results of the basic+NN SIS were equal to the basic SIS, because the basic+NN SIS was based on the basic SIS, for the same reason, the fuzzy+NN SIS was equal to the fuzzy SIS.

There is no difference among the results of all SISs in Fig. 3.6, because all SISs used the same sensor or same range sensor in their approaching process.

The fuzzy SIS was able to approach more quickly than the basic SIS in Fig. 3.6. Because the fuzzy SIS used the highest accurate sensors (sensor 7-10) only at the final approach (see Fig. 3.7(b)), and the basic SIS used the sensors more times than the fuzzy SIS did. So the fuzzy SIS changed the angle around y axis more quickly than the basic SIS did in Fig. 3.7(e).

Figure 3.8 and 3.9 show that SIS with NN can approach to the target even if some of sensors are failed. And the fuzzy+NN SIS was able to approach more quickly than the basic+NN SIS (Fig. 3.9). The reason was the same as in case of Fig. 3.7.

SISs without NN were not able to approach to the target, because these SISs used the failed sensors. Table 3.2 shows the effect of each SIS.

3.4 Conclusions

We proposed SIS based on fuzzy inference and neural network and showed effects of the SIS through experiments as follows.

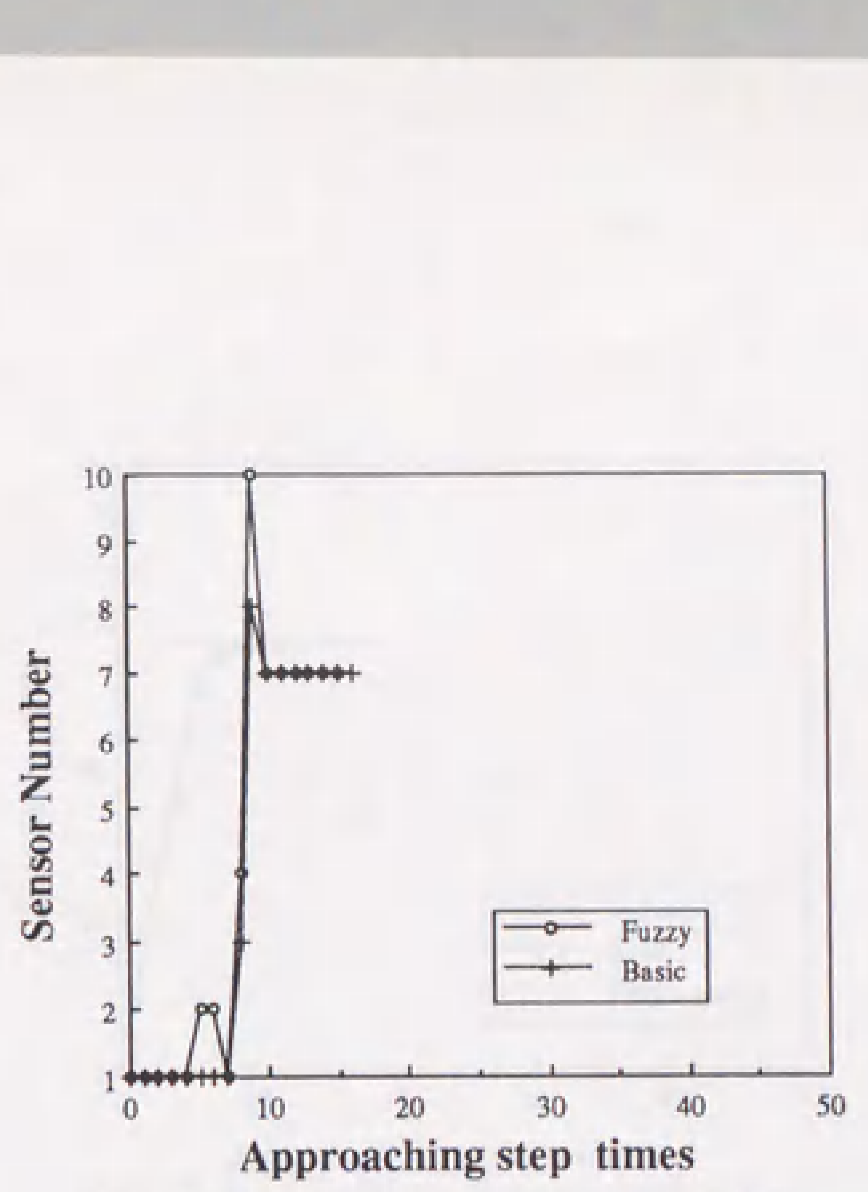
(1) Considering the information of angle between sensors and the target on each sensor as a factor of sensing condition in fuzzy inference, the sensor system could approach to the target effectively at any case of angle difference between sensors and the target.

(2) NN eliminated the failed data of sensors and the system could continue to work in safety even if some of sensors were failed.

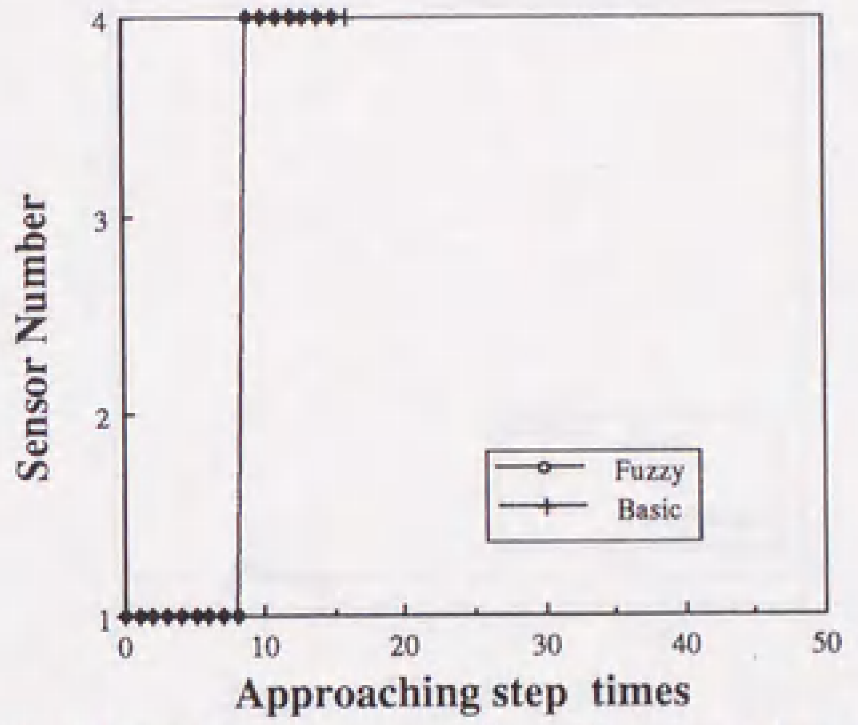
Problems in future are written as follows.

(1) How to get the more accurate information of angle

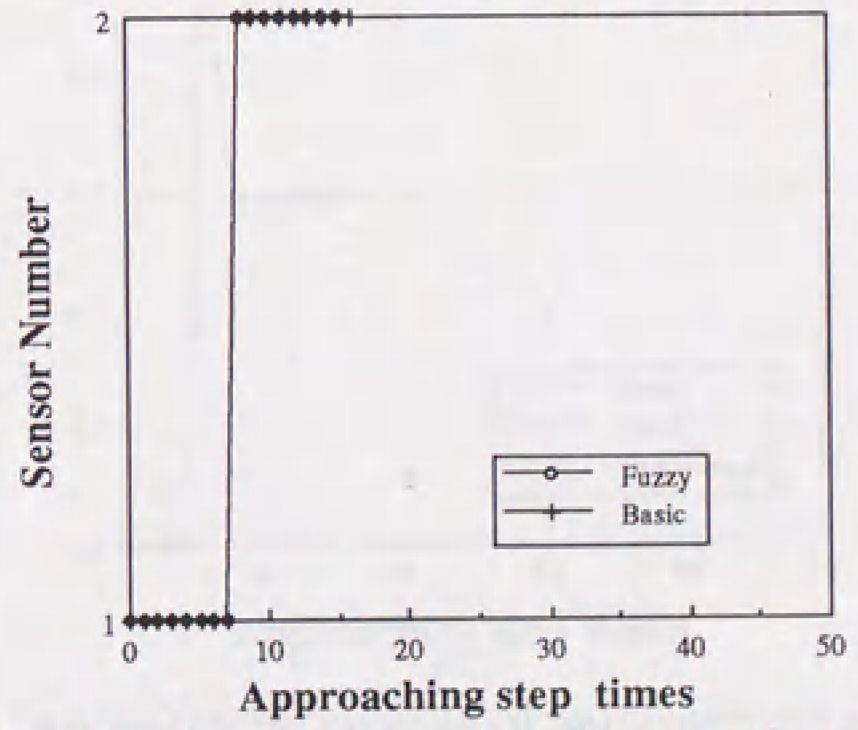
(2) How to optimize the number of units of NN in order to reduce the learning time.



(a) Sensing process of x axis.

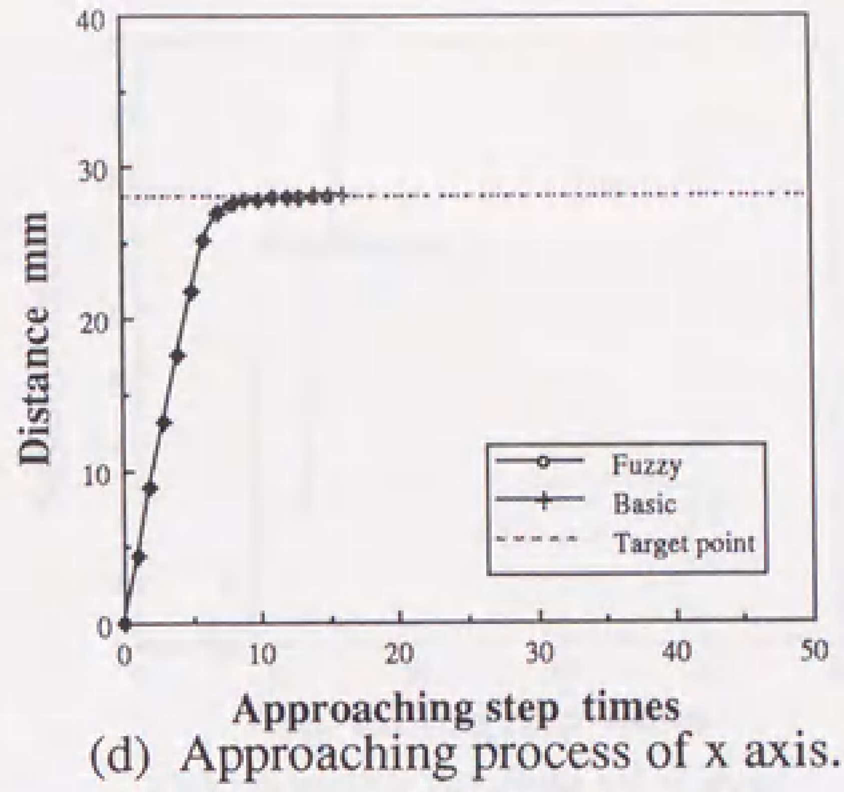


(b) Sensing process of angle around y axis

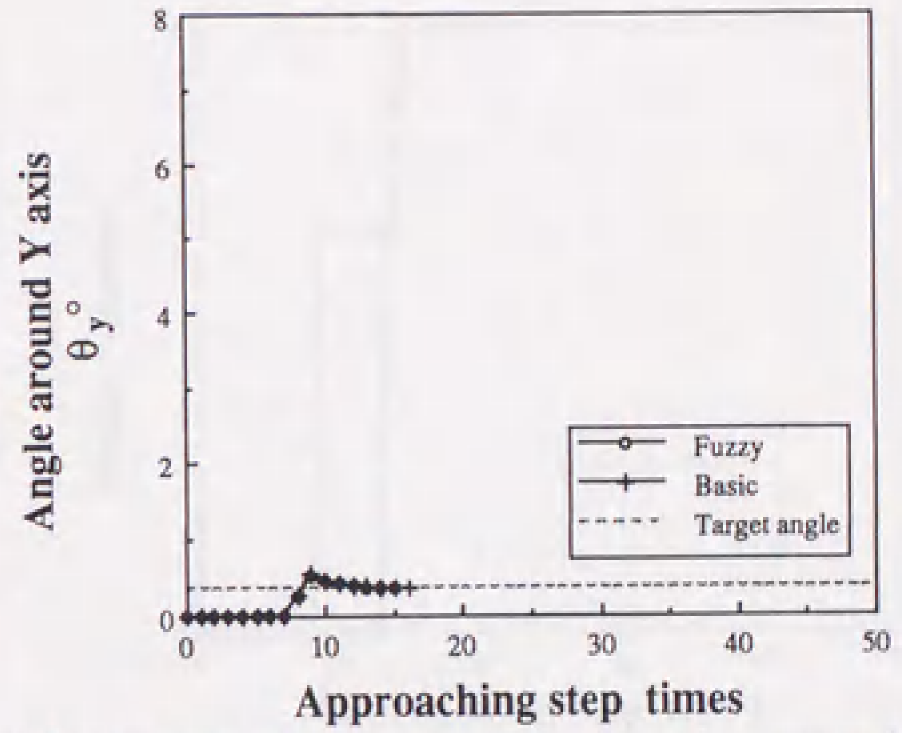


(c) Sensing process of angle around z axis.

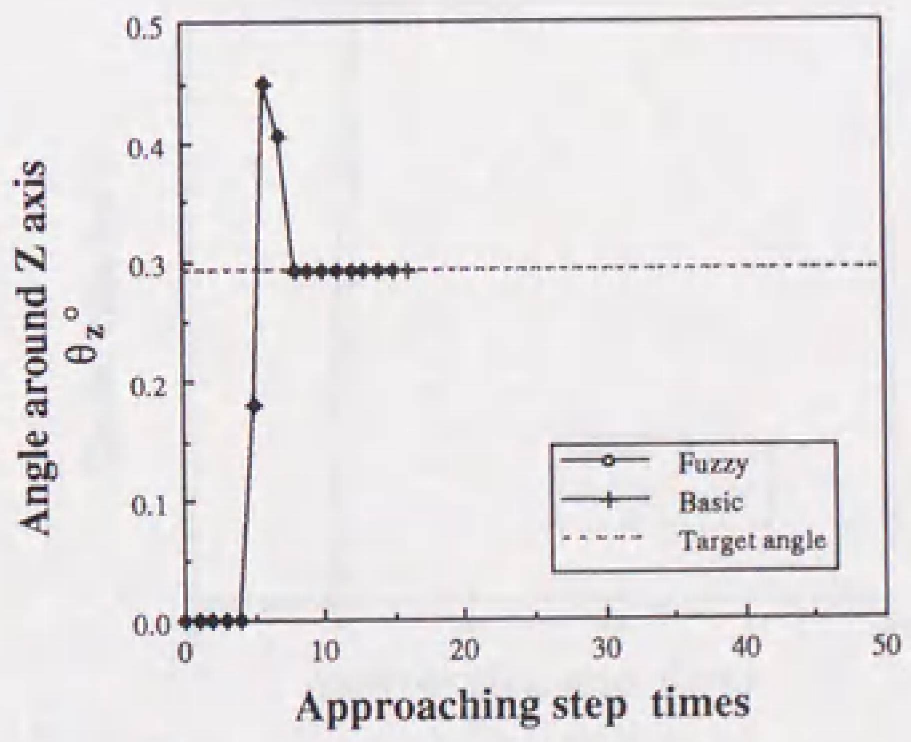
Fig. 3.6 Experimental results.
All sensors were normal and the initial angle around y axis was small.



(d) Approaching process of x axis.



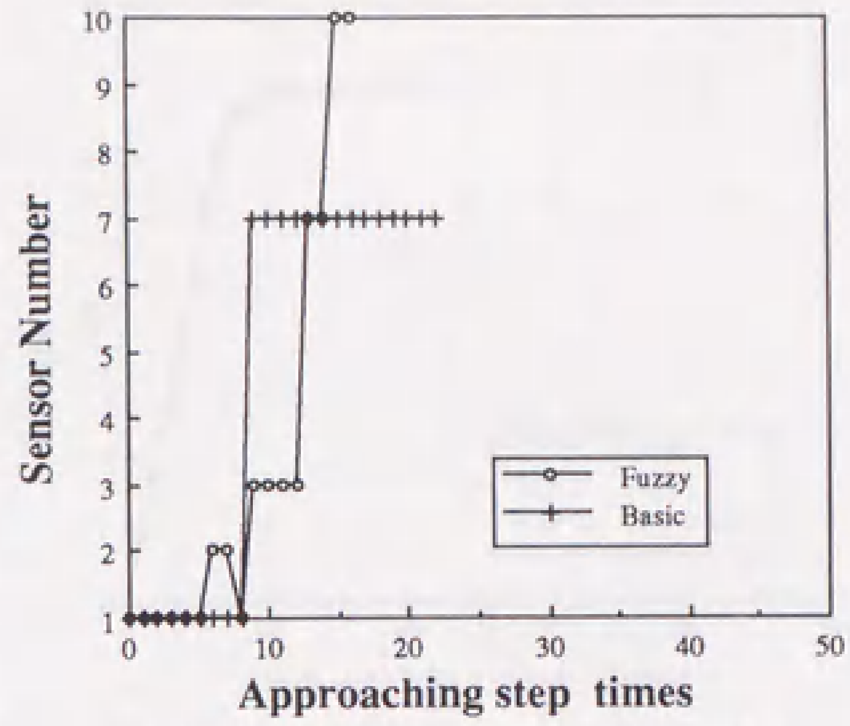
(e) Approaching process of angle around y axis.



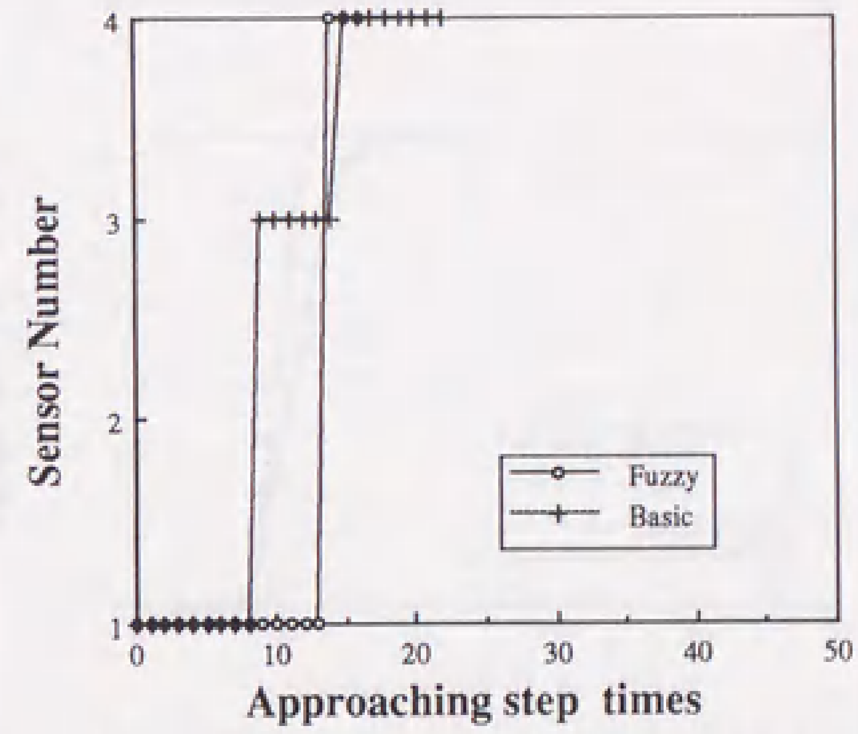
(f) Approaching process of angle around z axis.

Fig. 3.6 Experimental results.

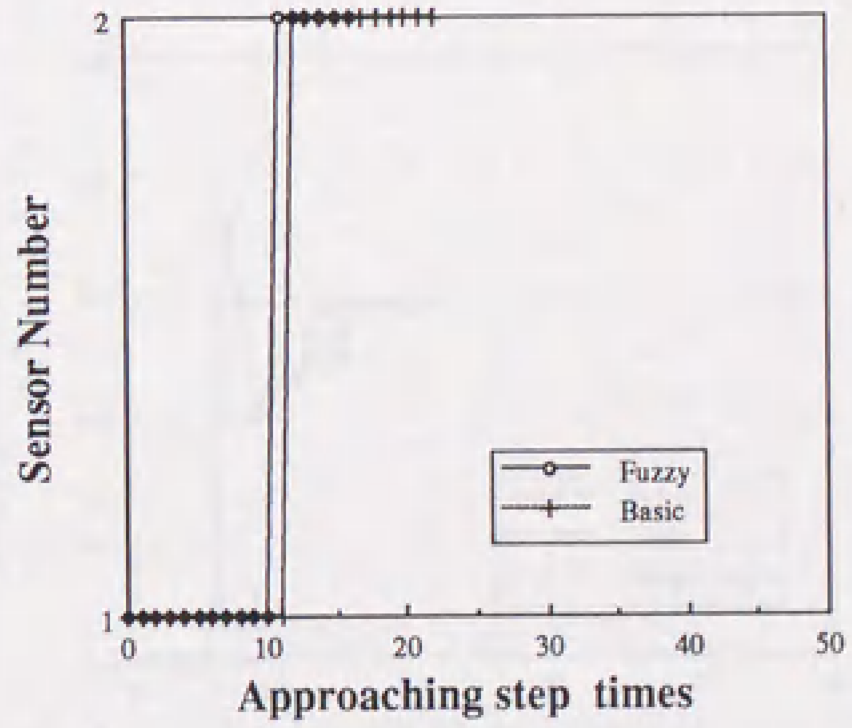
All sensors were normal and the initial angle around y axis was small.



(a) Sensing process of x axis.



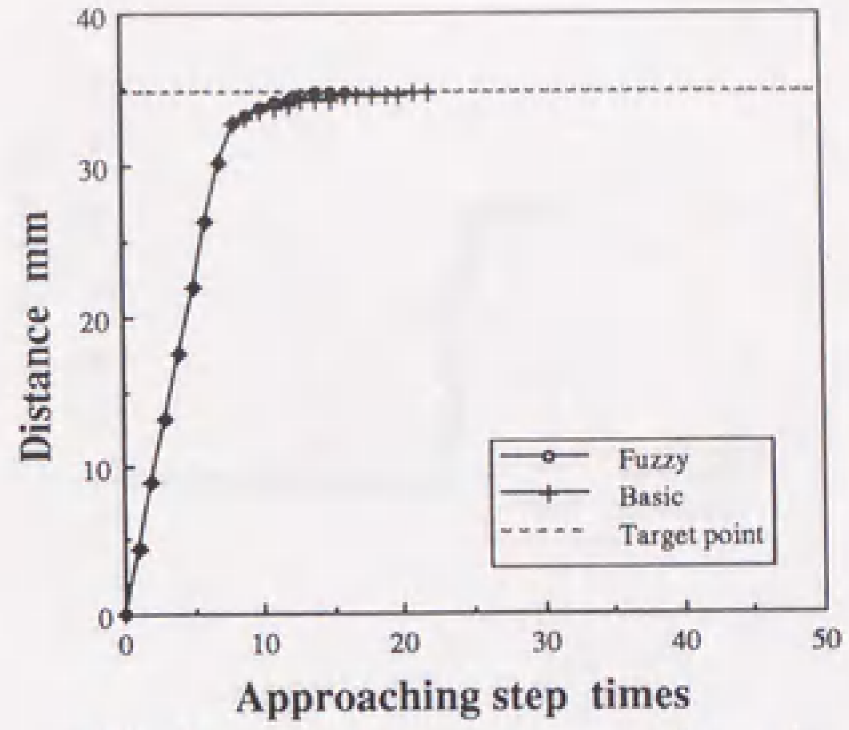
(b) Sensing process of angle around y axis.



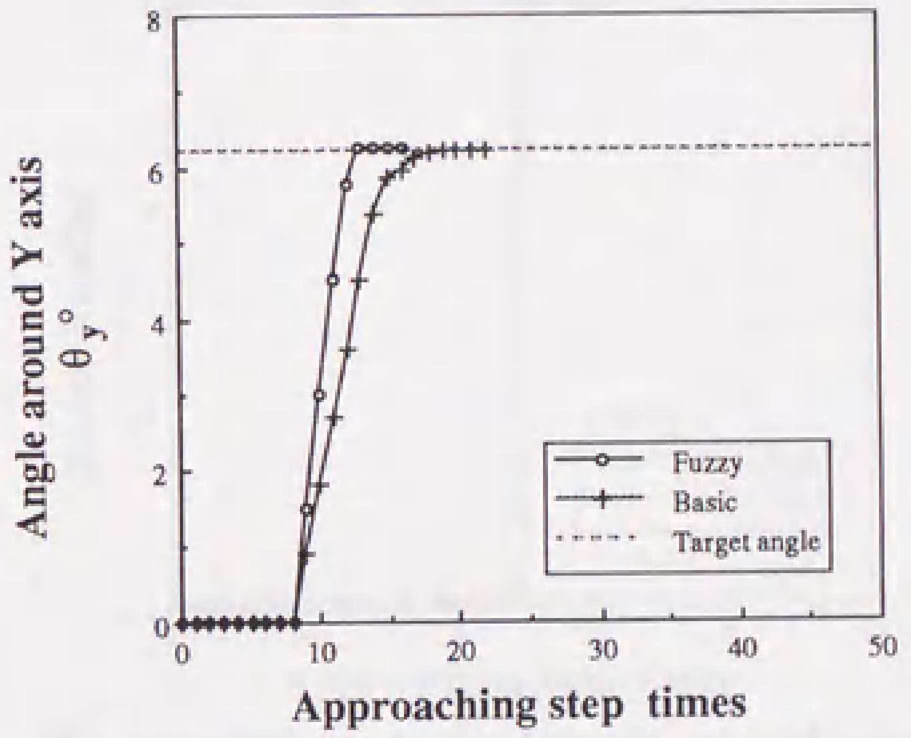
(c) Sensing process of angle around z axis.

Fig. 3.7 Experimental results.

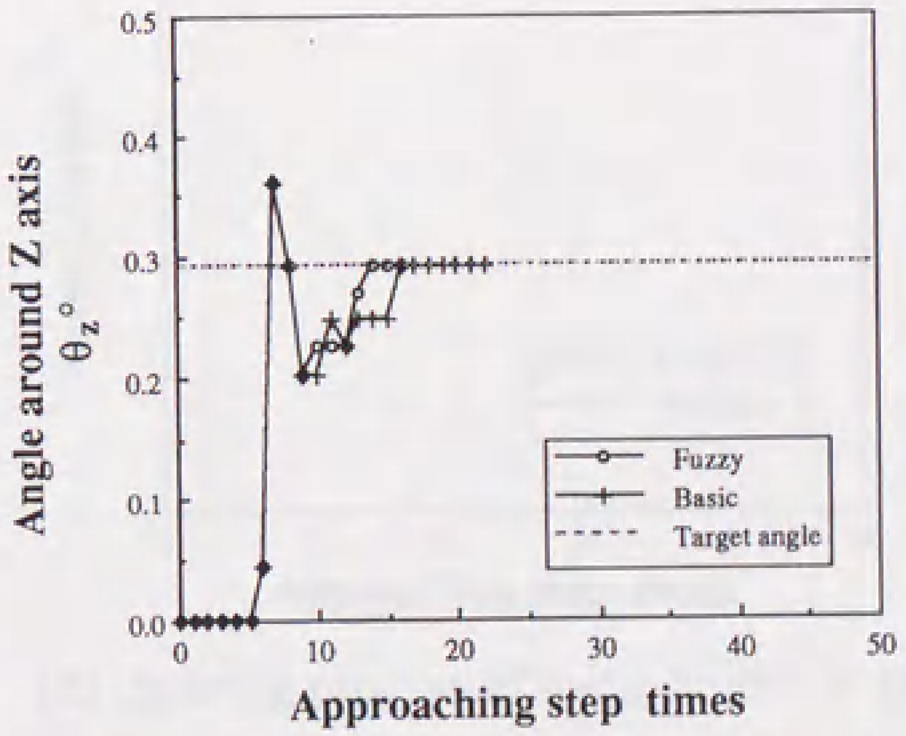
All sensors were normal and the initial angle around y axis was large.



(d) Approaching process of x axis.



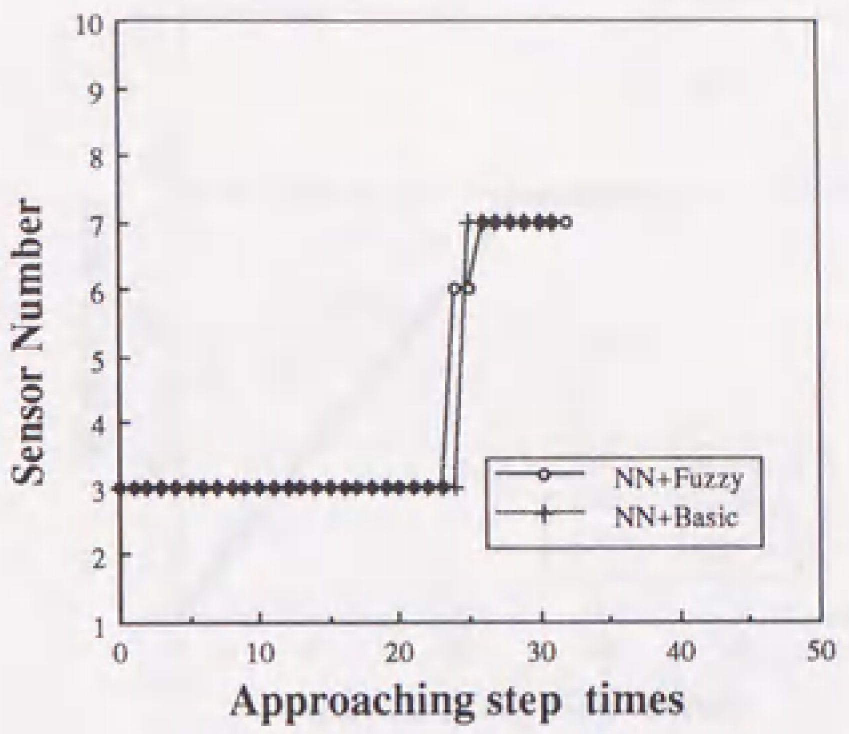
(e) Approaching process of angle around y axis.



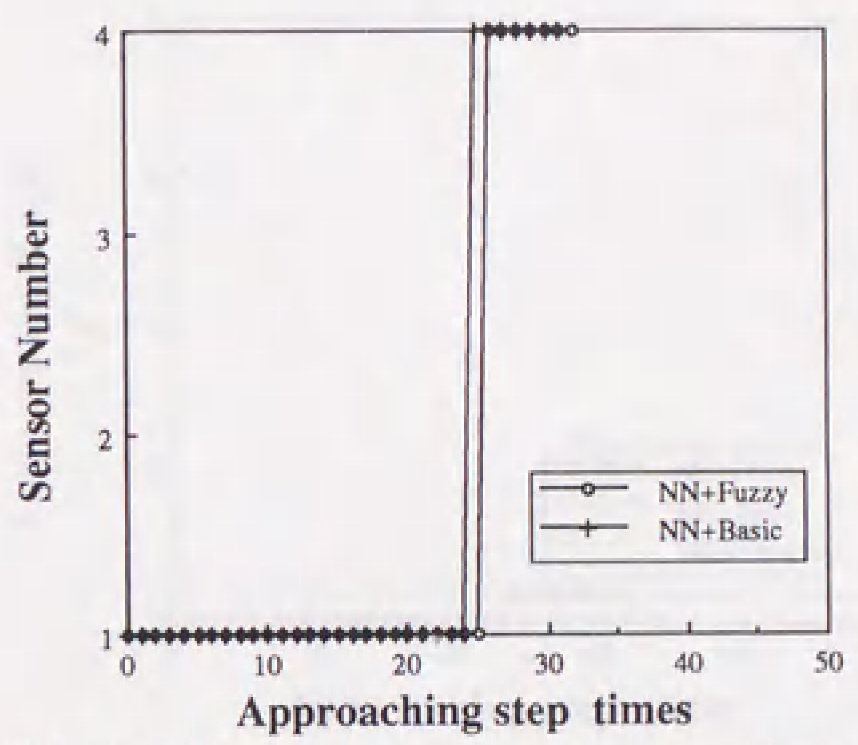
(f) Approaching process of angle around z axis.

Fig. 3.7 Experimental results.

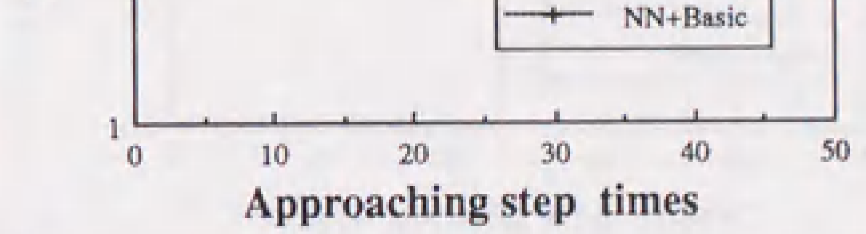
All sensors were normal and the initial angle around y axis was large.



(a) Sensing process of x axis.



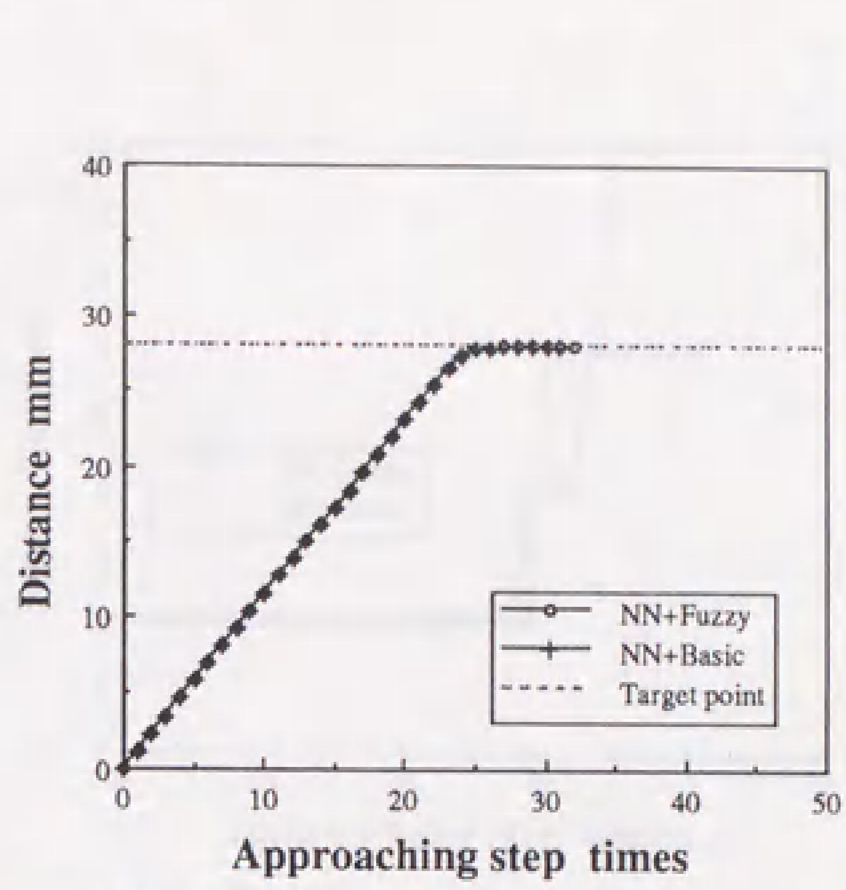
(b) Sensing process of angle around y axis.



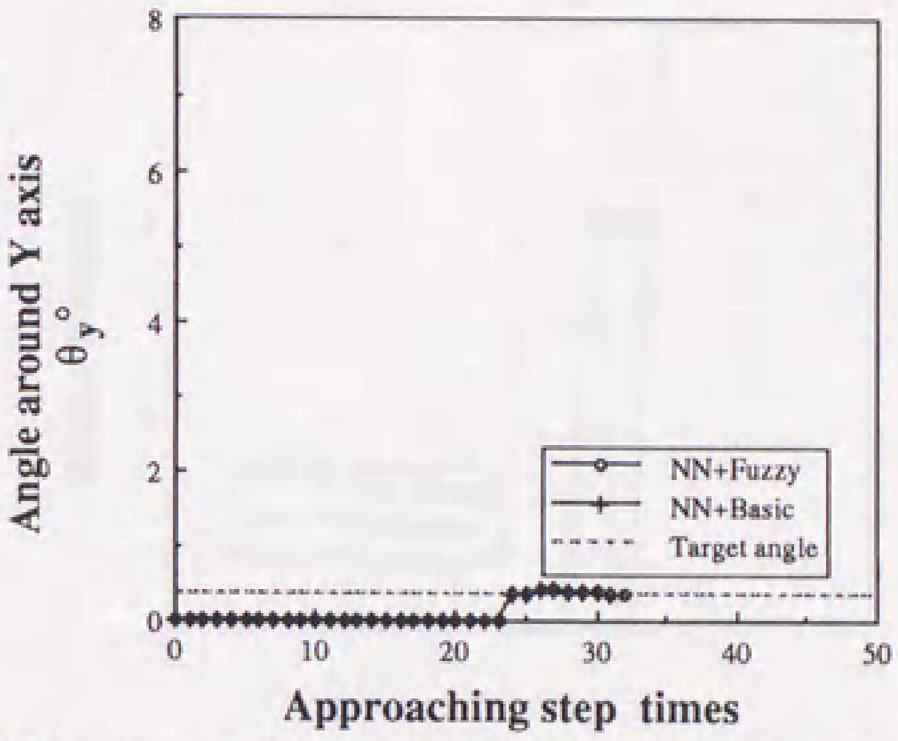
(c) Sensing process of angle around z axis.

Fig. 3.8 Experimental results.

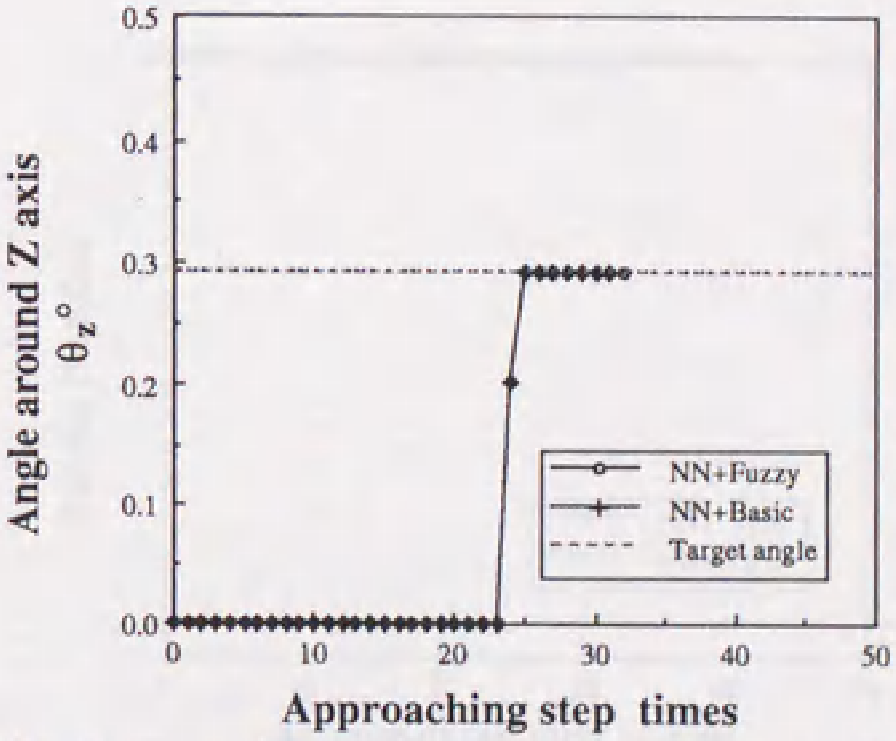
Sensor 1,2 were failed and the initial angle around y axis was small.



(d) Approaching process of x axis.

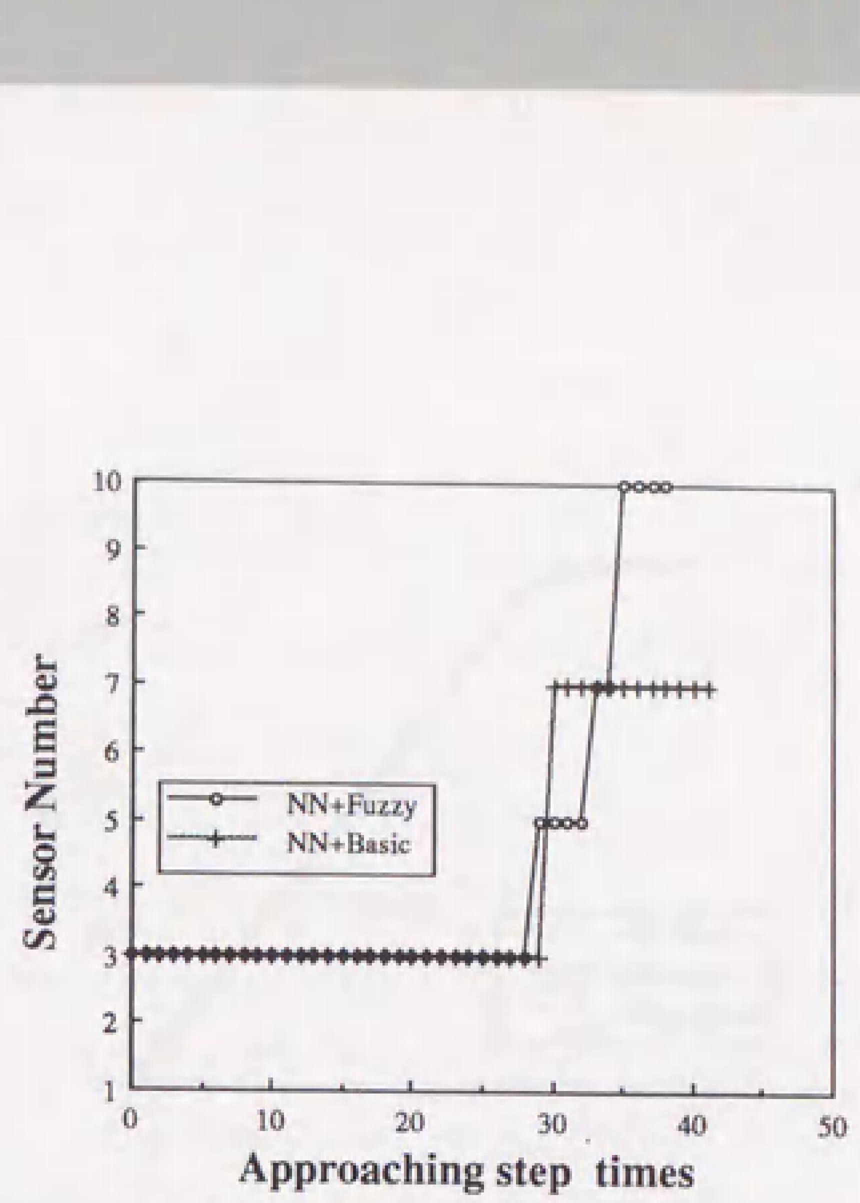


(e) Approaching process of angle around y axis.

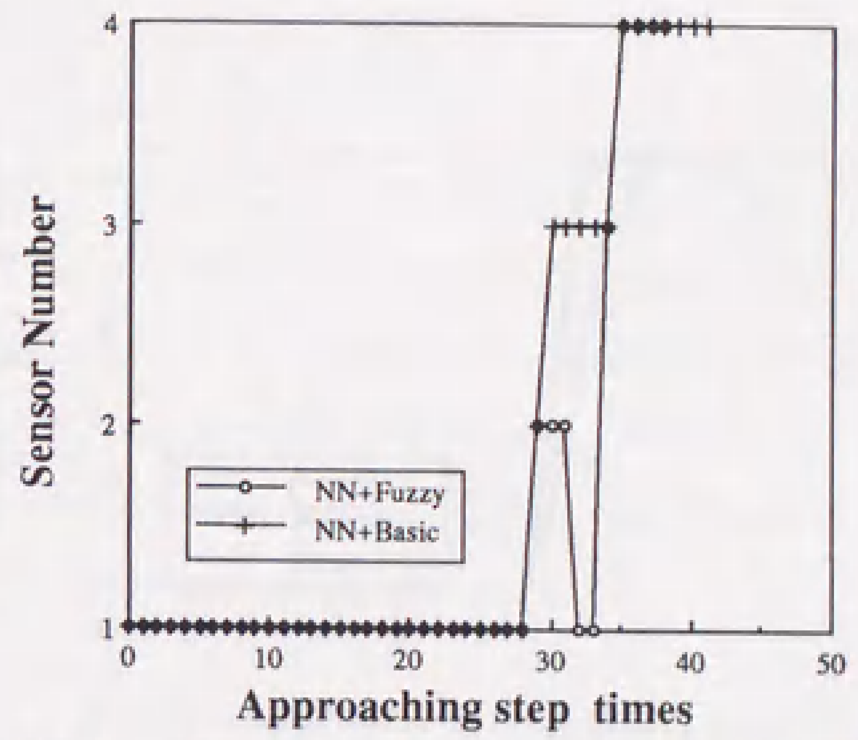


(f) Approaching process of angle around z axis.

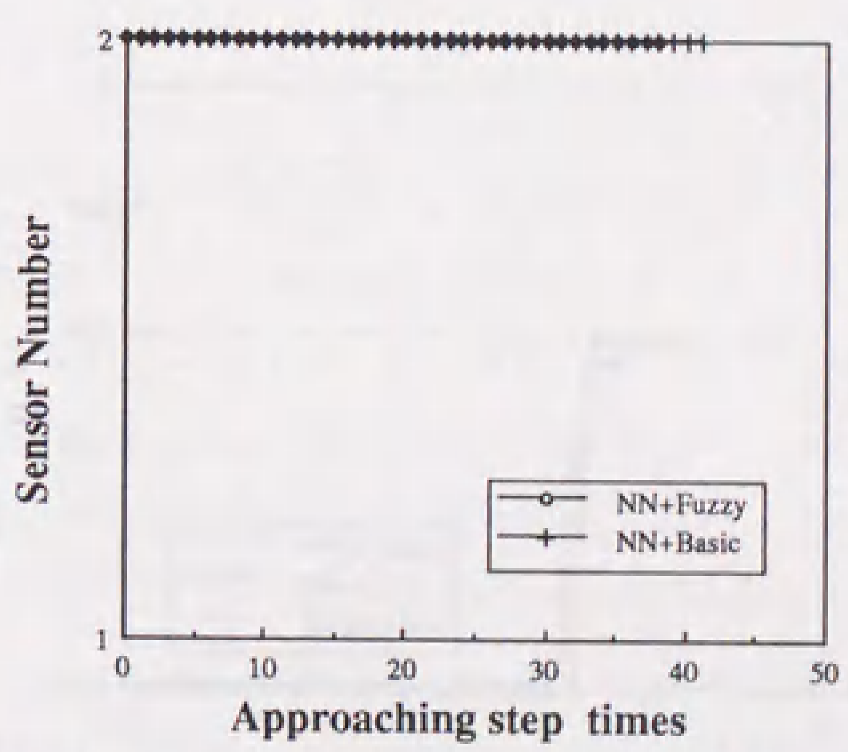
Fig. 3.8 Experimental results.
Sensor 1,2 were failed and the initial angle around y axis was small.



(a) Sensing process of x axis.



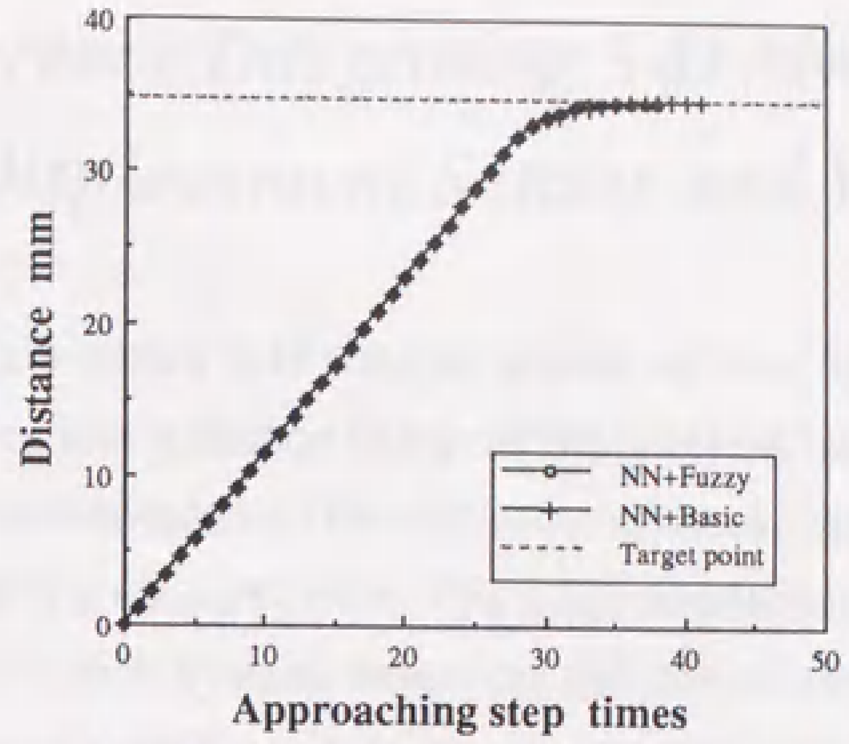
(b) Sensing process of angle around y axis.



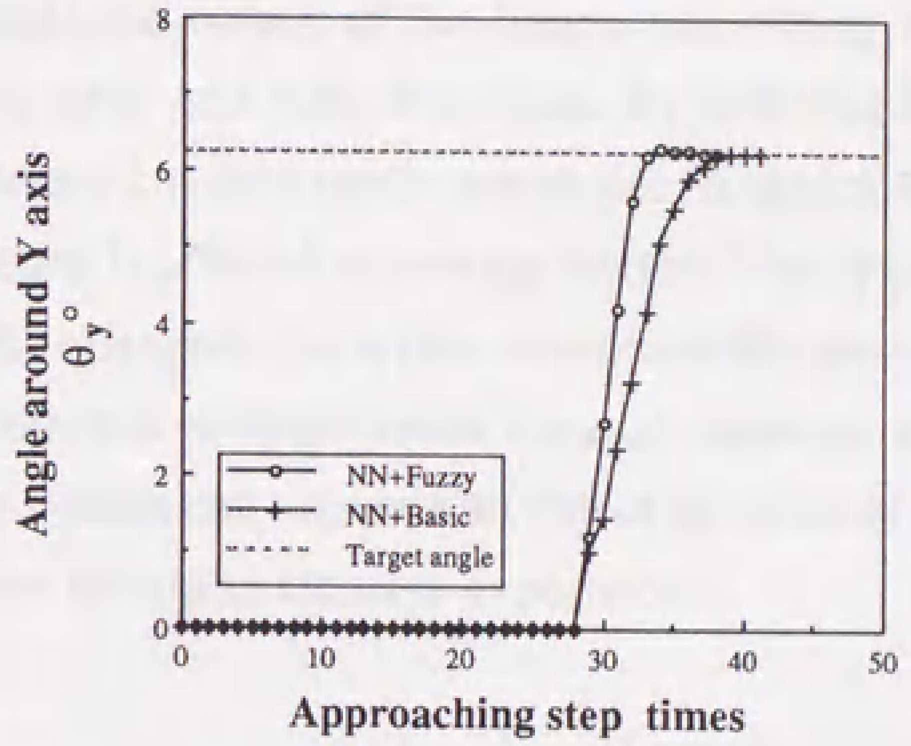
(c) Sensing process of angle around z axis.

Fig. 3.9 Experimental results.

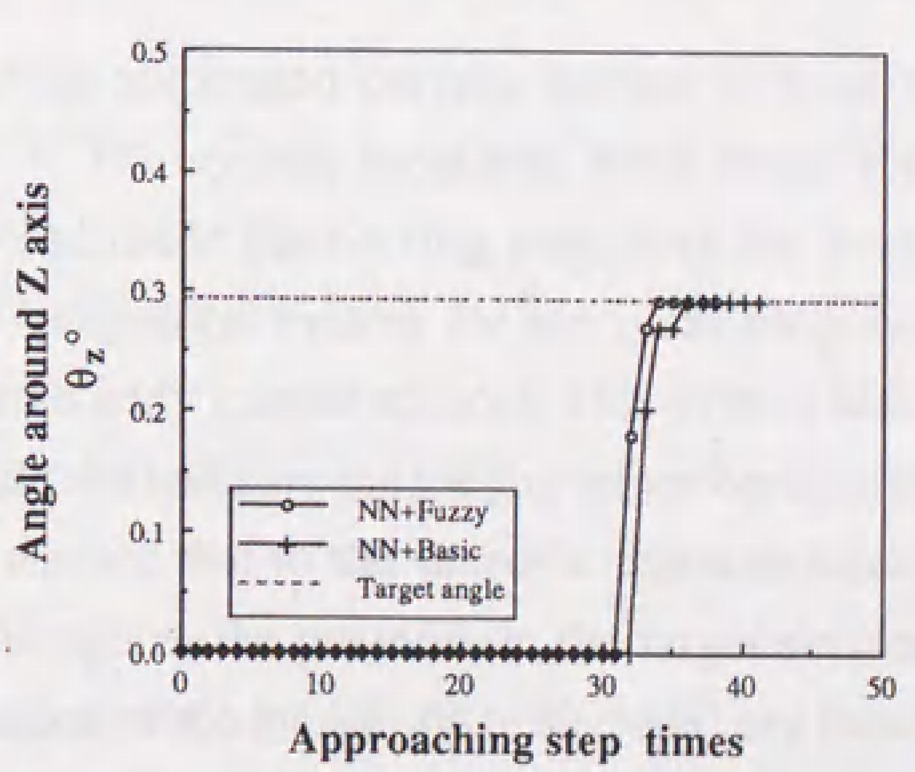
Sensor 1,2 were failed and the initial angle around y axis was large.



(d) Approaching process of x axis.



(e) Approaching process of angle around y axis.



(f) Approaching process of angle around z axis.

Fig. 3.9 Experimental results.
Sensor 1,2 were failed and the initial angle around y axis was large.

4. Fuzzy Inference Integrating 3-D Measuring System with LED Displacement Sensor and Vision System

This chapter deals with a **3-D measurement system** applied to a curved metal surface carving system, and a **sensor integration method** based on **fuzzy inference**. The measurement system consists of two different sensors. One is a LED displacement sensor, while the other is a vision system. The LED displacement sensor's spot-light is used as a part of the vision system based on the active stereo sensing method. In addition, the LED displacement sensor's outputs are used for calibrating camera parameters. Therefore, the camera parameters can be calibrated easily. Then, **neural networks** compensate the output of the image processing for some errors, such as camera parameter's error and lens distortion. By utilizing the **neural networks**, a vision system can be used as accurately as possible. A sensor integration method based on the **fuzzy set theory** is utilized to manage sensors. Fuzzy inference's input consists of information on the change in the sensor output and the position change of the sensor system, together with the environmental data of measurement. For this integration system, the sensory system can measure an object **accurately**. The proposed system is shown to be effective through extensive experiments.

4.1 Introduction

We proposed an automated carving system with an integrated measurement system in chapter 3. The system measured each target's surface shapes with the measuring system and made the carving path from the measurement data. We also proposed a sensor integration system for the measuring system. In this measuring system, we used some eddy current sensors. This system had two problems. One was that this system could not measure the rough surface because the sensors had to be very close to the target surface due to the sensor's characteristics. The other was that the system could not recognize the position on the target surface where the system was measuring. Recognition of the measuring position is very important for precise carving because the carving path is made from the measuring path; therefore, the measuring path and the carving path are closely linked together.

For these problems, we propose a new measurement system and its integration method. The system consists of two LED displacement sensors (this sensor can measure displacement at a distance of 40 mm) and two CCD cameras (for the measuring point's recognition on the target surface). The LED displacement sensor is not only used as a displacement sensor but also as a marker of the measuring point for the vision system. Therefore, the measurement system can measure the surface shape of the target at a distance and recognize the measuring point.

The vision system consists of a CCD camera and a LED displacement sensor, with which the active stereo method is applied. This vision system has two characteristics. One is that the calibration of the camera parameters is very easy because the system calibrates the camera parameters by the measurement data of the LED displacement sensor. The other is that a neural network (**NN**) is utilized as a compensator of the vision system's output errors, such as camera parameters' error and lens distortion. By utilizing the neural network, we can use the vision system as accurately as possible.

In the previous system, we used a **SIS** using the **fuzzy inference** to integrate the measurement data. These **SIS**s evaluated the suitability for the environment of each sensor, e.g., the intensity of a spot-light's reflection for the LED displacement sensor, and then used the appropriate sensor for sensors' environments. This **SIS**, however, could not evaluate internal conditions of sensors, e.g., the sensitivity for the intensity of the spot-light's reflection for the LED displacement sensor and camera parameters for the vision system.

The measurement system proposed here is mounted at the tip of the manipulator. Then changes in outputs of a sensor are caused by the position changes of the manipulator. Therefore, new **SIS**'s inputs consist of information on both the change in sensor outputs and the changes of the manipulator's position, together with the environmental data of a sensor. Then the new **SIS** can evaluate both the suitability for sensors' environments and the internal condition of a sensor in order to integrate the measurement data.

For this sensor integration system, the measurement system can measure the object as accurately as possible under any sensors' environments and internal conditions. The effect of this **SIS** is shown through extensive experiments.

4.2 3-D Measurement system

The previous system used plural eddy current sensors. An eddy current sensor cannot measure displacement at a distance, therefore the measurement system had to be close to the work's surface. As a result, the system could not measure a rough surface. The system also could not recognize the measurement point on the target surface where the system was measuring because the system did not have a vision system. In this automated manufacturing system, the height of the measurement system along the z axis (see Fig. 4.1) is very important for precise carving, because the height of the measurement system along the z axis in measuring is that of the air cutter along the z axis in carving.

For these problems, we propose a new measurement system, which can measure displacement from a distance and recognize the point where the system measures. The fundamental measurement system consists of a set of a CCD camera and a LED displacement sensor. In this chapter, we use a pair of the measurement system in order to measure the angle around the y axis. Figure 4.1 shows the relation among sensors and the object in the operational space.

The specifications of the measurement system are as follows:

LED displacement sensor:	measurable region	35mm to 45mm.
	measurement accuracy	20 μm.
CCD camera 1:	the focal distance	7.5mm.
CCD camera 2:	the focal distance	15mm.
Image processing board:	512 pixels x 512 pixels at 256 gray scale.	

For the combination of these sensors, the measurement system can measure the rough surface shape and recognize the height of the measurement system along the z axis accurately.

Accuracy of the LED displacement sensor is greatly effected by a reflection of an object surface. Accuracy of the vision system does not depend on the reflection of object surface but the shape of the LED displacement sensor's spot-light. In order to integrate these sensor outputs in consideration of each sensors' specification, we use a sensor integration system based on the fuzzy inference. Figure 4.2 shows the outline of the sensor integration system.

4.2.1 LED displacement sensor

The measurement system has 2 LED displacement sensors. The sensors measure distance to the object surface along the x axis and the angle between the sensor and the object surface around the y axis. The spot-light of the LED displacement sensor is also utilized in the vision system based on the triangulation method as a marker of the measurement point on the object surface. The output of the LED displacement sensor is utilized for calibrating the camera parameters of the vision system.

4.2.2 Vision system

The image data obtained through the CCD camera is utilized for measuring distance to the object surface both along the x axis and the z axis. A large number of studies have been made on the vision system based on the triangulation method. These vision systems are classified into two types, such as a passive stereo vision and an active stereo vision. The passive stereo method [Kanade 1991], e.g., the binocular vision and the photometric stereo, has the stereo matching problem. Accuracy of the measurement is related with that of the correspondences among different images. Furthermore, it takes much time to compute the distance. The active stereo method, e.g., using spot-light, slit-light and pattern-light [Sato 1985], [Gutsche 1991], can compute the distance from a single image, but this algorithm needs an artificial source of light such as a laser.

In this chapter, considering the image processing speed and accuracy in measurement, we apply the active stereo method to the 3-D measurement system where the source of light is the LED displacement sensor. The position of the sensor

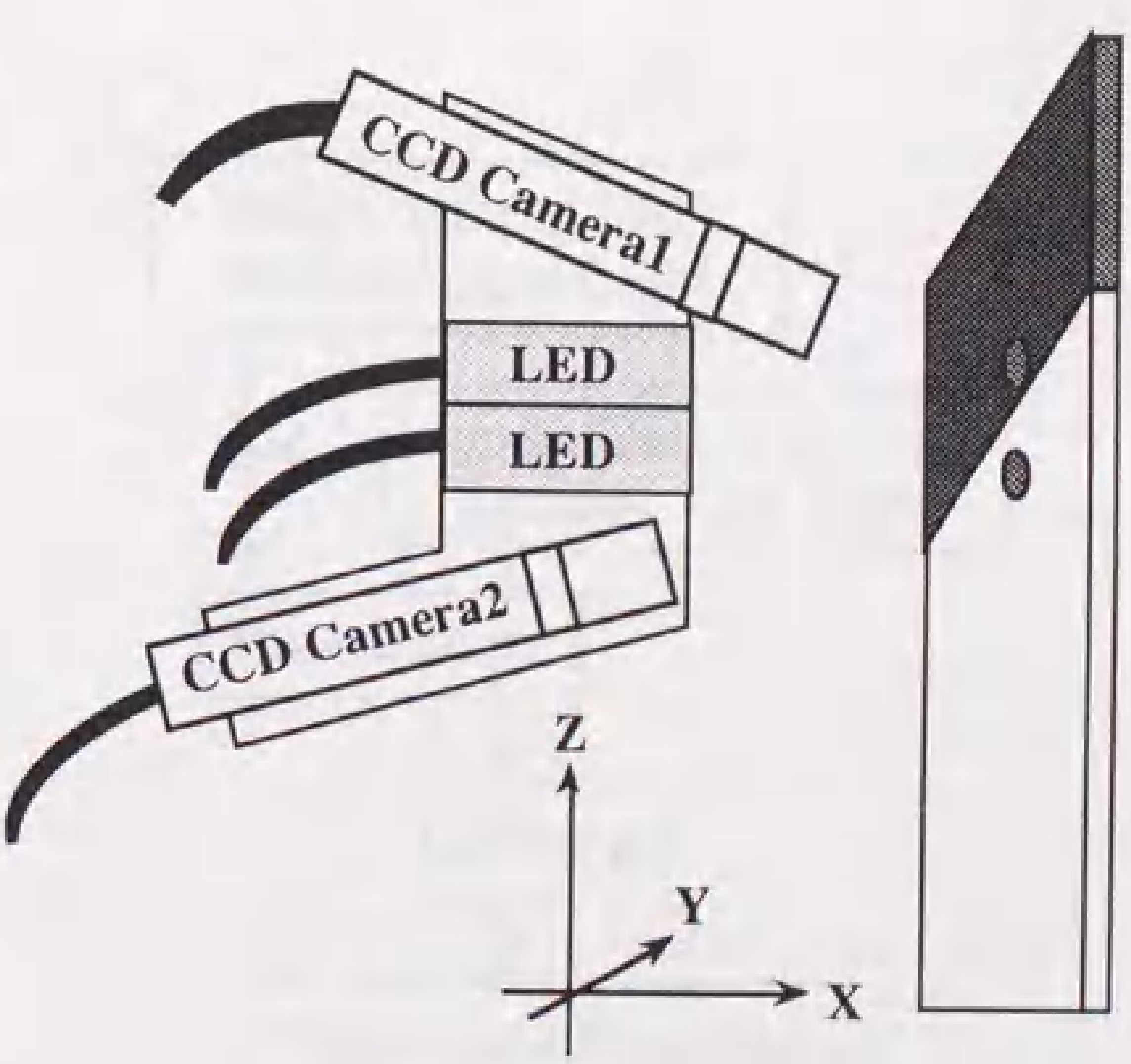


Fig. 4.1 Distribution of Sensors and Coordinate System

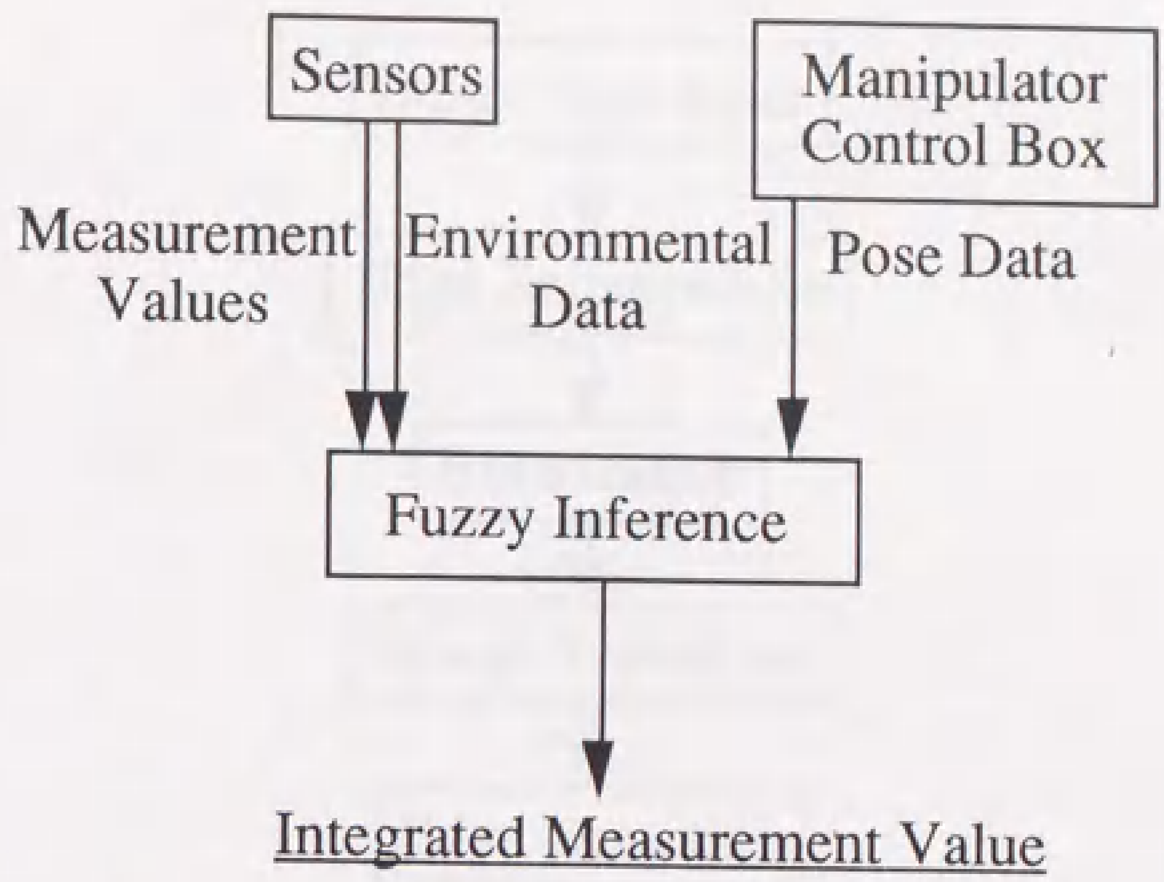


Fig. 4.2 Sensor Integration System based on the fuzzy inference.

system along the z axis is determined by recognition of both spot-lights' positions and the border line between the carving part and the no-carving part on the object. Figure 4.3 shows the spot-light's detection flow chart and Fig. 4.4 shows the border line detection flow chart.

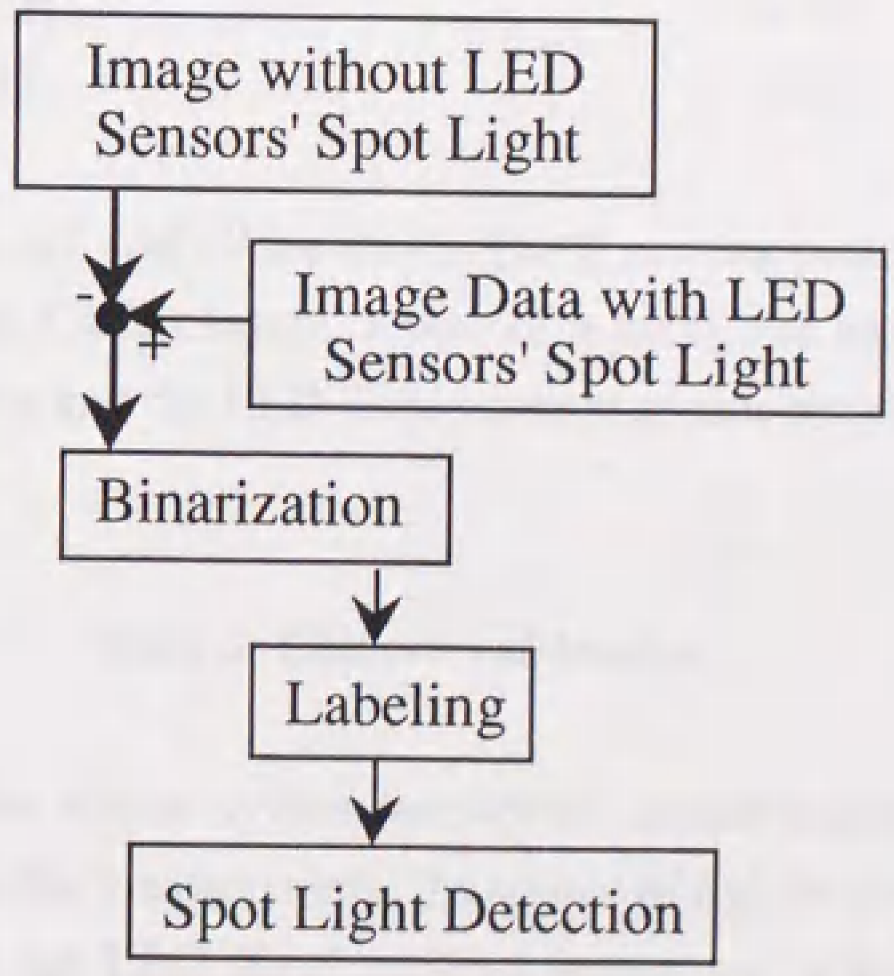


Fig. 4.3 Flow chart of the Spot-light detection.

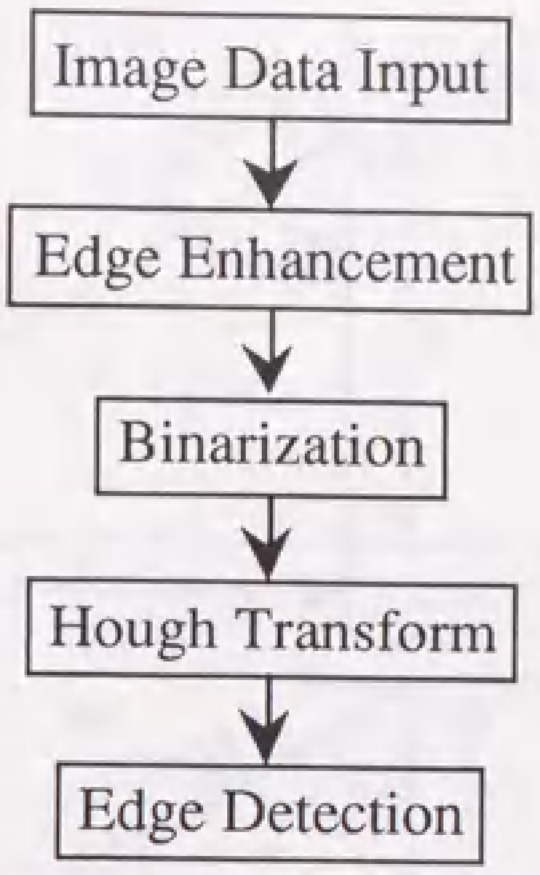


Fig.4.4 Flow chart of the border line detection.

4.2.2.1 Active stereo method

Distance between the sensor and the object is measured from the spot-light's position of the LED displacement sensor based on the triangulation method (see Figs. 4.5 and 4.6). Distances along the x axis (Li) and the z axis (Zi) between the sensor and the object are calculated as follows:

$$Li = Z0 \cdot \tan(q0 + qi) \qquad (4.1)$$
$$Zi = Li / \tan(q0 + qi) \qquad (4.2)$$
$$\tan qi = dFx \cdot Fxi / fi \qquad (4.3)$$

where Fxi, fi, dFx, q0, and Z0 means the gravity center position of the spot-light, the focal distance of the CCD camera, a size of a pixel, the angle and the distance between the CCD camera and the LED displacement sensor respectively.

4.2.2.2 Camera calibration

In order to use the vision system accurately, camera parameters have to be calibrated accurately. In this vision system, the source of light is the LED displacement sensor, and outputs of the LED displacement sensor are utilized for the camera calibration data. Therefore, camera calibration is very easy and accurate. In this system, we calibrate q0, Z0, and dFx.

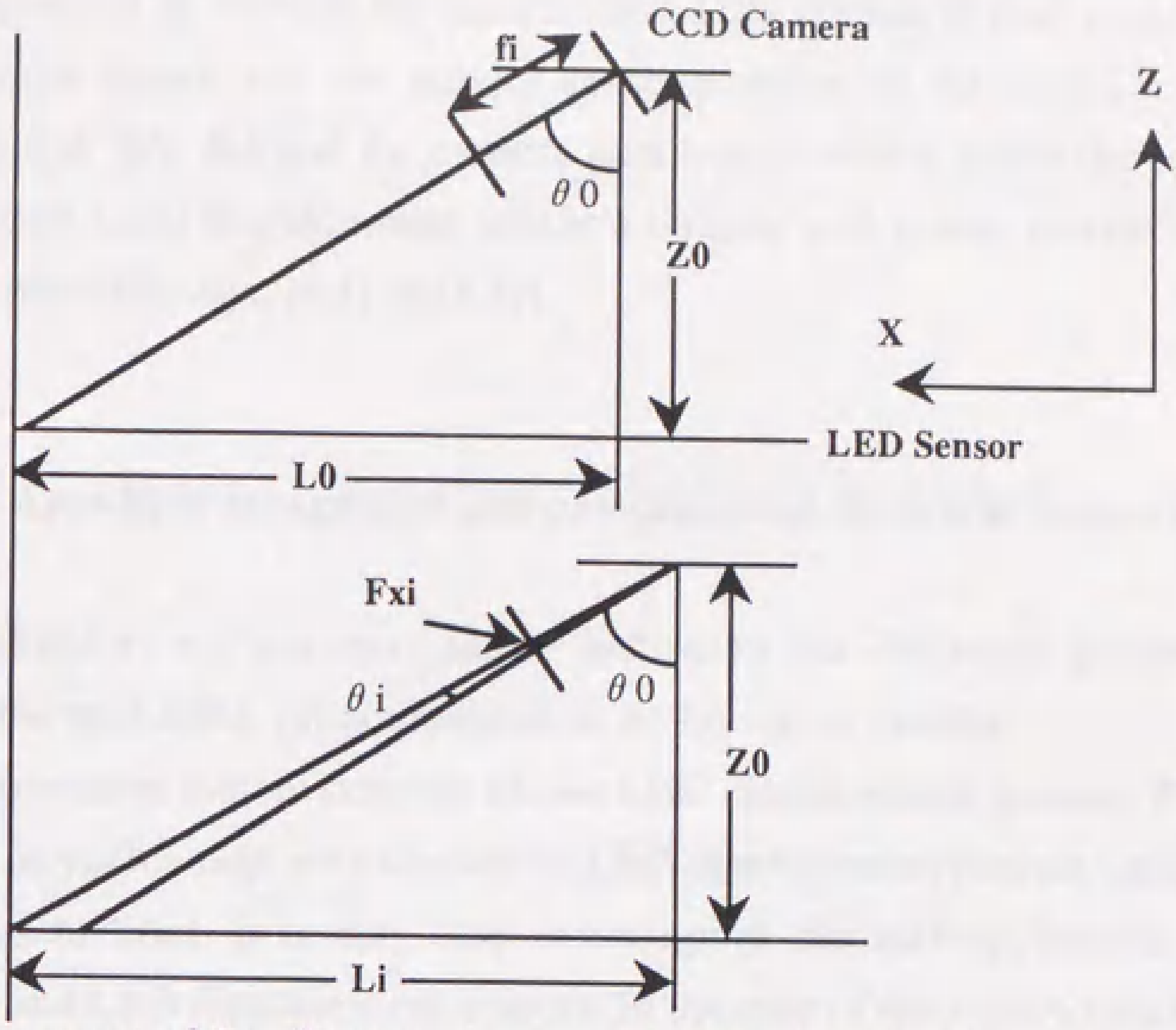


Fig. 4.5 Measurement of the distance along x axis based on the triangulation method.

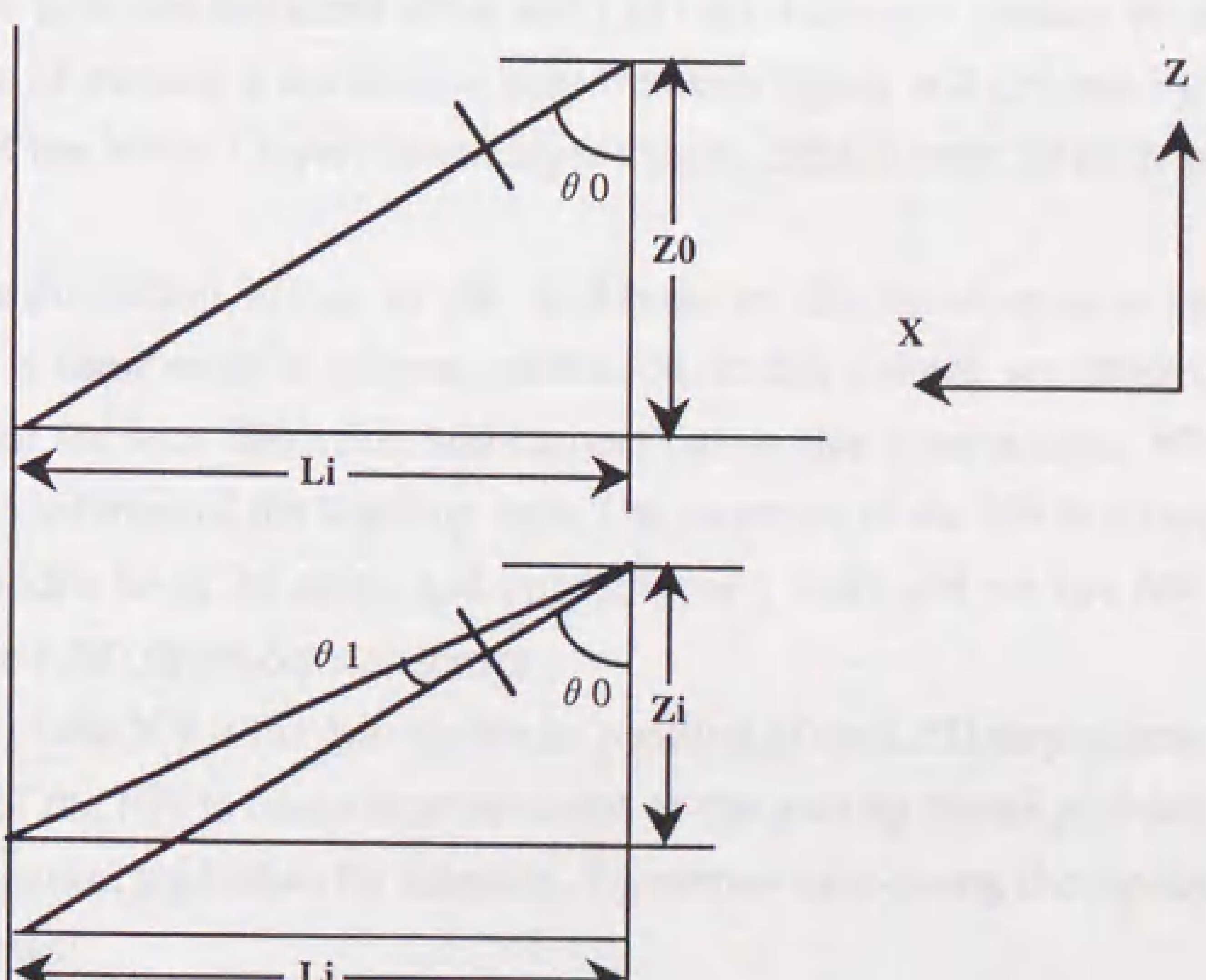


Fig. 4.6 Measurement of the distance along z axis based on the triangulation method.

The sensor system is mounted at the tip of the manipulator. Data for the camera calibration is obtained by moving the manipulator. Data consist of both outputs of the LED displacement sensor and the gravity center position of the spot-light at each measurement point. We defined the camera parameters, which make the total error minimum between LED displacement sensor's outputs and vision system's outputs (which are calculated by eqs. (4.1) to (4.3)).

4.2.2.3 Spot-light recognition and compensation by neural network.

In this chapter, we use two neural networks for different purposes: (1) recognition of the spot-light, (2) compensation of the vision system.

The measurement system consists of two LED displacement sensors. Therefore, two large areas on each image are extracted as LED displacement sensors' spot-light. If there are two extractions, it is very easy to recognize the correspondence between extracted areas and LED displacement sensors. In the case of only one extraction from an image, it is difficult to recognize the correspondence without many rules about the correspondence because the gravity center position is moved by the distance between the CCD camera and the object. We use a neural network (**NN**) for recognition of the correspondence between extracted areas and LED displacement sensors because **NN**s have a function of making a correlative map between inputs and outputs by learning. The structure of the **NN** is 3 layers (input layer 4 units, hidden layer 10 units and output layer 4 units).

The lens distortion is one of the problems in the measurement system. In addition, there is some error in camera calibration. In this system, we utilize a **NN** for compensation of the lens distortion and camera calibration's error since **NN**s have a function of interpolation of the learning data. The structure of the **NN** is 3 layers (input layer 1 unit, hidden layer 30 units, and output layer 1 unit) and we use **NN** for each spot-light of the LED displacement sensor.

An input of the **NN** is the gravity center position of the LED displacement sensor and an output of the **NN** is compensation value of the gravity center position. We use the back propagation algorithm for learning. Equations concerning the input/output of **NN** are as follows:

$$In=Gn/512 \qquad (4.4)$$

$$Tn=(Rn-Gn+40)/80 \qquad (4.5)$$

where In, Gn, Tn, and Rn means the input of the **NN**, the gravity center position of the LED displacement sensor, the training data, and the gravity center position calculated from the distance between sensors and the object respectively. In this chapter, we determine the maximum of compensation as 40 pixels. Figure 4.7 shows the construction of the vision system.

4.3 Integration of measurement values by the fuzzy inference

In this measurement system, we can obtain 3 measurement values at the same measurement point. One is a LED displacement sensor, while the others are two CCD cameras.

The measurement system is mounted at the tip of the industrial 5 axis manipulator. Therefore, if the manipulator can move accurately, we can select or integrate the measurement values by comparing the variation of each sensor output with the variation of manipulator's positions. In ordinary industrial manipulator systems, because of characteristics of a actuator, accuracy of linkage setting, friction, and backlash, there is a difference between desired trajectory and actual trajectory, and we cannot measure a magnitude of the difference.

In order to integrate the measurement values, we propose the **SIS** based on the **fuzzy inference**. We consider the rate of the variation of manipulator's positions to the variation of sensors' outputs as one of the inputs of the fuzzy inference. The rate is expressed in eq. (4.6) as X1.

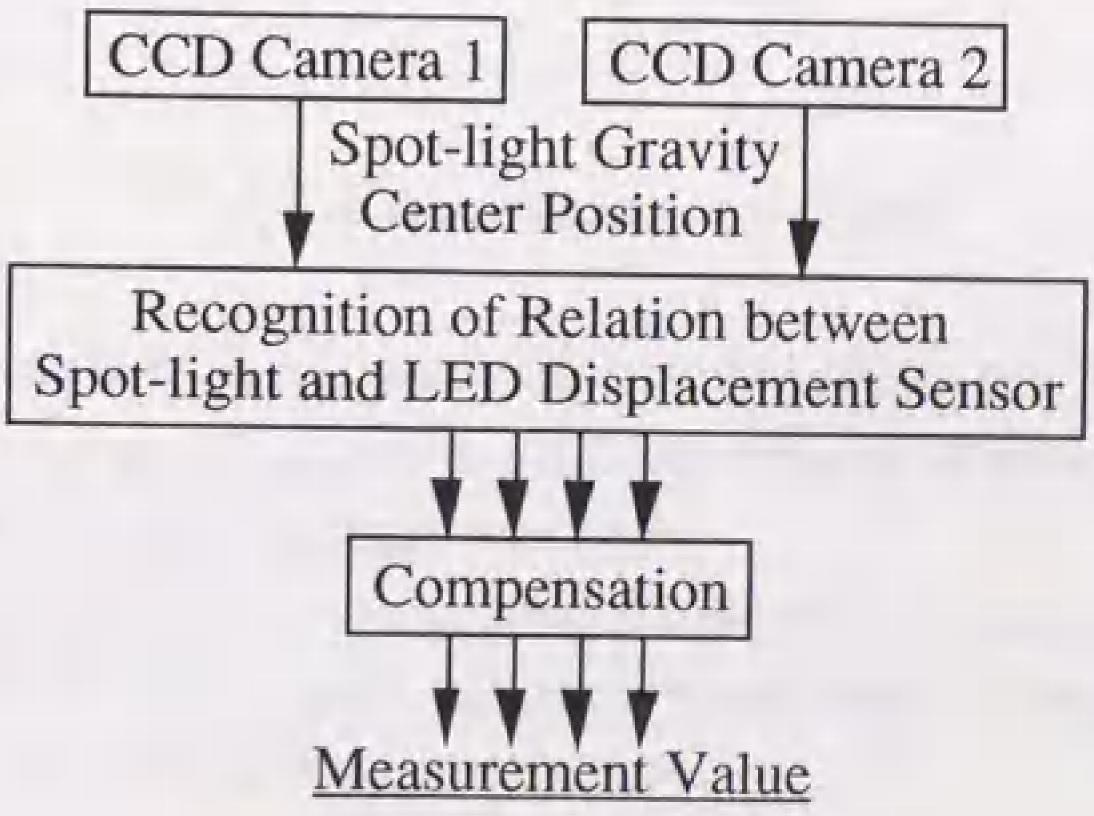


Fig.4.7 Outline of vision system

If $P(t)-P(t-1)\neq 0$:

$$X1=\frac{|S(t)-Si(t-1)-(P(t)-P(t-1))|}{|P(t)-P(t-1)|} \tag{4.6}$$

If $P(t)-P(t-1)=0$:

$$X1=P(t)-P(t-1)$$

where P(t) means the position of the sensor system at time t, Si(t) means the output of the SIS.

The LED displacement sensor's output is affected by the intensity of a spot-light's reflection, while the output of the vision system is affected by the aspect value of the spot-light on the image and accuracy of camera calibration not the intensity. Another fuzzy inference's input X2 is the affected factor of a sensor, such as the intensity of the spot-light of the LED displacement sensor and the aspect value of the vision sensor. The normalized value of X2 means the environmental data of measurement and if X2 is nearly equal to 1, the condition is suitable for a sensor, and in the case of X2 nearly equal to 0, the condition is almost prohibitive for a sensor. The fuzzy inference's output is used as the suitability of each sensor for measurement and the SIS's output is determined by comparing the suitabilities of all sensors.

Table 4.1 expresses the fuzzy rules. In the table, the suitability of a sensor for measuring is higher in order of **S**, **MS**, **M**, **MB**, and **B**. For example, if the X1 is **S** (X1 is around zero) and X2 is **B** (the environment is suitable for the sensor) then fuzzy inferences's output is **B** (the estimated suitability is very high). We determined the membership functions and rules by operator's experience.

4.4 Experiments and results

Experiments were carried out by using the industrial 5 axis manipulator and the sensor system (see Fig. 4.8) set at the tip of the manipulator. A measurement object was set on the X-Z table whose accuracy was 10μm.

Three types of experiments were performed: 1) camera calibration, 2) compensation for the vision system utilizing NN, and 3) sensor integration system. The reference data were obtained from the X-Z table.

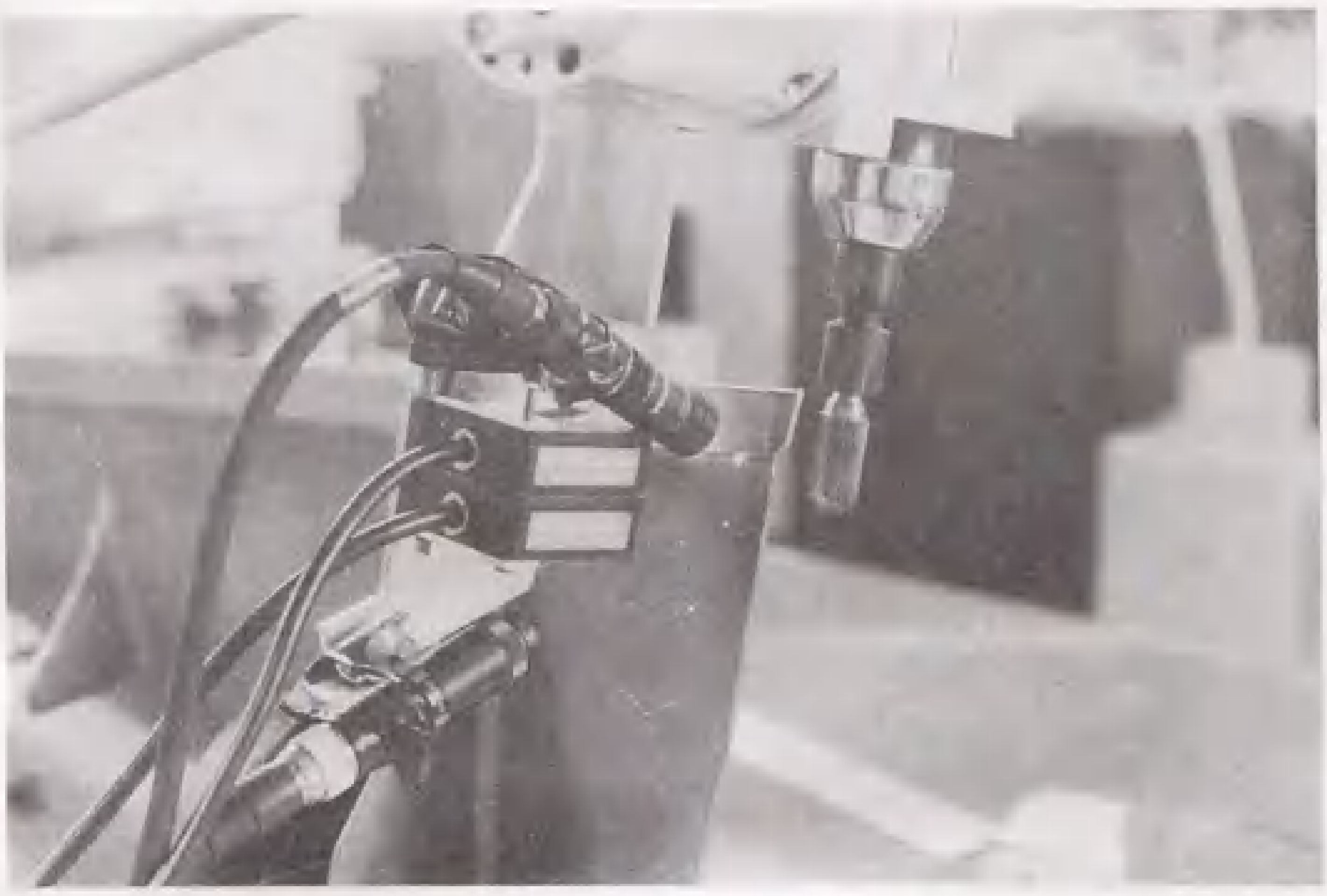


Fig. 4.8 Experimental System

4.4.1 Calibration and compensation

Parameters of the vision system were calibrated by two ways. One was that the manipulator was moved to several different points in order to move the sensor system and then the camera parameters calibrated by the outputs of the LED displacement sensor of each point. The other was that the X-Z table was moved to several different points in order to move the object, and the parameters calibrated by the output of the X-Z table.

Two NNs were trained to compensate for the measurement error of the vision system. One was used for the vision system calibrated by the LED displacement sensor. The NN was trained by the output of the LED displacement sensor when the object was in the area of the LED displacement sensor's measurable region and by the manipulator's pose data when the object was out of the measurable range. The other was used for the vision system calibrated by the X-Z table and trained by the outputs of the X-Z table. The number of each training data set was 56.

Experiments were carried out by moving the X-Z table to move the object. Figures 4.9 and 4.10 show results of measurement of the vision system calibrated by the LED displacement sensor and the X-Z table with/without NNs' compensation. Figures 4.11 and 4.12 show the error between the reference data obtained from the X-Z table and the measurement values of Figs. 4.9 and 4.10. Table 4.2 shows the average

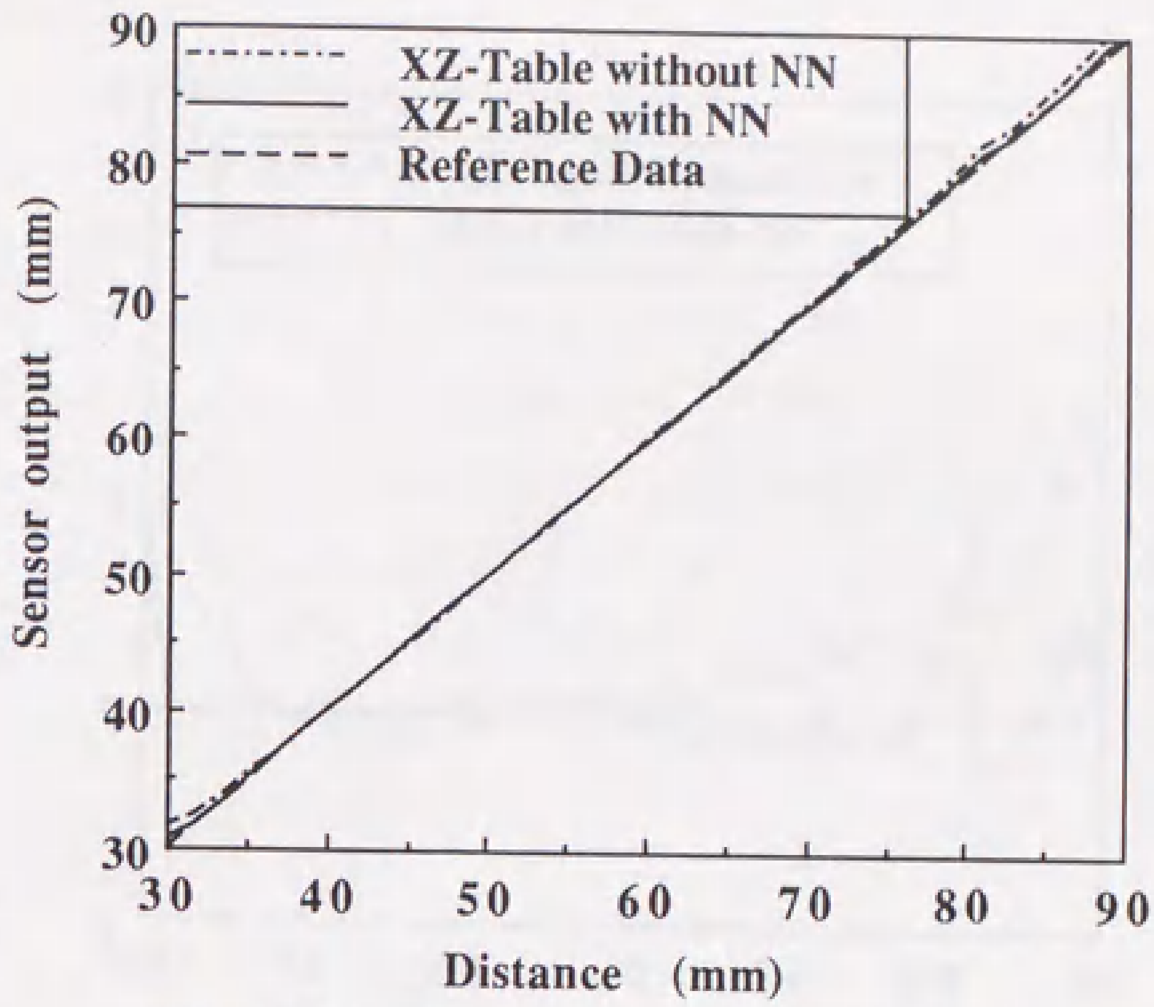


Fig. 4.9 Results of measuring (X-Z table)

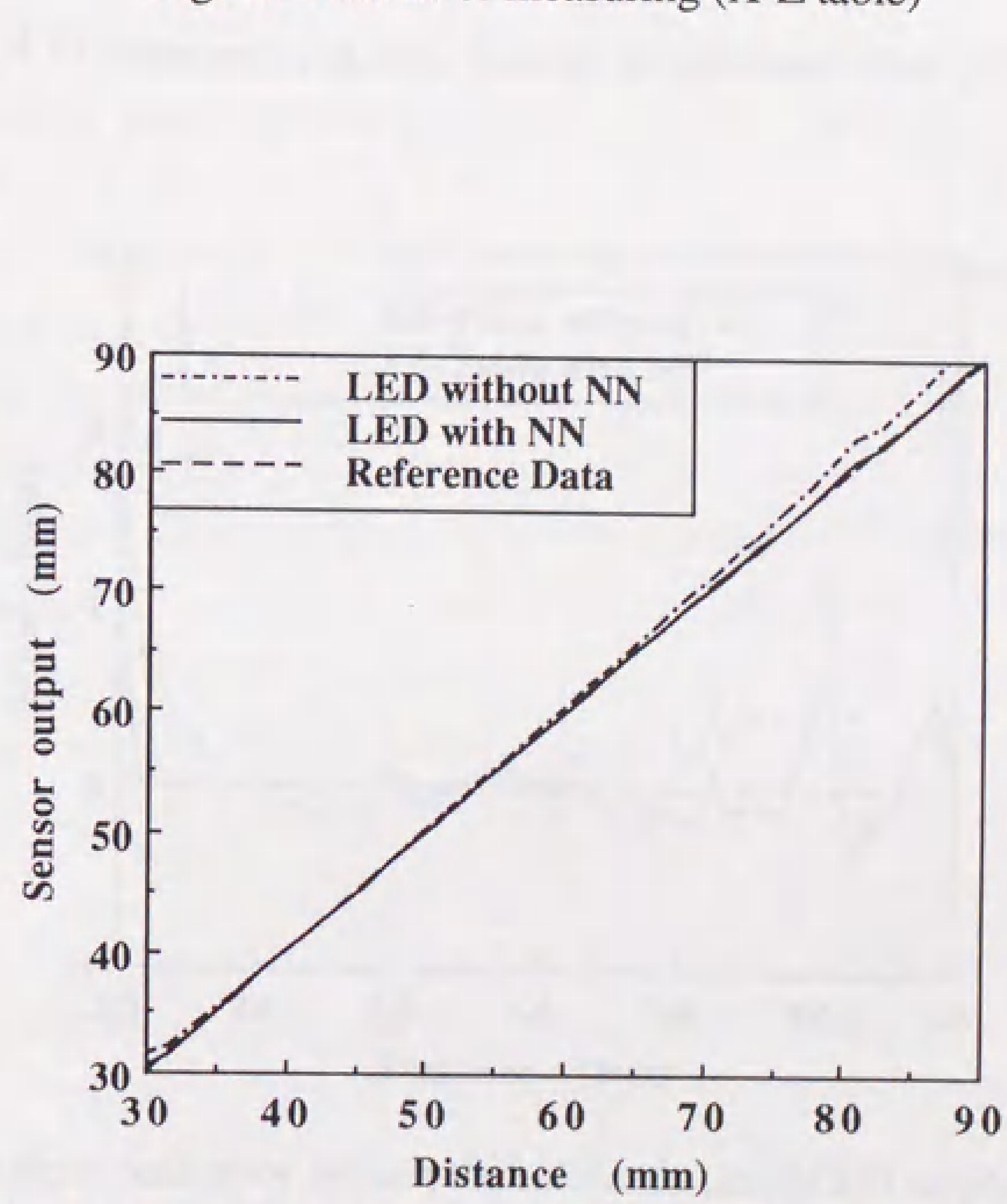


Fig. 4.10 Results of measuring (LED displacement sensor)

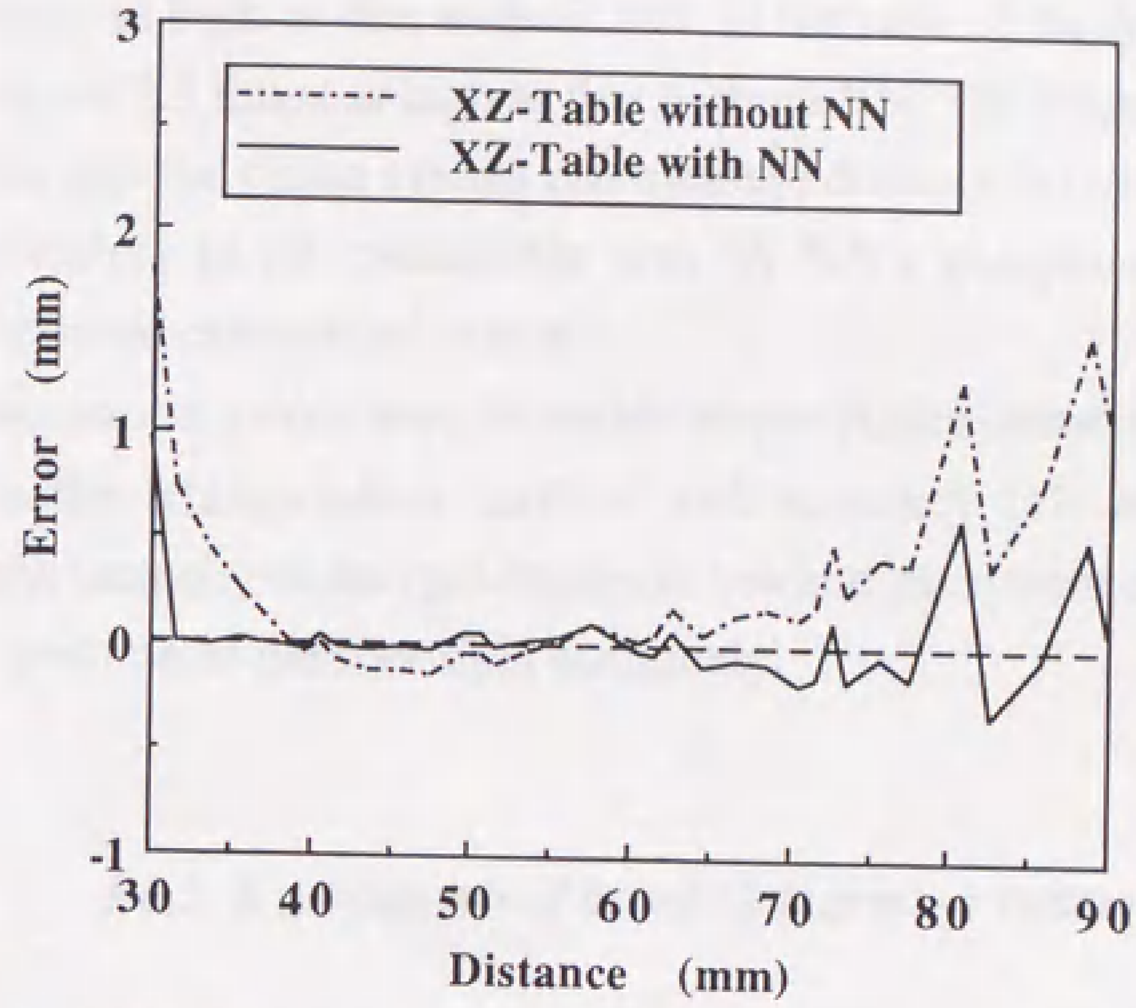


Fig. 4.11 Measurement error against the reference data (X-Z table)

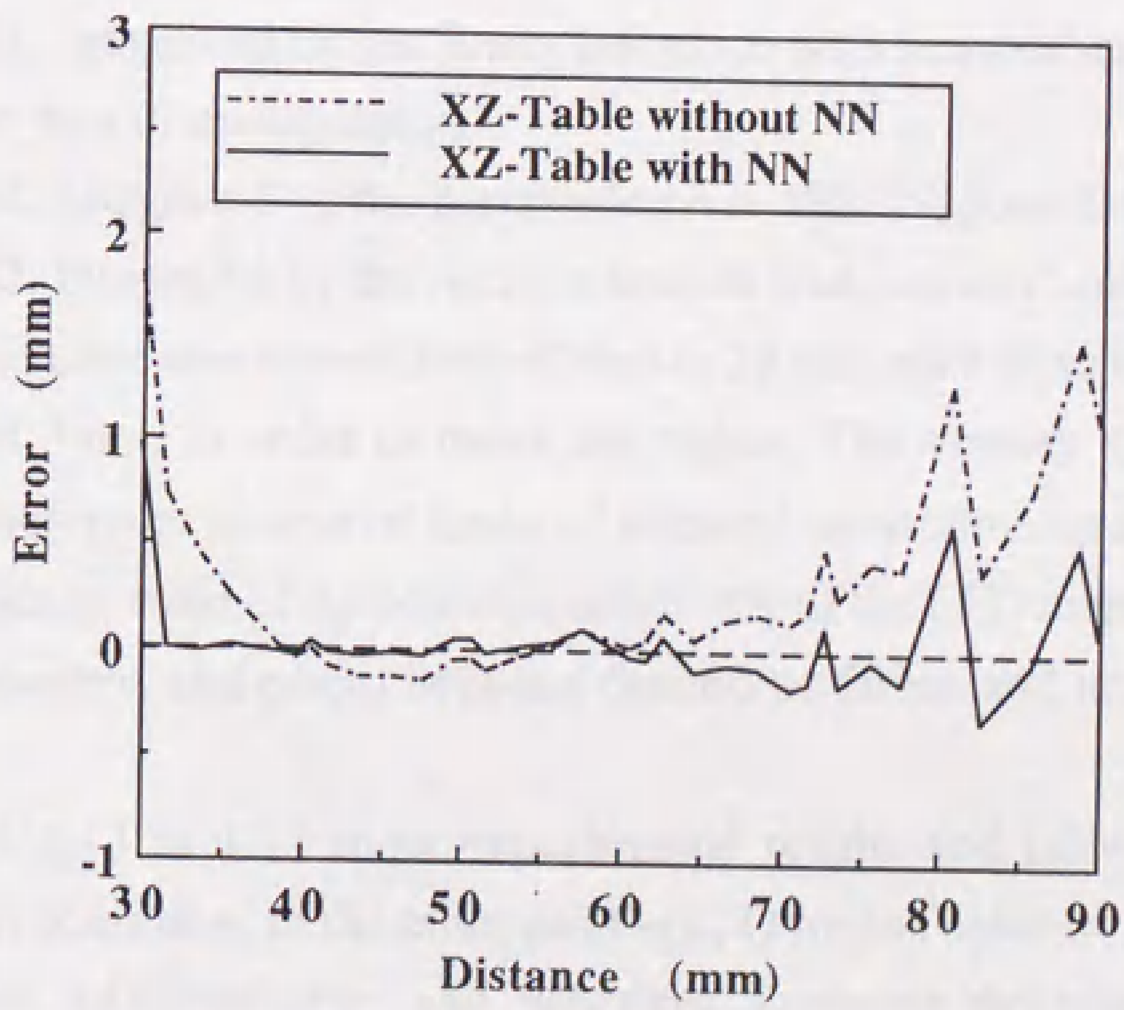


Fig. 4.12 Measurement error against the reference data (LED displacement sensor)

error between the measurement value and the reference.

Experimental results showed that accuracy of calibration by the X-Z table was about 2 times as high as that by the LED displacement sensor. Utilizing **NN**'s compensator, accuracy of the vision system calibrated by the LED displacement sensor was about 5 times as high as that without NN. In the case of the X-Z table, accuracy with **NN** was about 2.5 times as high as that without NN. The reason of improvement of accuracy was that the vision system can measure distance between the sensors and the object accurately in all measurable area by **NN**'s compensation for the lens distortion and camera calibration's error.

The measurement errors were increased above 70mm because the vision system was based on the triangulation method and accuracy fell with the distance. Furthermore, the intensity of the spot-light was low and the system could not detect the gravity center position of the spot-light accurately.

4.4.2 Experiments of sensor integration system

We experimented with the **SIS** with the environmental data of measurement and the pose data of the manipulator to compare it with other **SIS**s. Experimental **SIS**s were 3 types:

SIS1: Integrated by the fuzzy inference with sensors' environments and the pose data of manipulator.

SIS2: Integrated by the fuzzy inference with the pose data of manipulator.

SIS3: Integrated by the fuzzy inference with sensors' environments.

The X-Z table was moved from 45mm to 35 mm apart from the sensory system at an interval of 1mm, in order to move the object. The sensory system measured the distance at each point in several cases of sensors' environments and sensors' internal conditions such as color of the object, a sensitivity of the LED displacement sensor, the camera parameters, and errors between desired positions and actual positions of the manipulator.

Figures 4.13 to 4.18 show experimental results and table 4.3 shows average errors in each condition. In the table and Figs., O means color of the object, (B/black, DG/dark gray, LG/light gray, and W/white), L means the sensitivity of the LED displacement sensor, (B/for a black object and W/for a white), C means accuracy of camera parameters, (G/camera parameters with little errors and B/camera parameters with some errors), and +/0/- means errors between desired positions and actual positions of the manipulator, (+/the actual position is larger than the desired positions

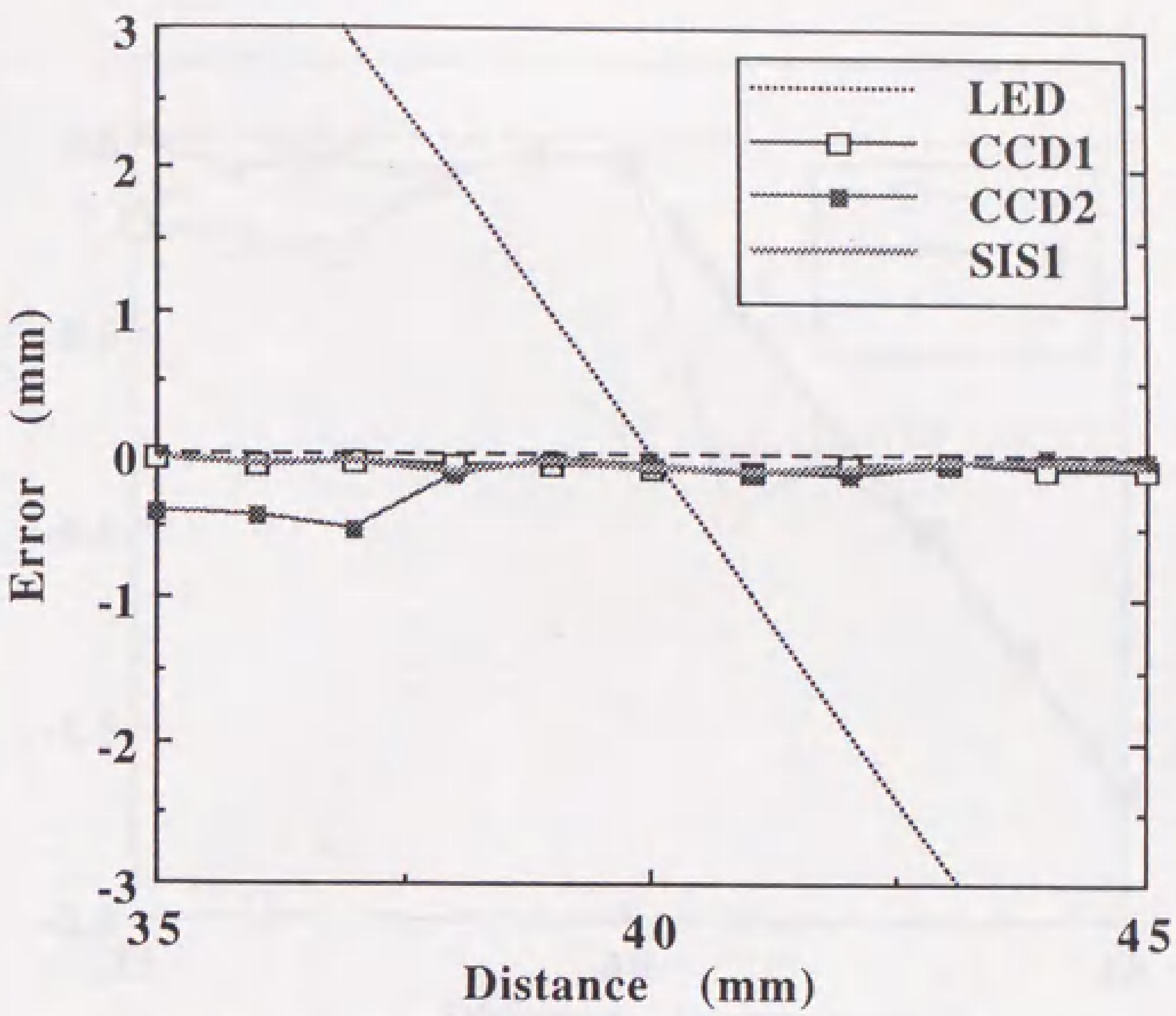


Fig. 4.13 Measurement error of each sensor (O/B, L/W, C/G)

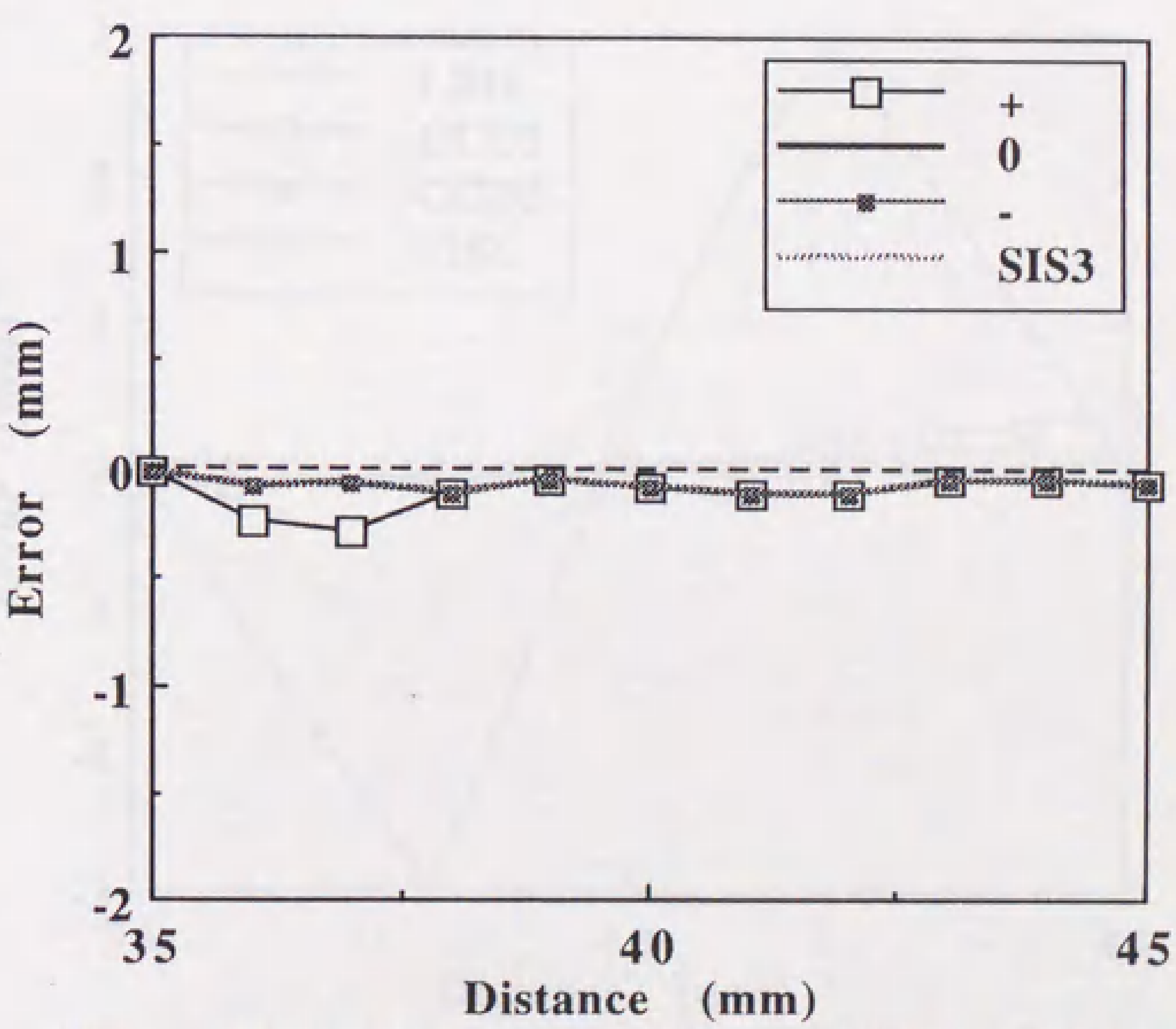


Fig. 4.14 Measurement error of SIS1 and SIS3 (O/B, L/W, C/G)

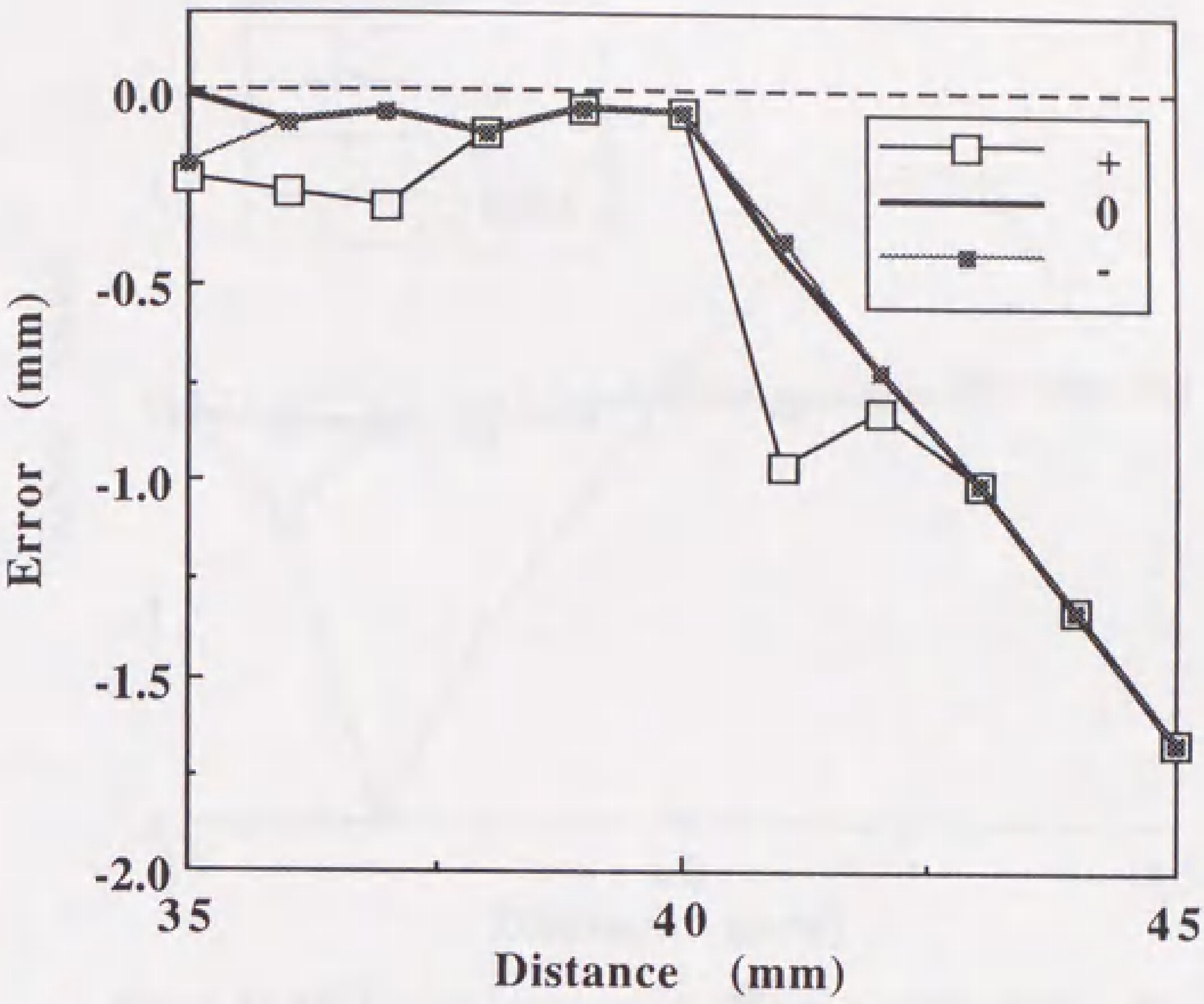


Fig. 4.15 Measurement error of SIS2 (O/B, L/W, C/G)

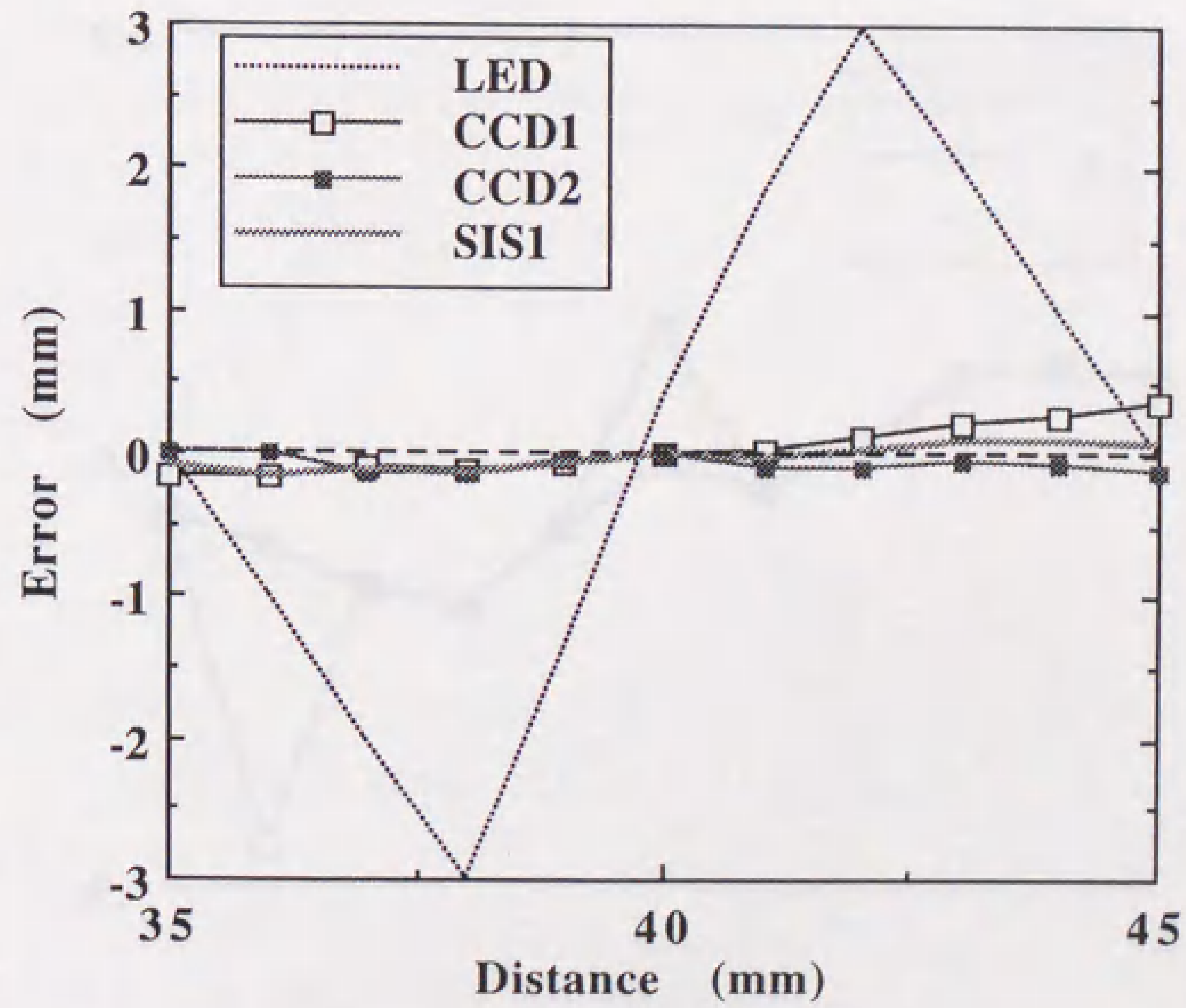


Fig. 4.16 Measurement error of each sensor (O/W, L/B, C/B)

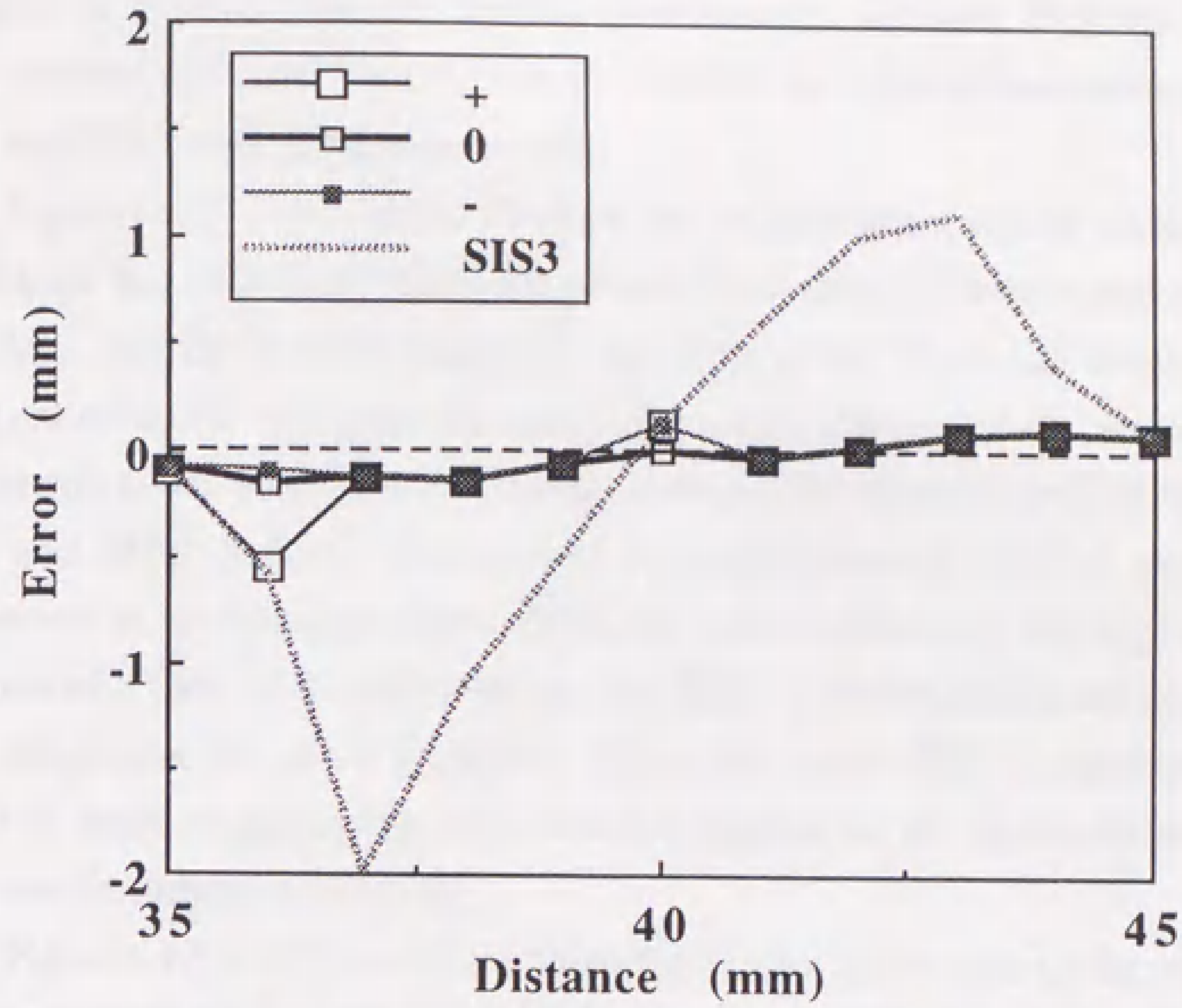


Fig. 4.17 Measurement error of SIS1 and SIS3 (O/W, L/B, C/B)

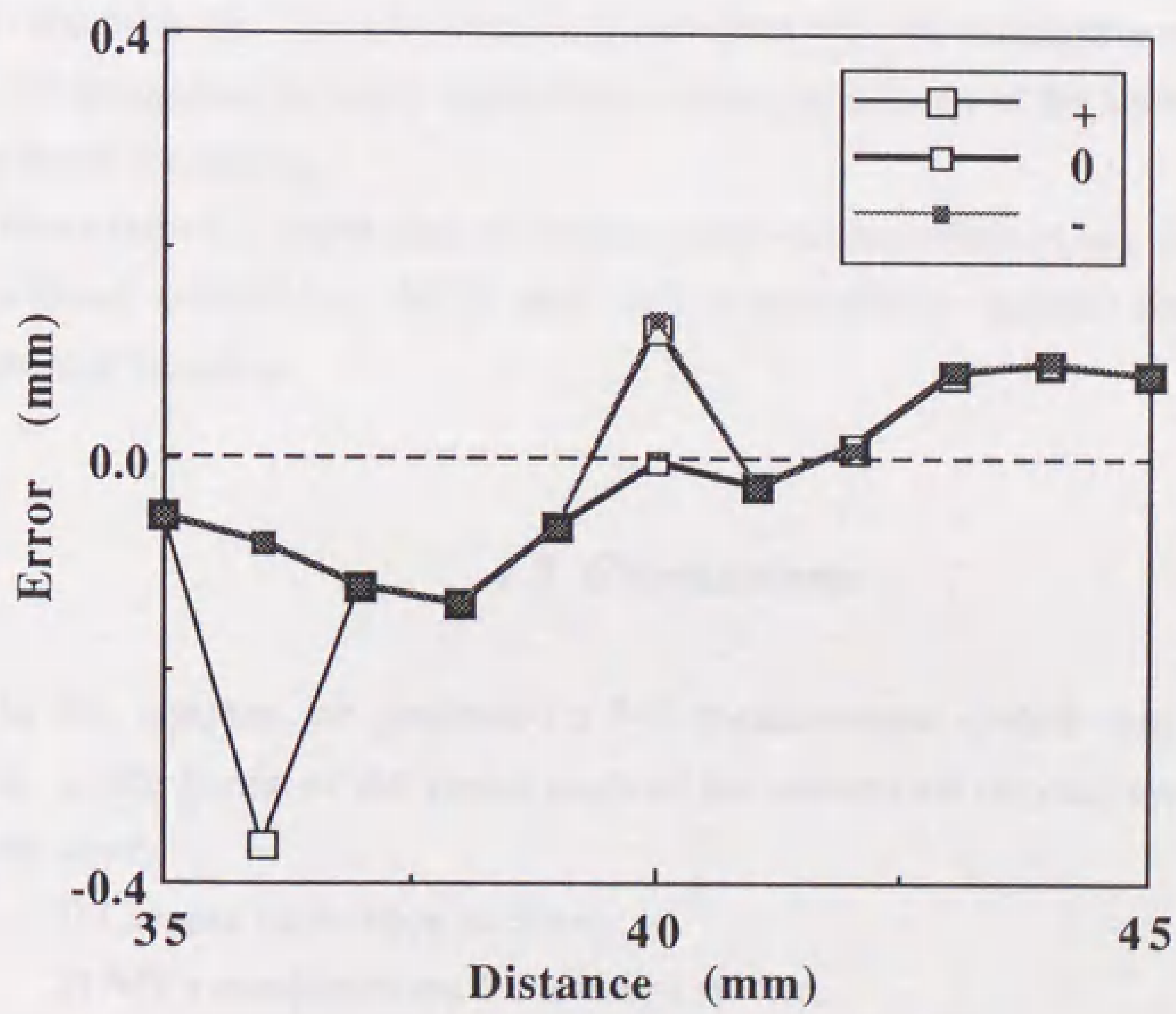


Fig. 4.18 Measurement error of SIS2 (O/W, L/B, C/B)

by 200μm, 0/the actual positions are equal to the desired positions, and -/the actual positions is smaller than the desired positions by 200μm). Figures 4.13 and 4.16, Figs.4.14 and 4.17, and Figs. 4.15 and 4.18 show the measurement error of each sensor, **SIS1** and **SIS3**, and **SIS2** respectively.

Figures 4.13, 4.14, and 4.15 show the experimental results under the following conditions: the object was black, the sensitivity of the LED displacement sensor is used for white, and the camera parameter has little error. The LED displacement sensor could not sense the spot-light because of the unsuitable sensitivity, the sensor could not measure distance. **SIS1** and **SIS3** could measure the distance accurately, because both **SIS1** and **SIS3** had the information of environmental data of measurement for integration of measurement data and integrated the data with the appropriate sensors. Because of a lack of the information, the **SIS2** suffered measurement error from the LED displacement sensor's outputs. However, since **SIS2** integrated measurement values at each measurement with the information of the manipulator's motion, the error was decreased at each step.

Figures 4.16, 4.17, and 4.18 show the results in the case of the white object, the sensitivity for black, and camera parameters with some errors. Because of the unsuitable sensitivity, outputs of the LED displacement sensor were over-sensitive to the spot-light and had measurement errors. **SIS1** and **SIS2** could measure distance accurately, because of information of the manipulator's motion. Both **SIS1** and **SIS2** could recognize the sensors accurately and integrate the measurement values. **SIS3** could not recognize the error caused by internal parameters of the sensor and thus did not measure accurately.

From table 4.3, **SIS1** was the most accurate of three **SIS**s in any sensors' external and internal conditions. **SIS1** also had a robustness against the error of the manipulator's motion.

4.5 Conclusions

In this chapter, we presented a 3-D measurement system and its integration method, which is one of the major parts of the automated carving system. Proposed methods were:

1) Camera calibration method,
2) **NN**'s compensation for a vision system,
3) Sensor integration system based on the fuzzy inference with information of sensors' environments and the manipulator's pose.

We also showed effectiveness of the proposed SIS through some experiments as follows:

1) Utilizing outputs of the LED displacement sensor, camera parameters can be calibrated easily.

2) Using NN's compensator for the lens distortion and camera calibration's errors, the vision system can measure accurately.

3) Utilizing the fuzzy inference with moving data of the sensor system and environmental data of measurement, the measurement system can measure accurately and is stable against variation of environments and internal parameters of sensors.

Future works are: 1) improvement of the image processing time, 2) parameter calibration of the manipulator for accurate sensor data integration, and 3) optimization of the membership functions and rules of the fuzzy inference to optimize sensor data integration.

Table 4.1 Fuzzy rules

		X1				
		S	MS	M	MB	B
X2	S	M	MS	MS	S	S
	MS	M	M	MS	MS	S
	M	MB	M	M	MS	MS
	MB	MB	MB	M	M	MS
	B	B	MB	MB	M	M

Table 4.2 Average measurement error (mm)
Measurement range (30mm to 100mm)/the calibration area

	With NN	Without NN
LED Sensor	0.20/0.08	1.04/0.13
X-Z Table	0.22/0.02	0.50/0.17

Table 4.3 Average measurement error in different conditions (mm)

Condition	Sensor			SIS1			SIS2			SIS3
	LED	CCD1	CCD2	+	0	-	+	0	-	
O/W, L/W, C/G	0.06	0.02	0.06	0.03	0.03	0.03	0.03	0.03	0.03	0.04
O/W, L/W, C/B	0.06	0.15	0.06	0.05	0.04	0.04	0.04	0.04	0.05	0.05
O/W, L/B, C/G	1.42	0.02	0.07	0.09	0.04	0.05	0.05	0.04	0.05	0.64
O/W, L/B, C/B	1.42	0.15	0.07	0.13	0.08	0.08	0.10	0.07	0.08	0.69
O/LG, L/W, C/G	0.06	0.07	0.10	0.05	0.05	0.05	0.06	0.04	0.05	0.06
O/DG, L/W, C/B	0.14	0.14	0.12	0.12	0.11	0.07	0.08	0.10	0.07	0.12
O/B, L/W, C/G	2.63	0.07	0.18	0.11	0.07	0.07	0.62	0.50	0.51	0.07
O/B, L/W, C/B	2.63	0.16	0.18	0.15	0.13	0.13	0.62	0.55	0.54	0.13
O/B, L/B, C/G	0.12	0.09	0.25	0.15	0.11	0.11	0.16	0.11	0.11	0.11
O/B, L/B, C/B	0.12	0.16	0.25	0.16	0.13	0.15	0.15	0.12	0.15	0.13

5. *Fuzzy Inference Integrating 3-D Measuring System with Adaptive Sensing Strategy*

This chapter deals with a **adaptive sensing strategy sensor integration method** based on **fuzzy inference** and . The measurement system consists of two different sensors. One is a LED displacement sensor, while the other is a vision system. The LED displacement sensor's spot-light is used as a part of the vision system based on the active stereo sensing method. In addition, the LED displacement sensor's outputs are used for calibrating camera parameters. A sensor integration method based on the **fuzzy set theory** manages sensors. Fuzzy inference's input consists of information on the change in the sensor output and the position change of the sensor system, together with the environmental data of measurement. For this integration system, the sensory system can measure **accurately**. Vision system can obtain the various information and be used various environmental condition, but it takes long time. The LED displacement sensor can obtain the information quickly, but it can be used in limited environmental condition. In order to measure the object quickly and accurately, the sensor integration system has an **adaptive sensing strategy**. The sensing strategy depends on a relation between the state of the object, e.g. color, temperature, and etc., and the sensor specification. The proposed system is shown to be effective through extensive experiments.

5.1 Introduction

We proposed a measurement system and its integration method in chapter 4. The system consists of two LED displacement sensors (this sensor can measure displacement at a distance of 40 mm) and two CCD cameras (for the measuring point's recognition on the target surface). The LED displacement sensor is not only used as a displacement sensor but also as a marker of the measuring point for the vision system. Therefore, the measurement system can measure the surface shape of the target at a distance and recognize the measuring point.

The vision system consists of a CCD camera and a LED displacement sensor, with which the active stereo method is applied. This vision system has two characteristics. One is that the calibration of the camera parameters is very easy because the system calibrates the camera parameters by the measurement data of the LED displacement sensor. The other is that a neural network (**NN**) is utilized as a compensator of the vision system's output errors, such as camera parameters' error and lens distortion. By utilizing the neural network, we can use the vision system as accurately as possible.

In the previous system, we used a **SIS** using the **fuzzy inference** to integrate the measurement data. These **SIS**s evaluated the suitability for the environment of each sensor, e.g., the intensity of a spot-light's reflection for the LED displacement sensor, and then used the appropriate sensor for sensors' environments. This **SIS**, however, could not evaluate internal conditions of sensors, e.g., the sensitivity for the intensity of the spot-light's reflection for the LED displacement sensor and camera parameters for the vision system.

The measurement system proposed here is mounted at the tip of the manipulator. Then changes in outputs of a sensor are caused by the position changes of the manipulator. Therefore, **SIS's** inputs in chapter 5 consist of information on both the change in sensor outputs and the changes of the manipulator's position, together with the environmental data of a sensor. Then the **SIS** can evaluate both the suitability for sensors' environments and the internal condition of a sensor in order to integrate the measurement data.

The vision system can obtain various information and be affected a little by the change of sensor's environments, but the system takes much time to measure. On the contrary, the LED displacement sensor takes a short time to measure a distance, but the sensor can only obtain the distance information and is affected by the changing of the environments. In order to use the sensory system effectively (speedy and accurately), the sensory system has the adaptive sensing strategy with the **SIS**. The sensing strategy is depends on the output of the **SIS** for each sensor as a suitability for sensing an object.

For this sensor integration system with the adaptive sensing strategy, the measurement system can measure the object as accurately as possible under any sensors' environments and internal conditions. The effect of this **SIS** is shown through extensive experiments.

5.2 Adaptive sensing strategy based on SIS

A sensor has a character individually. In our measurement system, the vision system can measure a distance in various sensor environment and obtain the various information such as the information of the object surface, however it takes a long time to obtain the information. The LED displacement sensor can measure quickly, but the sensor's output is affected by the change of its environment and the suitable environment for the sensor is limited.

When the sensory system uses both the vision system and the LED displacement sensor, the sensory system can measure the object accurately, however it takes a long time. If the object is suitable for the LED displacement sensor and the sensor is active, the vision system is not necessary. On the contrary, the object is not suitable for the LED displacement sensor, the system must use the vision system to keep the accuracy.

In order to measure the object quickly and accurately, the sensory system must change the sensing strategy. The determination of the sensing strategy is based on the suitability of sensors that are calculated by **SIS**. When the suitability of the LED displacement sensor is high, i.e. the object is suitable for the sensor, the sensory system uses only the LED displacement sensors. In other hand, the suitability of the LED displacement sensor is low, i.e. the object is not suitable for the sensor, the system uses

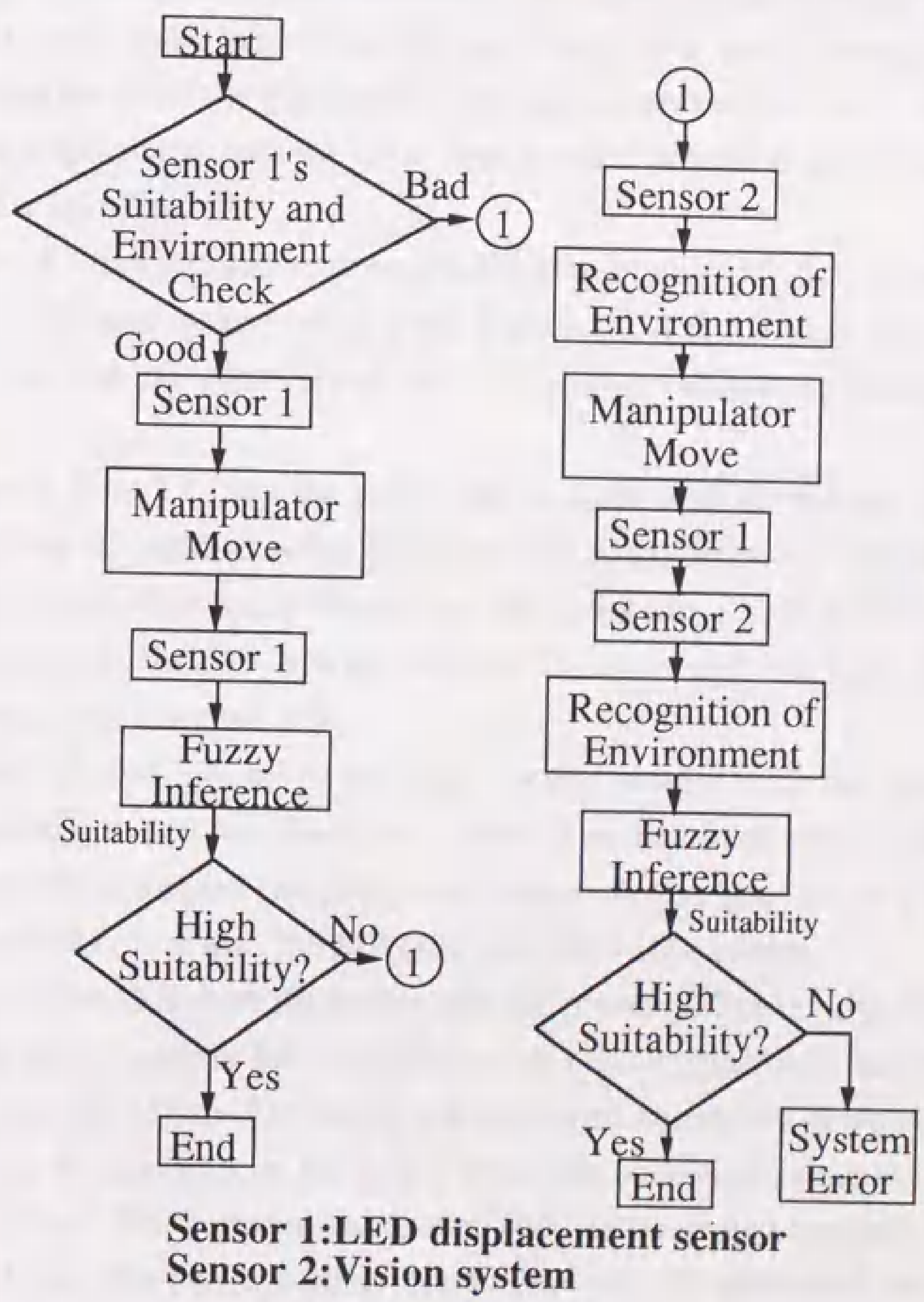


Fig.5.1 Adaptive sensing strategy

only use the vision system. In other case, both suitability are almost same, the system uses both sensors and integrated the sensory data based on the suitability of sensors.

Adaptive sensing strategy can make the sensory system to measure accurately and quickly by using the vision system when the measuring system recognizes the object is not suitable for the LED displacement sensor. Figure 5.1 shows the adaptive sensing strategy.

5.3 Experiments of sensor integration system with adaptive sensing strategy

We experimented with the **SIS** with the adaptive sensing strategy. Experiments were carried out by using the industrial 5 axis manipulator and the sensor system (see Fig. 4.8) set at the tip of the manipulator. A measurement object was a sheet 1.2 mm thick. We attached papers with the sheet. One is white, others are gradation color from black to white (see Fig.5.2).

Figures 5.3 to 5.10 show experimental results. Figures 5.3, 5.5, 5.7 and 5.9 show the output of **SIS** and measurement error. Figure 5.4, 5.6, 5.8, and 5.10 show **SIS**'s selected sensor and the suitability of the LED displacement sensor estimated by the **SIS**.

Figures 5.3 and 5.4 show the experimental results with the pattern 1 (white color object). The object's color is white therefore the suitability of the LED displacement sensor is very high. Figure 5.4 shows that the suitability of the LED displacement sensor estimated by the **SIS** is high, and the **SIS** only used the LED displacement sensor through measuring the object.

Figures 5.5 and 5.6 show the experimental results with the pattern 2. The suitability decreases, because the object's color is change from white to black. Figure 5.6 shows that the estimated suitability decreases with changing of the object's color. When the suitability was low, the **SIS** only used the vision system.

Figure 5.7 and 5.8 show the results with the pattern 3. The middle of the object is black or dark gray therefore the suitability of the LED displacement sensor decreases and then increases. Figure 5.8 shows the estimated suitability decreased and then increased with the changing of the color. When the estimated suitability is high, the **SIS** only used the LED displacement sensor. Then the estimated suitability decreased, the **SIS** used only the vision system. Around 90 mm, the estimated suitability was increasing, then the **SIS** used both the LED displacement sensor and the vision system.

Then the estimated suitability increased, the **SIS** only used the LED displacement sensor again.

Figures 5.9 and 5.10 show the results in the case of the object's color is white (pattern 1) and the LED displacement sensor is breakdown. The suitability of the LED displacement sensor is as high as in the case of Figs. 5.3 and 5.4, however the estimated suitability of the LED displacement sensor is low and the **SIS** only used the vision sensor. Because the **SIS** recognized the breakdown of the LED displacement sensor.

Experimental results show that the **SIS** use the vision system when the **SIS** estimated the LED displacement sensor was not suitable for measuring the object or the LED displacement sensor was breakdown. The **SIS** keeps the average of measurement error under 4.0×10^{-5} m.

5.4 Conclusions

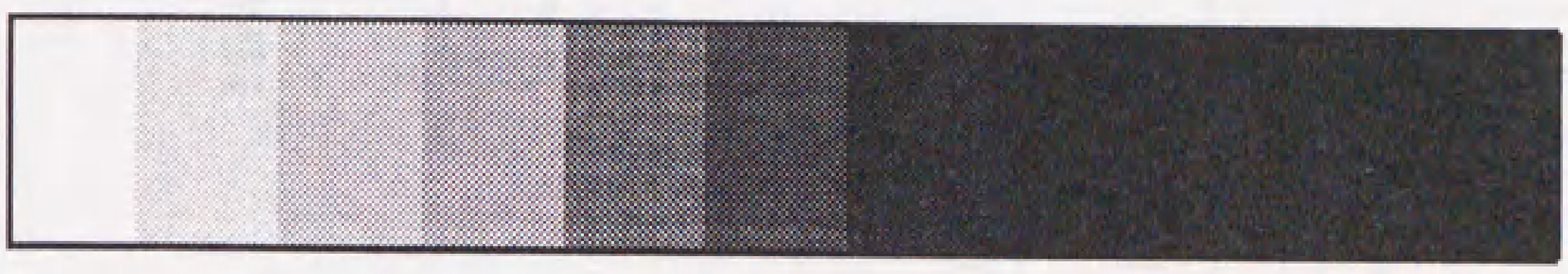
In this chapter, we presented a 3-D measurement system and its integration method with adaptive sensing strategy, which is one of the major parts of the automated carving system.

We also showed effectiveness of the proposed SIS through some experiments as follows:

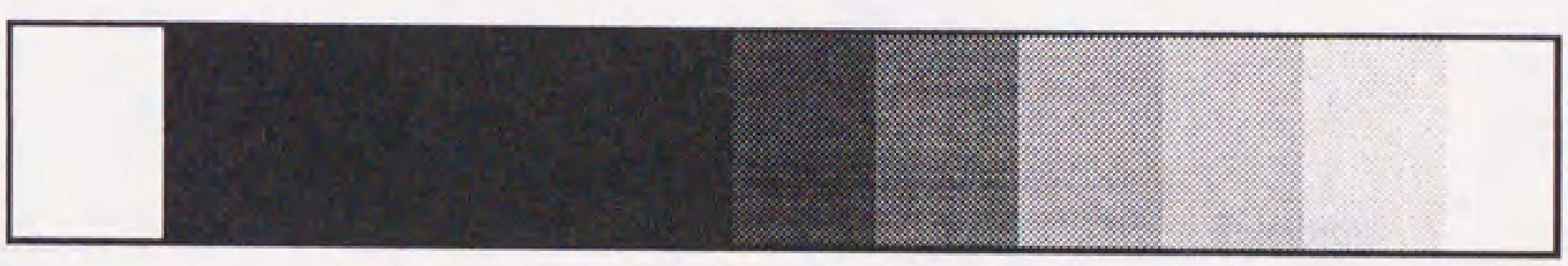
> Utilizing the adaptive sensing strategy, the **SIS** uses the vision system which takes long time to measure when the **SIS** estimates the LED displacement sensor cannot measure the object, and then the system achieves fast and accurate measuring.

Future works are: 1) improvement of the image processing time, 2) parameter calibration of the manipulator for accurate sensor data integration, and 3) automatic extraction of sensor specification and making the fuzzy rules and membership function.

Pattern 1



Pattern 2



Pattern 3

Fig.5.2 The object of experiments

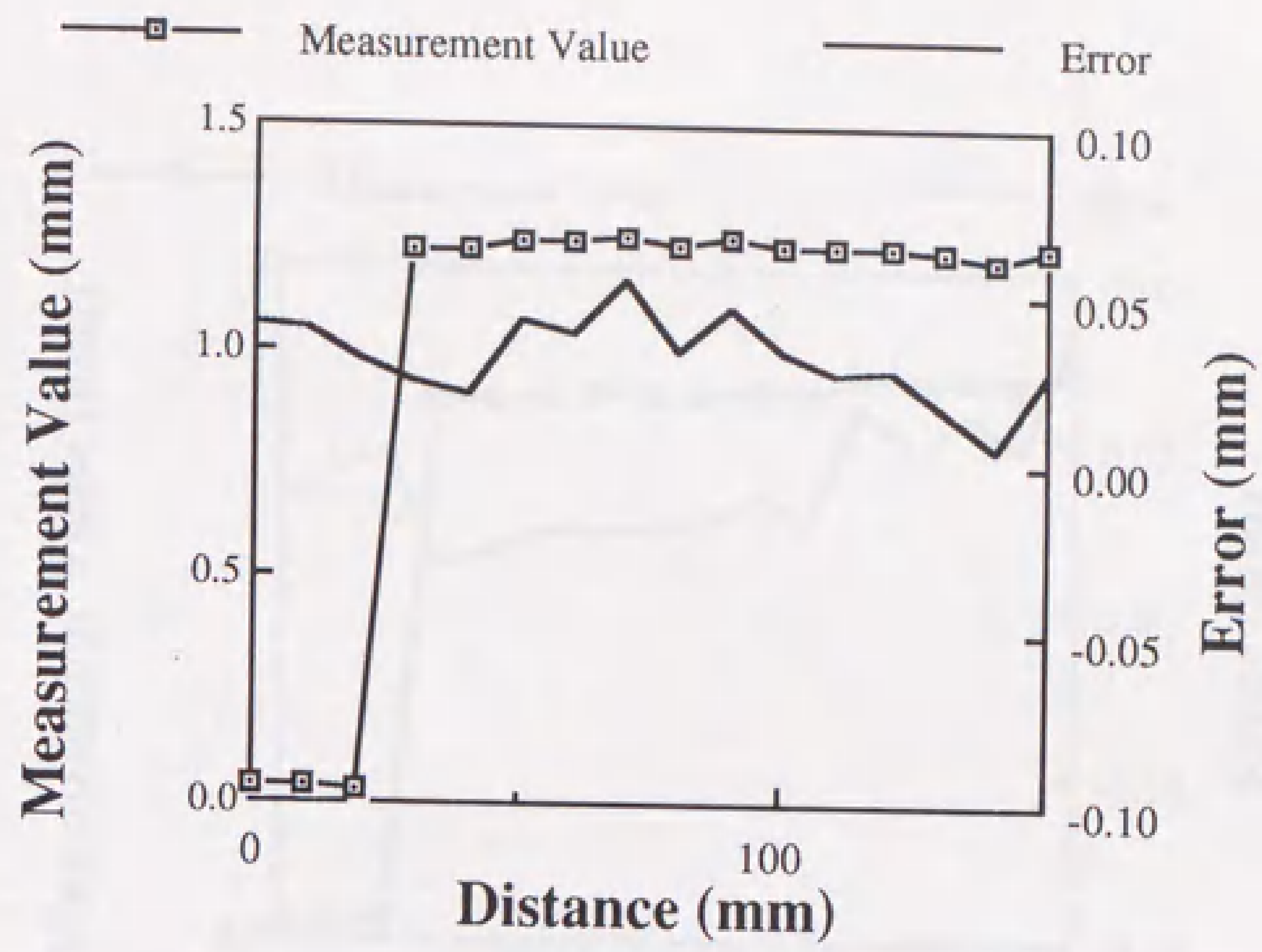


Fig. 5.3 Experimental result (Pattern 1)

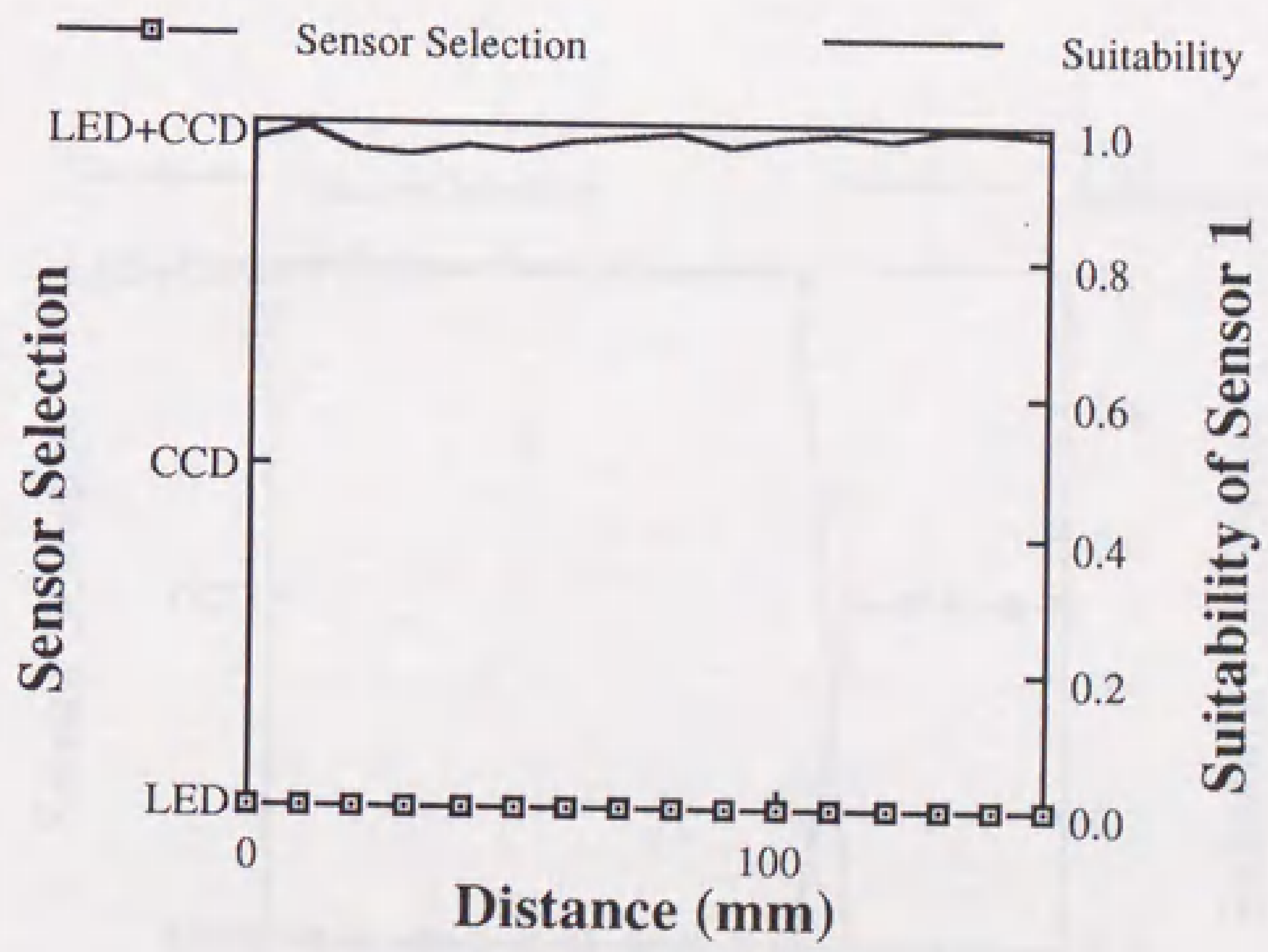


Fig. 5.4 Experimental result (Pattern 1)

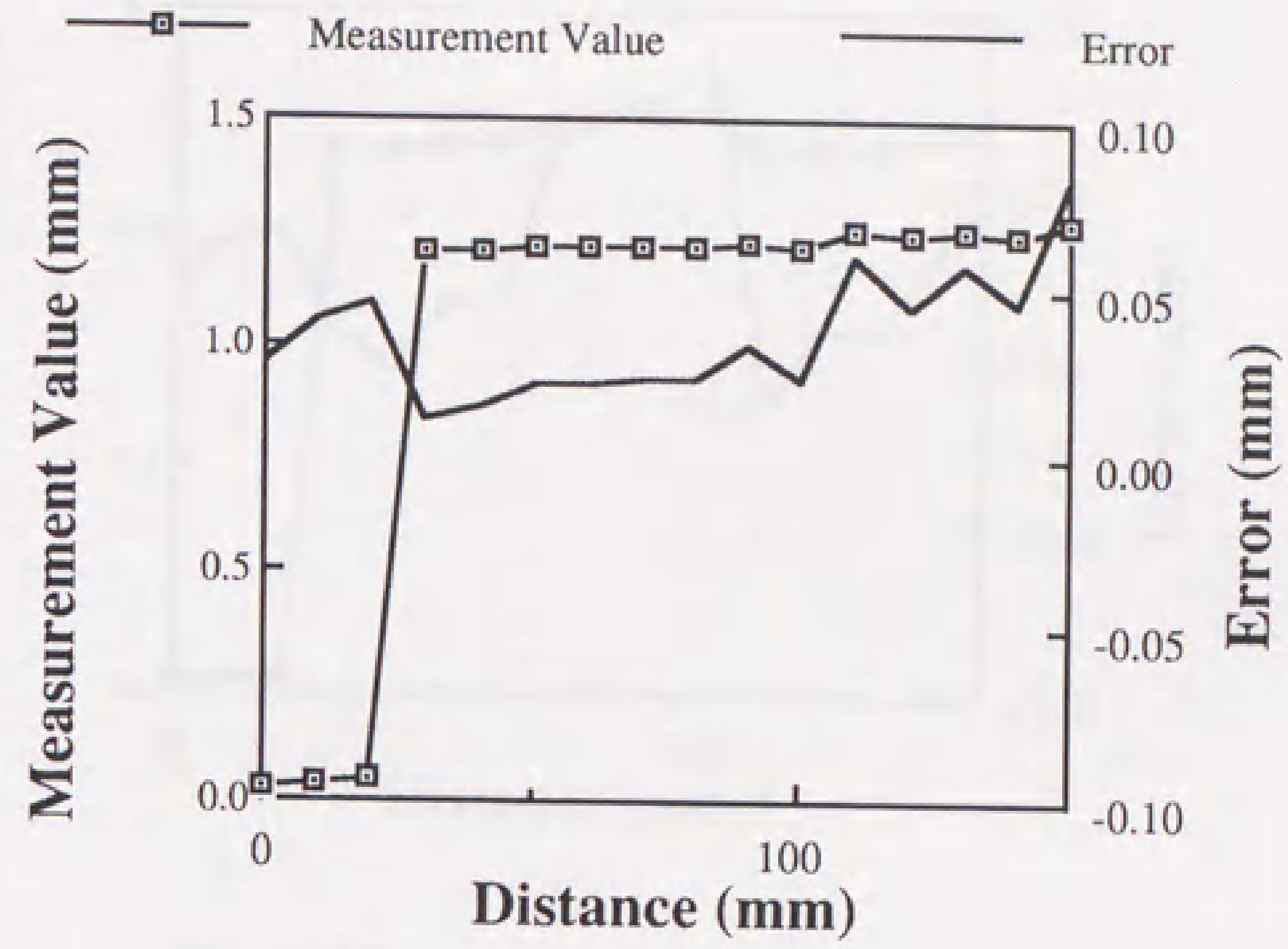


Fig. 5.5 Experimental result (Pattern 2)

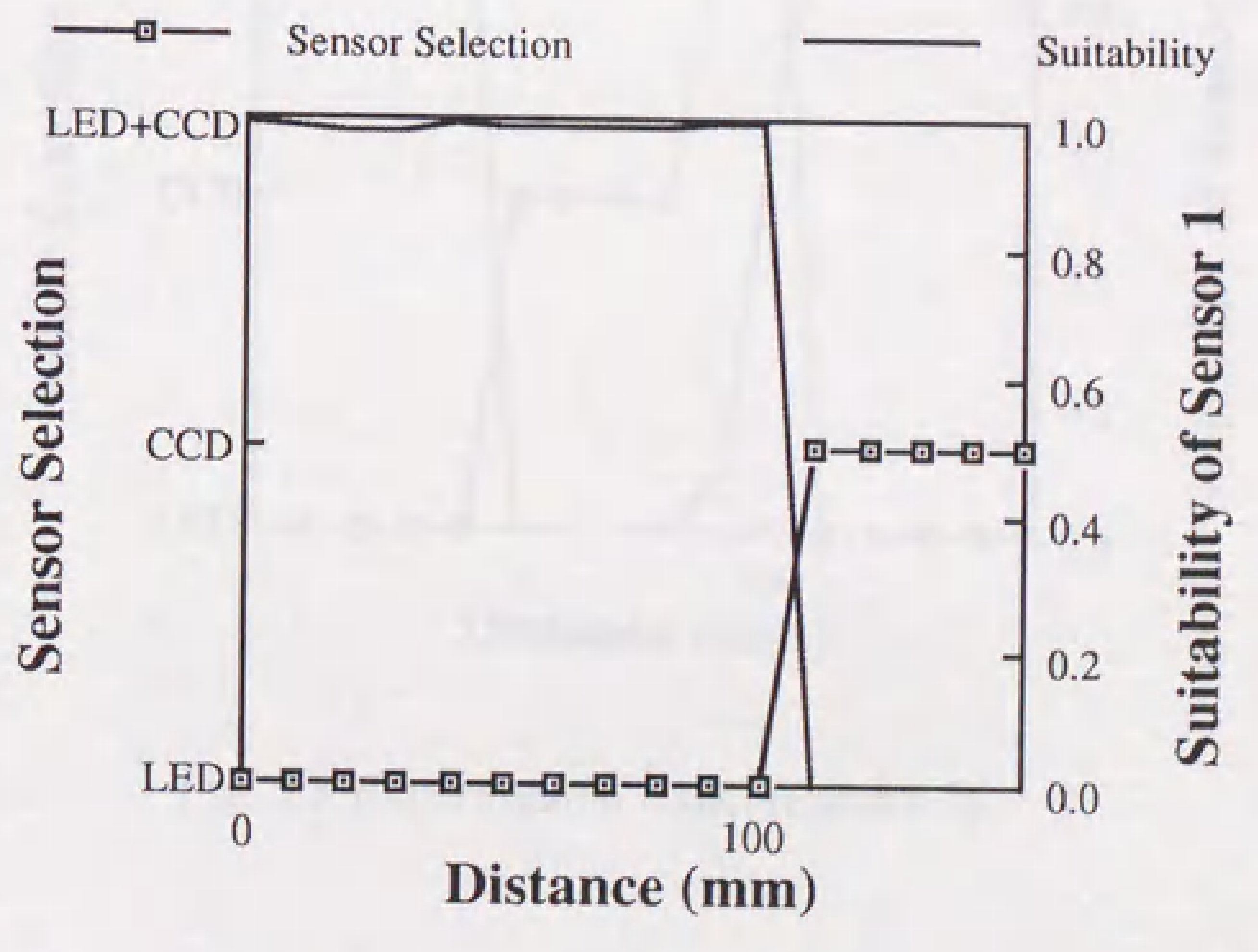


Fig. 5.6 Experimental result (Pattern 2)

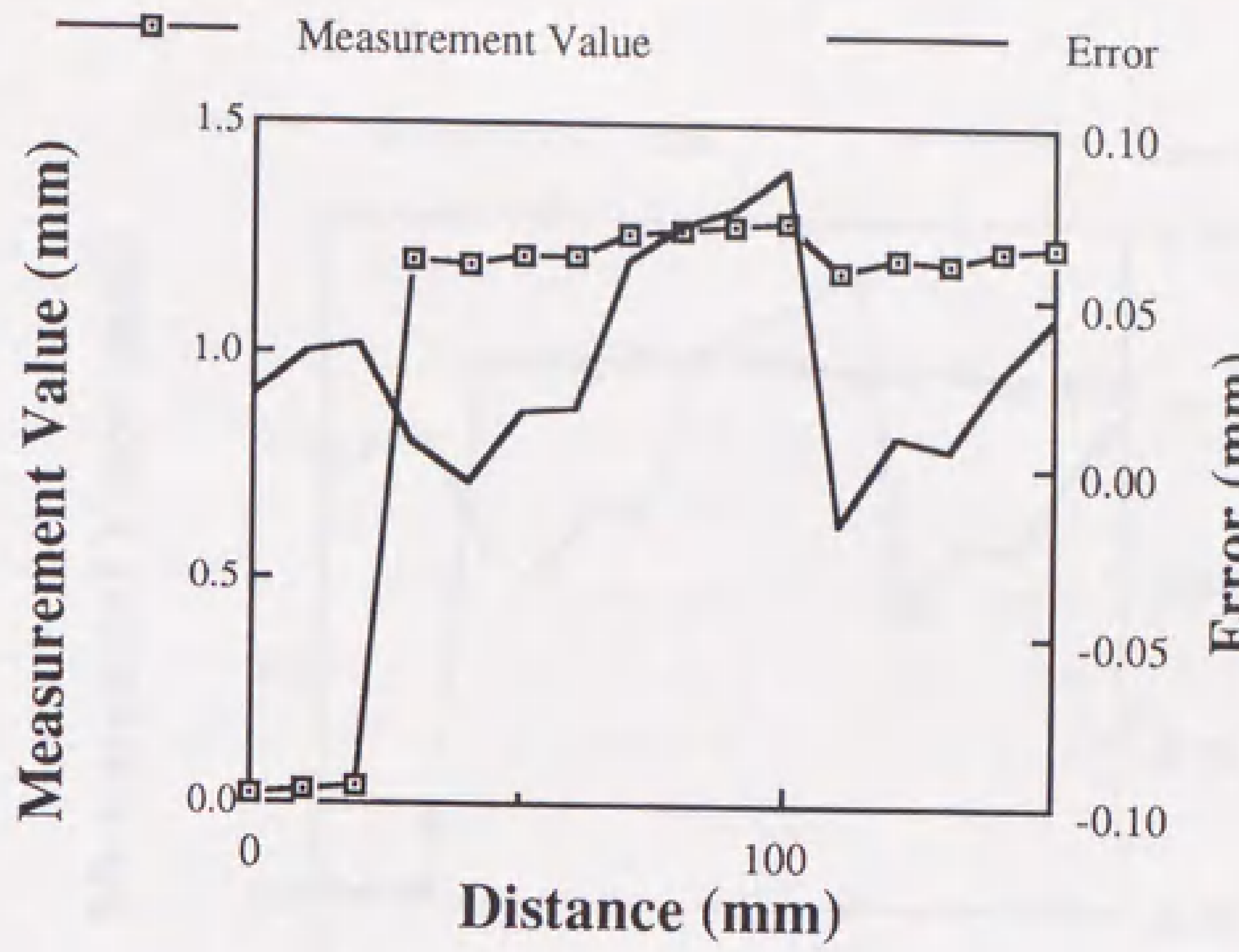


Fig. 5.7 Experimental result (Pattern 3)

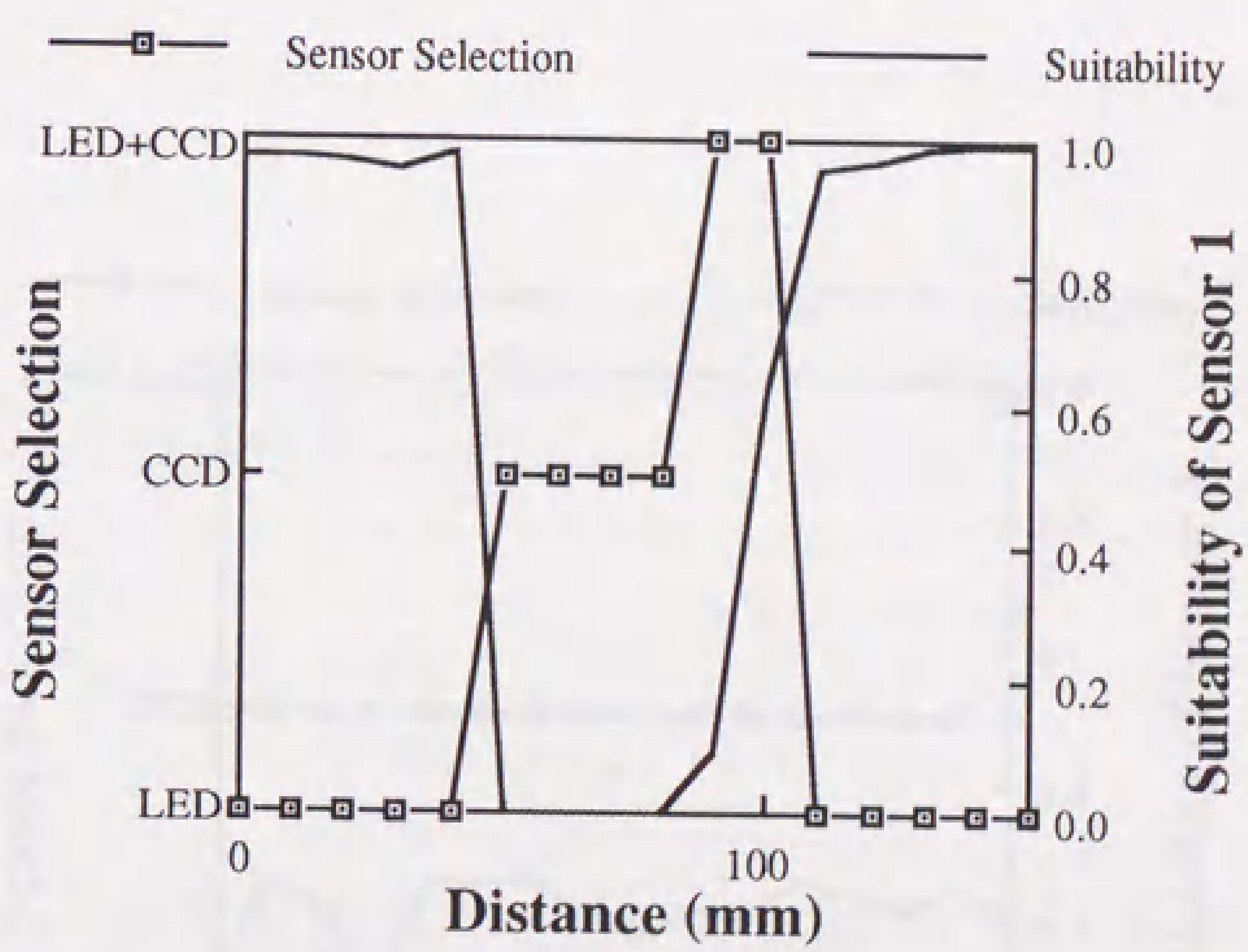


Fig. 5.8 Experimental result (Pattern 3)

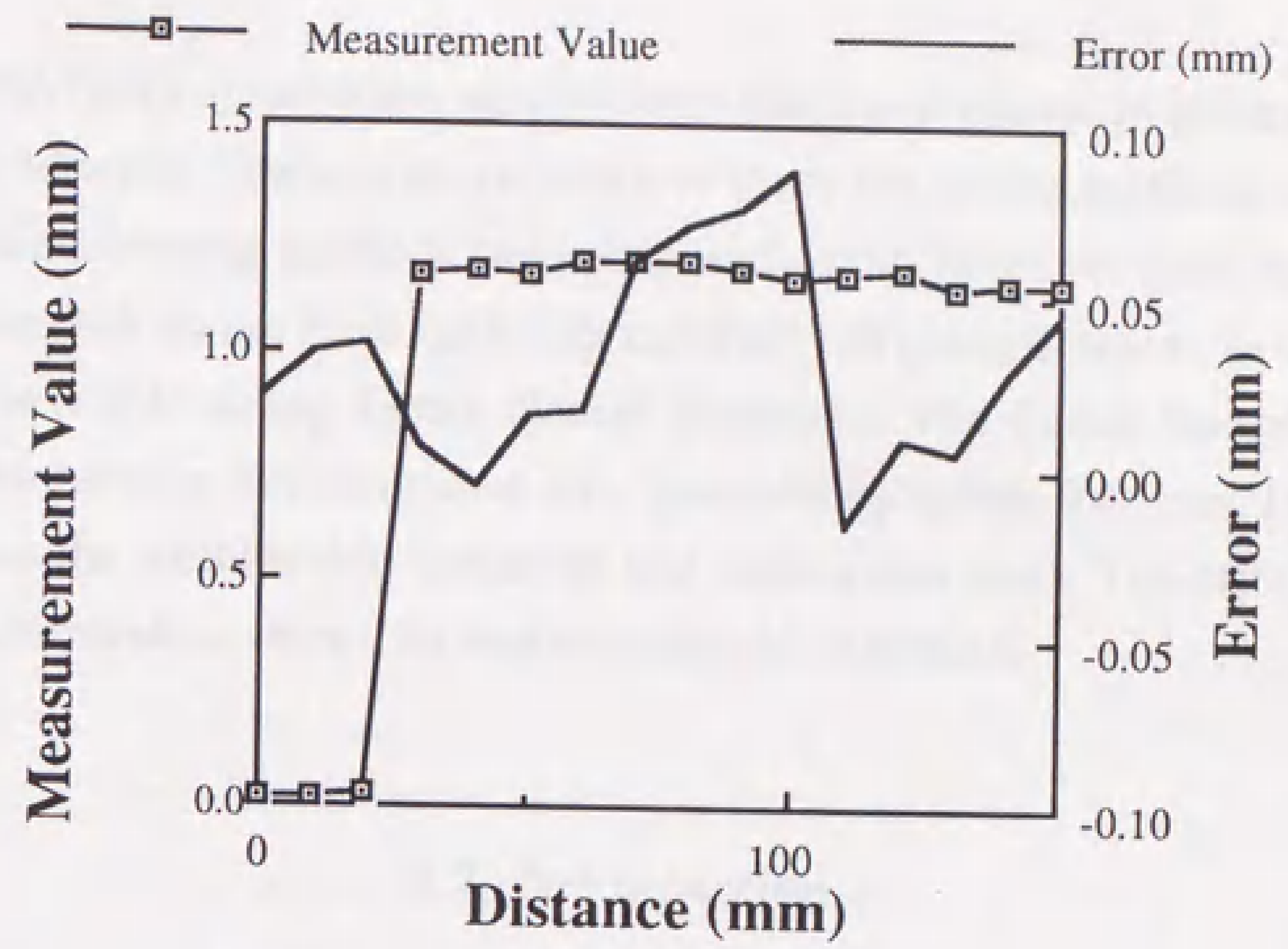


Fig. 5.9 Experimental result (Pattern 1, LED sensor is breakdown)

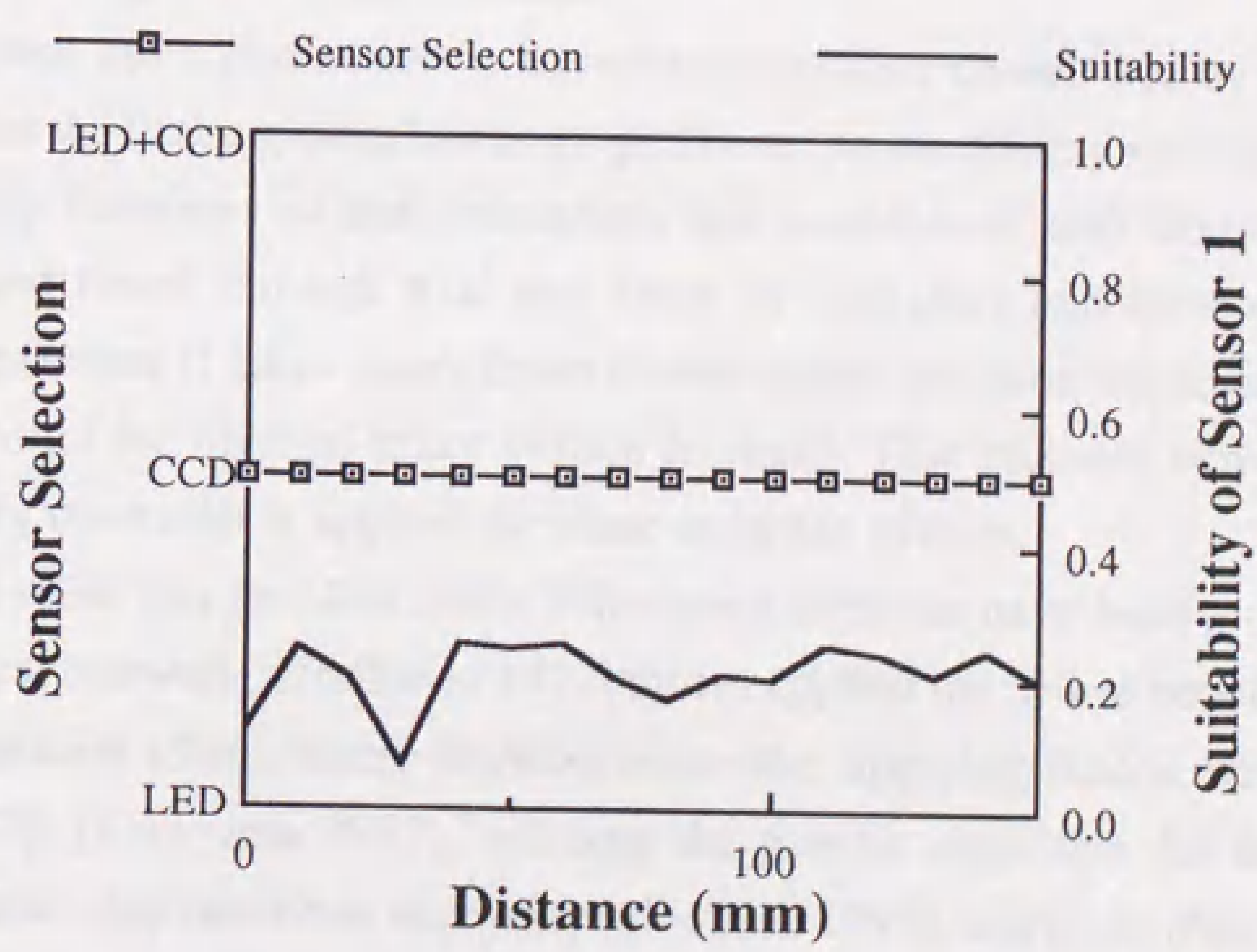


Fig. 5.10 Experimental result (Pattern 1, LED sensor is breakdown)

6. Fuzzy Inference based on Spline Function

Recently, fuzzy systems are used in many fields and places. In order to apply the fuzzy system to wider fields, it is necessary to study the tuning methods of the fuzzy system. Some self-tuning methods were proposed so far. However these conventional self-tuning methods do not have sufficient capability of generalization. In this chapter, we propose new self-tuning Fuzzy Neural Networks. The Fuzzy Neural Networks consist of membership functions that are expressed by spline function. Delta rule is applied to tune the membership functions and consequent parts. The effectiveness of the proposed methods is shown by some numerical examples.

6.1 Introduction

In recent years, fuzzy systems such as fuzzy reasoning, fuzzy modeling, and fuzzy logic controllers are utilized in many fields as engineering, medical engineering, and even social science. Some fuzzy control system already can be seen in home appliance, transportation system, and so on. We also have been studying about the sensor integration system applied fuzzy inference.

Fuzzy system has a characteristic to represent human knowledge by some fuzzy rules. However the fuzzy system has some problems. In most fuzzy systems, the shape of membership functions of the antecedent, the consequent, and fuzzy rules were determined and tuned through trial and error by operators and their experienced knowledge, therefore it takes many times to determine and tune them, and it is very difficult to design the optimal fuzzy system in detail. This problem is more serious, when the fuzzy controller is applied the more complex system.

In order to solve this problem, some self-tuning methods have been proposed such as Fuzzy Neural Network [Horikawa 1992] that is applied the neural network learning method [Rumelhart 1986], fuzzy learning controller applying Radial basis function [Linkens 1993], [Katayama 1993], utilizing the genetic algorithm for deciding the shapes of membership functions and fuzzy rules [Lee 1993], and so on [Nomura 1991].

These methods can learn faster than neural networks. However operator must determine the number and shapes of membership functions before learning, and the learning ability and accuracy of approximation are related to the number or shape of membership functions. Fuzzy inference with much membership function and fuzzy rules has high learning ability, however there are some redundant rules or unlearned rules. The number of rules is product of the number of membership function for each input, and the number of rules is increased as exponential with increase of the input's dimension. Therefore operators must pay attention to determine the structure of the membership functions. For this problem, the hierarchical fuzzy inference has been proposed to reduce fuzzy rules. However this method also has two problems. One is that the number of rules is increased with increase of the input's dimension. Other is that the operator must design the fuzzy inference considering the relation of each input because inputs are classified into some groups and the relation of each input is cut into off.

[Katayama 1993] and [Lee 1993] utilize Radial Basis Function and make a fuzzy inference adding a new rule for the maximal error point through learning process. Therefore, fuzzy rule depends on the learning data set and if the learning data is biased, there are some unlearning area. These methods also have the increasing fuzzy rule problem and adding of fuzzy rules are cause of consuming the calculation time and memory. These methods do not integrate or delete a fuzzy rule, only add a new fuzzy rule.

Self-tuning fuzzy inference based on B-spline [Curry 1966] has been proposed [Watanabe 1990]. The characteristic of this method is that each membership function is utilized as B-spline and three membership functions is fired for one input and then the output is C^1 function. However for n dimensional input system, fired rules are increased as 3^n and it needs much calculation. Learning is only carried out for the consequent part, and the learning ability is depends on the initial state because of no adding knot.

In this chapter, we propose a new type of self-tuning fuzzy inference. The membership function of the antecedent is expressed by the spline function. In [Watanabe 1990], a membership function (B-spline) only covers a part of the input space. On the contrary, the input space of each membership function covers the whole space of each input variable, thus this fuzzy inference can be constructed by less membership function and fuzzy rules and the initial state problem does not arise and it is able to learn in short time. In order to enhance the learning ability, this fuzzy inference adds/deletes a new knot that can make the spline function more complex shape. The added knot affects little to the calculation time of inference.

We describe the structure of the fuzzy inference based on spline function, it's learning method, the knot addition/deletion method, and show the results of numerical experiments.

6.2 *Fuzzy inference based on spline function*

6.2.1 *Construction*

The fuzzy inference based on spline function proposed here have the consequent with numerical value. Note that input variables are defined as x1, x2, ..., x_n and estimated result as y, then the i-th rule of fuzzy inference is expressed as follows;

$$\text{Rulei: If } x_1 \text{ is } M_{i1} \text{ and } x_2 \text{ is } M_{i2} \; ... \; and \; x_n \text{ is } M_{in}, \text{ then } y \text{ is } W_i (i = 1, 2, ... , m) \tag{6.1}$$

where W_i and M_{in} means numerical value of the consequent of the i-th fuzzy rule and the membership function for input variable x_n of the antecedent respectively.

The membership function of the antecedent M_{ij} is expressed by the natural cubic spline function, and each fuzzy rule consists of some membership functions individually. The natural cubic spline function can be expressed by the value, here the value is the grade of membership, and the second derivative on the knot with the simple equation (6.2) [Ahlberg 1967]. Thus grade of membership of the i-th rule M_{ij} against input x_j is the output μ_{ij} of the natural cubic spline function which expresses M_{ij}.

$$\begin{aligned}
\mu_{ij} &= m_{ijk-1}\frac{\left(x_{ijk}-x_j\right)^2\left(x_j-x_{ijk-1}\right)}{h_{ijk}^2} - m_{ijk}\frac{\left(x_j-x_{ijk-1}\right)^2\left(x_{ijk}-x_j\right)}{h_{ijk}^2} \\
&+\mu_{ijk-1}\frac{\left(x_{ijk}-x_j\right)^2\left\{2\left(x_j-x_{ijk-1}\right)+h_{ijk}\right\}}{h_{ijk}^3} \\
&+\mu_{ijk}\frac{\left(x_j-x_{ijk-1}\right)^2\left\{2\left(x_{ijk}-x_j\right)+h_{ijk}\right\}}{h_{ijk}^3} \\
h_{ijk} &= x_{ijk}-x_{ijk-1}
\end{aligned} \tag{6.2}$$

where x_{ijk}, μ_{ijk}, and m_{ijk} means position of knot, grade of membership at x_{ijk}, and the second order derivative at *xijk* respectively. Here, the grade of membership is limited as 0 to 1. Therefore a fitness of the antecedent of the i-th rule μ_i is given by eq. (6.3).

$$\mu_i = \mu_{i1} . \mu_{i2} \ldots \mu_{in} \tag{6.3}$$

then the result of estimation y is calculated by eq. (6.4).

$$y = \frac{\sum_{i=1}^{m} \mu_i \bullet W_i}{\sum_{i=1}^{m} \mu_i} \tag{6.4}$$

In ordinary fuzzy system, each rule does not cover the whole input space, because each membership function takes a part of the input domain. Our proposed membership function takes the whole input space. Therefore each rule of the fuzzy inference covers the whole input space.

Membership function of each rule implies the probability distribution map about the rule. Therefore it is difficult to express the probability distribution map like parity bit problem, because each learning data has contradictory learning data. The exclusive-or problem with 2-input and an output is an example. Now we select the learning data (x_1, x_2) as (0, 0), (0, 1), (1, 0), and (1,1) and we use two rules (the consequent value of rule_1 is 0, rule_2 is 1. When we think about input x_1, the value is 0 at (0, 0), however the value is 1 at (0, 1) and they are contradictory. This contradiction can be seen on all learning point, therefore the fuzzy inference cannot make a membership function for each rule.

In order to express the parity bit problem, proposed fuzzy inference has two more membership functions that express the position information of input data. One membership function is about the angle θ for 4-input given by eq. (6.5), and the other is about the distance D that is given by eq. (6.6). For these membership functions, the proposed fuzzy inference can learn the parity bit problem.

$$\theta = \tan^{-1}\left(\tan^{-1}(x_1, x_2), \tan^{-1}(x_3, x_4)\right) \tag{6.5}$$

$$D = \sqrt{\sum_{i=1}^{n} (x_{ic} - x_i)^2} \tag{6.6}$$

where x_{ic} means the center value of the input variable x_i. Membership function for θ is expressed by the cubic periodic spline function, others are expressed by the natural cubic non periodic spline function. Figure 6.1 shows the structure of the fuzzy inference based on the spline function and Fig. 6.2 shows the calculation way of the angle information θ.

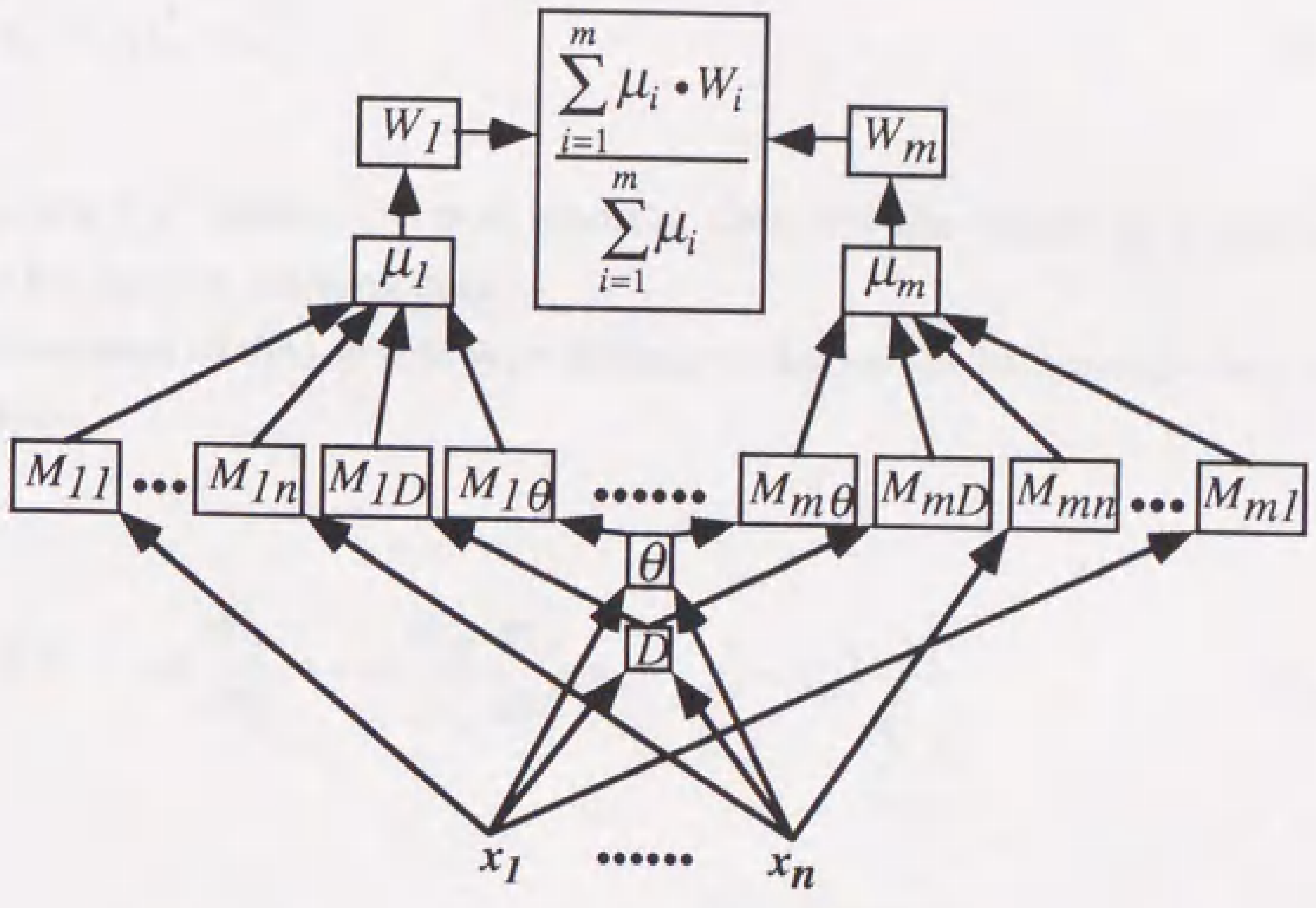


Fig. 6.1 Fuzzy inference based on Spline Function

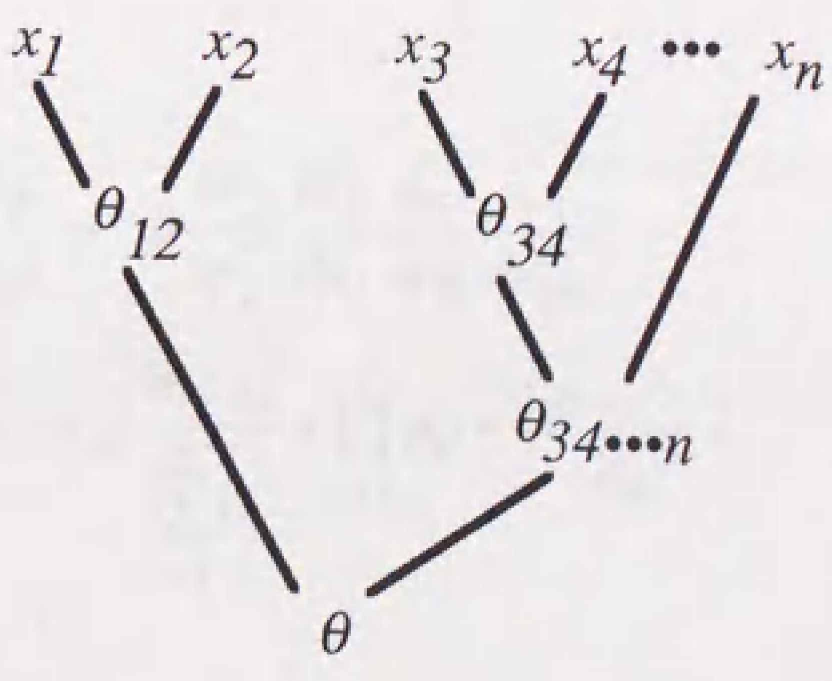


Fig. 6.2 Angle information θ

6.2.2 Learning law

Learning of membership functions of the antecedent and values of the consequent are conducted by delta rule. Eq. (6.7) defines the error function.

$$E_p = \frac{1}{2}\left(y_p^* - y_p\right)^2 \tag{6.7}$$

where y_p and y_p^* means the p-th learning data and the output of Fuzzy Neural Networks for the p-th learning data.

The consequent of the i-th rule W_i is refined by the partial differential of eq. (6.7) by W_i as follows,

$$\Delta W_i = -\alpha \frac{\partial E_p}{\partial W_i} = -\alpha \frac{\partial E_p}{\partial y_p^*} \frac{\partial y_p^*}{\partial W_i} = -\alpha\left(y_p^* - y_p\right) \frac{\mu_i}{\sum_{i=1}^{m} \mu_i} \tag{6.8}$$

where α means the learning rate of the consequent.

Learning of the antecedent is conducted by refining the knots of the spline function which satisfy $x_{ijk} \le x_j \le x_{ijk+1}$. The learning equations of μ_{ijk} and μ_{ijk+1} are defined by partial differentiate eq. (6.7) by μ_{ijk} / μ_{ijk+1} as follows,

$$\begin{aligned}\Delta \mu_{ijk} &= -\beta \frac{\partial E_p}{\partial \mu_{ijk}} = -\beta \frac{\partial E_p}{\partial y_p^*} \frac{\partial y_p^*}{\partial \mu_i} \frac{\partial \mu_i}{\partial \mu_{ij}} \frac{\partial \mu_{ij}}{\partial \mu_{ijk}} \\ &= -\beta\left(y_p^* - y_p\right) \frac{W_i - y_p^*}{\sum_{i=1}^{m} \mu_i} \bullet \prod_{l \ne j}^{n} \mu_{il} \bullet \frac{x_{ijk+1} - x_j}{h_{ijk}}\end{aligned} \tag{6.9}$$

$$\Delta\mu_{ijk+1} = -\beta\left(y_p^* - y_p\right)\frac{W_i - y_p^*}{\sum_{i=1}^{m}\mu_i} \bullet \prod_{l \neq j}^{n}\mu_{il} \bullet \frac{x_j - x_{ijk}}{h_{ijk}} \qquad (6.10)$$

The learning equations of x_{ijk} and x_{ijk+1} are defined as partial differentiate eq. (6.7) by x_{ijk} / x_{ijk+1} as follows,

$$\Delta x_{ijk} = -\gamma\left(y_p^* - y_p\right)\frac{W_i - y_p^*}{\sum_{i=1}^{m}\mu_i} \bullet \prod_{l \neq j}^{n}\mu_{il} \bullet X_{ijk}$$

$$X_{ijk} = \frac{x_{ijk+1} - x_j}{h_{ijk}{}^2}\left(\mu_{ijk} - \mu_{ijk+1}\right) \qquad (6.11)$$

$$\Delta x_{ijk+1} = -\gamma\left(y_p^* - y_p\right)\frac{W_i - y_p^*}{\sum_{i=1}^{m}\mu_i} \bullet \prod_{l \neq j}^{n}\mu_{il} \bullet X_{ijk+1}$$

$$X_{ijk+1} = \frac{x_j - x_{ijk}}{h_{ijk}{}^2}\left(\mu_{ijk} - \mu_{ijk+1}\right) \qquad (6.12)$$

where β and γ are the learning late of μ_{ijk} / μ_{ijk+1} and x_{ijk} / x_{ijk+1}.

6.2.3 Knot addition/deletion method

The proposed fuzzy inference consists of the spline function. The shapes of spline function depend on knots. The learning law of the section 6.2.2 is applied for changing the value and the position of the knots. However the number of knots limits the ability of the expression, thus the learning ability also is limited.

For this problem, the fuzzy inference adds or deletes knots of spline function in order to improve the ability of expression of membership function and the learning ability, not adds a new fuzzy rule.

Knot addition is carried out when the changing of mean square error (eq. (6.13)) is small, i.e. eq. (6.14) is satisfied for k times continuously. The position of the additional knot is the maximal error of the learning data and the value is the output of the spline function.

$$E_t = \frac{1}{\mathrm{P}}\sum_{\mathrm{P}}\left(y_p^* - y_p\right)^2 \tag{6.13}$$

$$\left|\frac{E_{t-1} - E_t}{E_{t-1}}\right| \leq e \tag{6.14}$$

where t means iteration time, k, and e are the constant value set before the learning.

By the learning process or the additional knot process, if there is a knot which cannot be carried out the learning, i.e., the knot is not used through a learning cycle, and the deletion of the knot is not affect the mean square error, the knot is deleted except knots of both ends.

6.2.4 Learning algorithm

In this chapter, we propose two different initial conditions of Fuzzy Neural Networks as follows;

(1) Shape of membership functions of the antecedent is initialized as the grade is 0.5 in any point as Fig. 6.3 and define the consequent value of each rule's.

(2) Shape of membership function is initialized as Fig. 6.5. The consequent is initialized as 0.0.

The number of rules of initial state(1) is that of the operator determined before learning. The minimal number is two from eq. (6.4). For initial state(2), the number of rules is product of each divided number of input space. For example, for 2-input system and each input space is divided into three parts, the number is nine.

Learning is carried out by two steps. For initial state (1), the antecedent is tuned using eqs. (6.9)-(6.12) as the first step. When the total error almost converges or the total error is smaller than the objective value of the first step, both the antecedent and the consequent is tuned simultaneously as the second step. For state (2), the first step is tuning of the consequent using eq. (6.9). The second step is the same as in case of initial state(1). Figure 6.5 shows the learning algorithm.

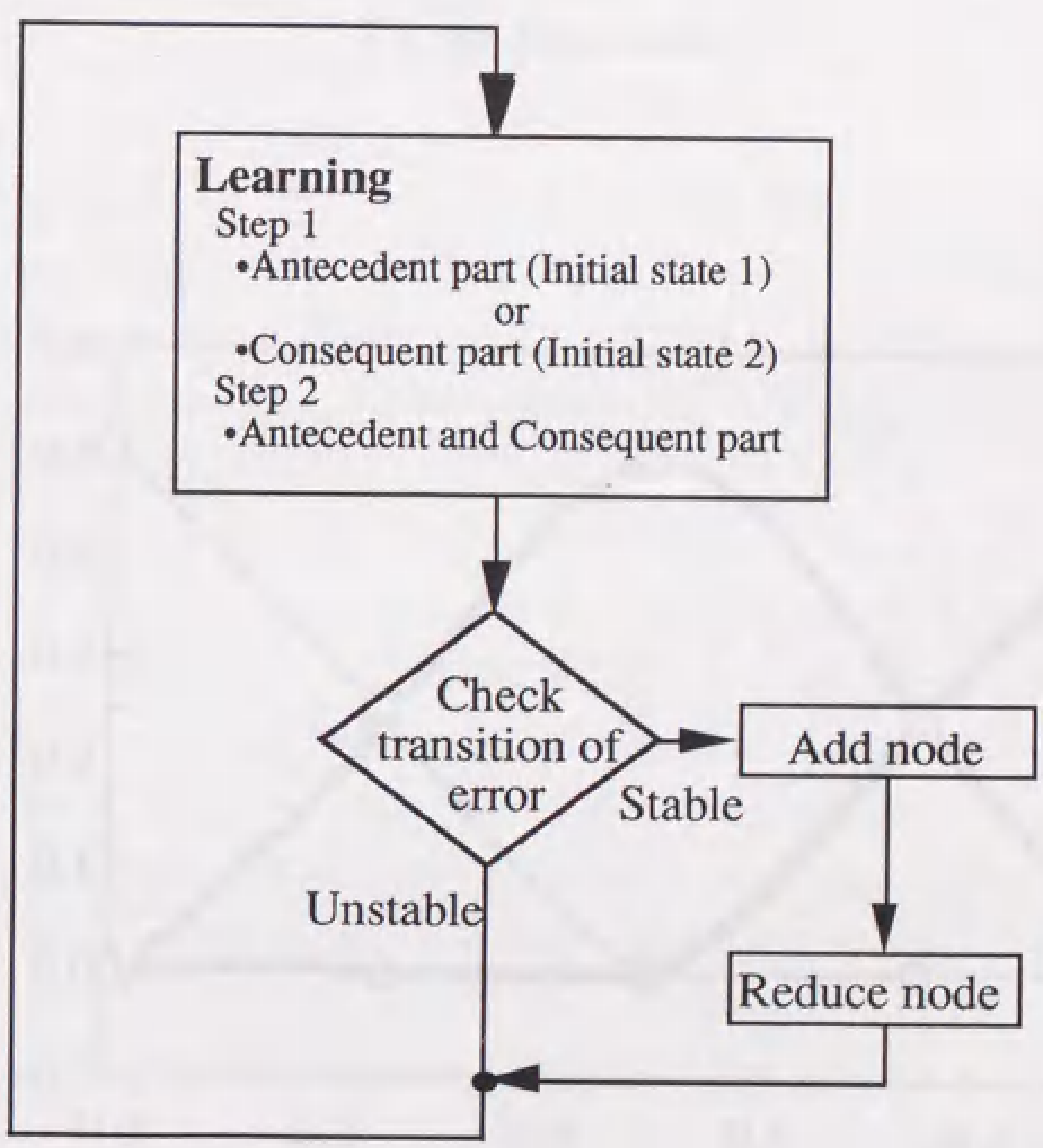


Fig. 6.5 Learning algorithm

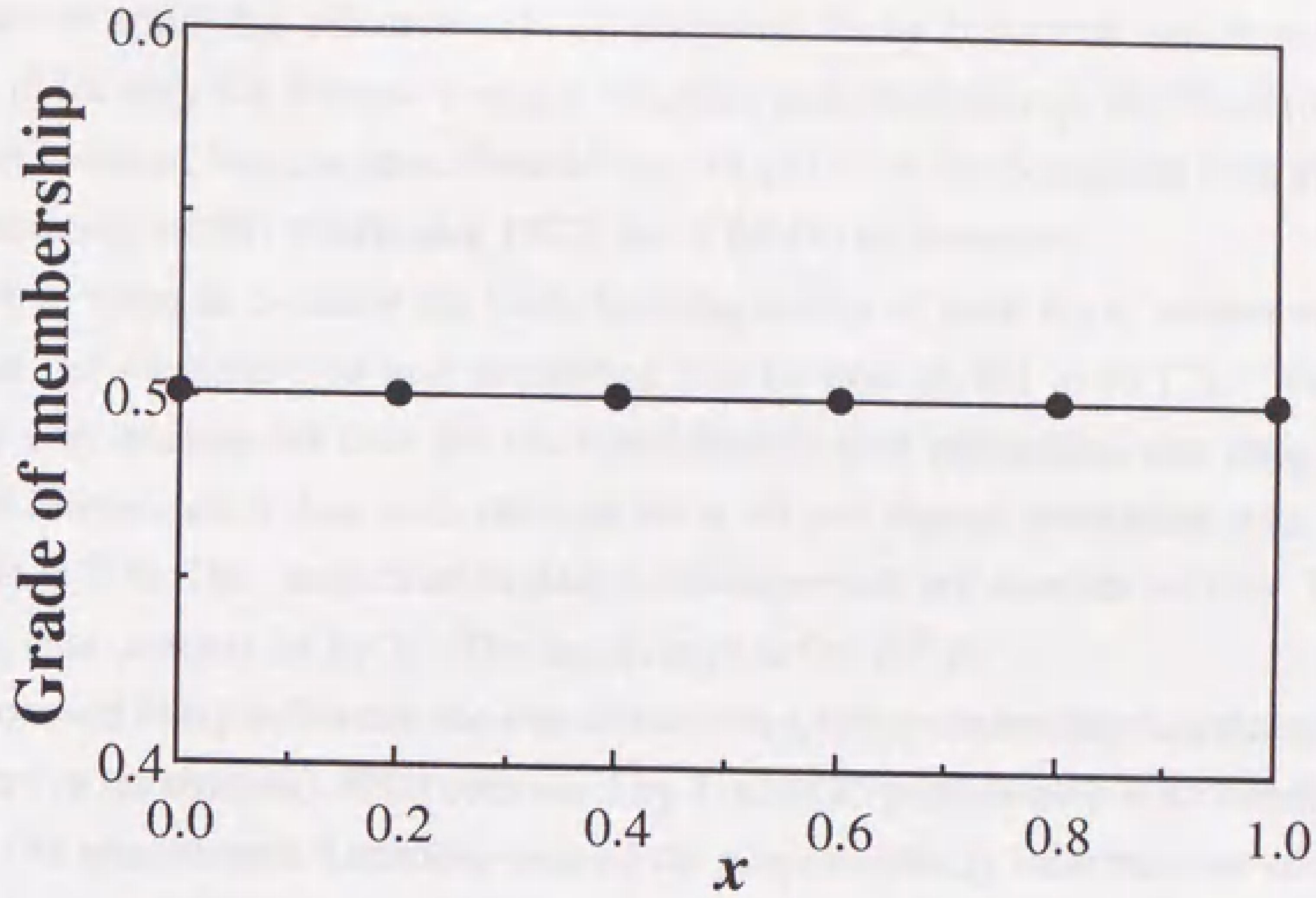


Fig. 6.3 Initial state (1)

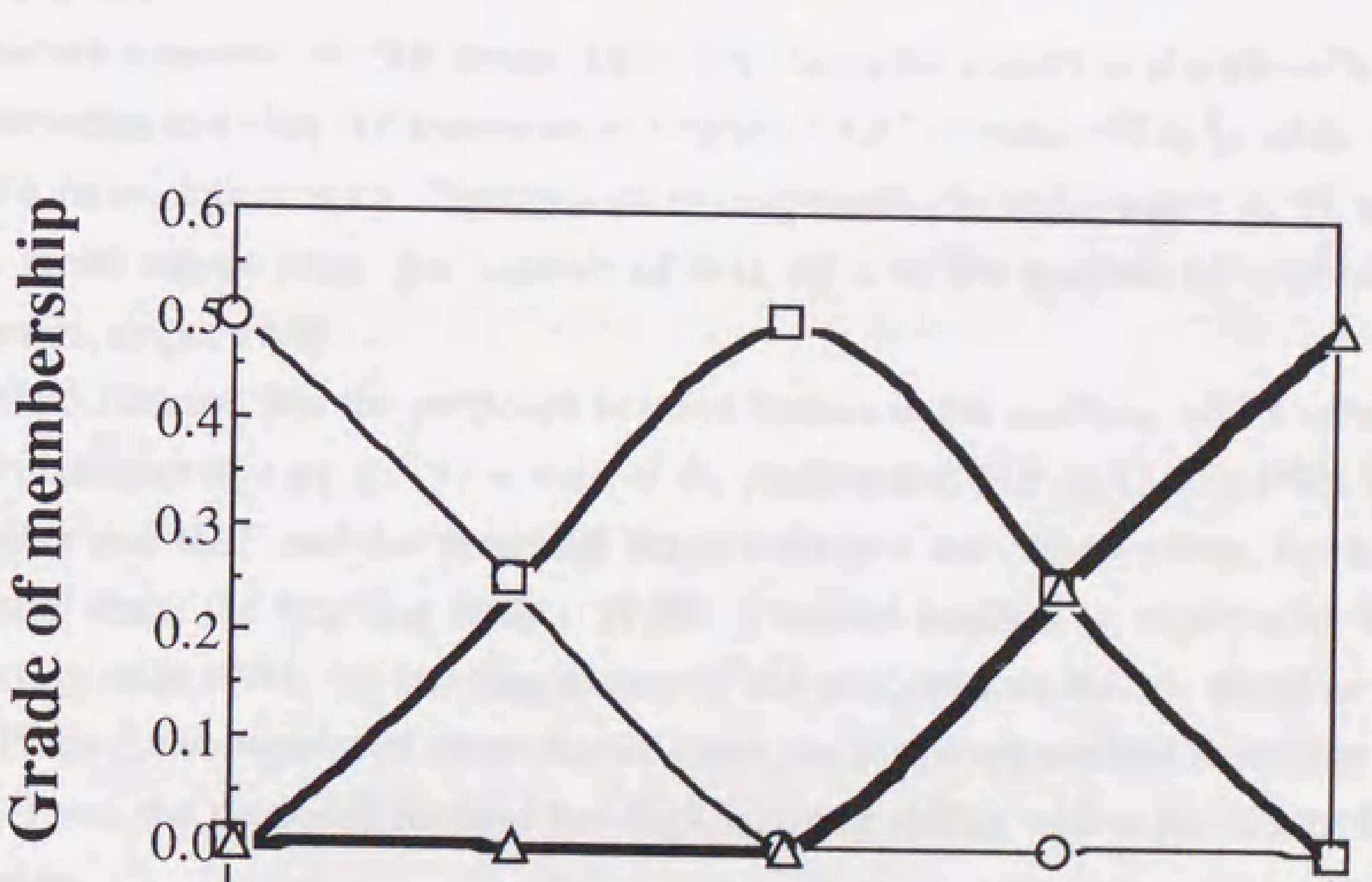


Fig. 6.4 Initial state (1)

6.3 Simulation results

In order to show the effectiveness of proposed fuzzy inference, we apply the inference to identify the 2-input 1-output function described by eqs. (6.15) to (6.20), the 3-input 1-output function described by eqs. (6.21) to (6.23) compared with Fuzzy Neural Networks (FNN) [Horikawa 1992] and RBF fuzzy inference.

At first, in order to examine the basic learning ability of each fuzzy inference, we carried out the identification and estimation test by eqs. (6.15) to (6.17). We use sequential and random set data for the identification and estimation test data. The number of identification data with random set is 50 and that of estimation data with random set is 300. The identification data with sequential set consists of 7 by 7, the estimation data consists 21 by 21. The input range is 0.0 to 1.0.

The proposed fuzzy inference consists of two rules, two membership functions with three knots (18 parameters). FNN consists 3 by 3 rules(25 parameters). RBF consists 3 by 3 rules (21 parameters). Learning rates of the proposed fuzzy inference are $\alpha=02$, $\beta=0.02$, and $\gamma=0.02$, and the additional / deletion knot process is not carried out. Those of FNN are 0.02 for the antecedent and 0.2 for the consequent, and of RBF are 0.001 and 0.1.

Iteration is carried out 500 times. Table 6.1 shows the results of the identification and estimation test after 500 iterations and value of AIC [Akaike 1974]. In table, MSE means a mean square error. Equation (6.24) expresses the AIC, where E, N, and k means mean square error, the number of data set, and the number of controllable parameters, respectively.

Table 6.1 shows that the proposed fuzzy inference is the smallest AIC's value for each equation except eq. (6.17) in case of the random set. For eq. (6.17), FNN is the best value and RBF and the proposed fuzzy inference are almost same. In case of sequential data, the learning ability of the proposed method is superior to RBF. Comparing with FNN, the learning ability of the proposed method is equal or over FNN. From the viewpoint of mean square error, the proposed method is smaller than others. Thus, the proposed method has high learning ability with a few controllable parameters.

In order to show the effectiveness of the knot addition / deletion, we used more complex learning model expressed eqs. (6.18) to (6.23). In this case, we use two types of learning sets, i.e., sequential data set and random data set. In case of the random set, the number of data set is 20 (2-input equation) and 30 (3-input). Sequential data set for the 2-input equation consists of 11 by 11 data points, 9 by 9 by 9 data points for the 3-input equation. Learning is carried out until the mean square error converges under

0.001 for the random data set, 0.0001 for the sequential data set, or iteration reaches 500 times.

The proposed fuzzy inference with initial state(1) consists of two rules, eight membership functions. The number of knots for each input is 6, that of the distance and angle information is 11(2-input), 16(3-input). For initial state(2), the input space is divided into 3, and each membership consists of 5 knots. The membership function for the distance and angle information consists of 9 knots (2-input), 13 knots (3-input). FNN and RBF consist 4 by 4 rules. Learning rates of the proposed fuzzy inference are α=0.2, β=0.02, γ=0.02, e=0.1, and k=5. Those of FNN are 0.02 for the antecedent and 0.2 for the consequent, and of RBF are 0.001 and 0.1.

Table 6.2, 6.3, and 6.4 shows the results of the proposed fuzzy inference with random data set, with sequential data set, and FNN and RBF, respectively. In table, MSE, MAE, and "-" means a mean square error, a maximal absolute error, and MSE does not converge under 1.0×10^{-3}, respectively. Figure 6.6, 6.7, 6.8, and 6.9 shows the error curve (initial state(2), eq. (6.20), sequential data set), the changing of the number of knots, the membership function after learning (initial state (1)), and the membership function after learning (initial state (2)).

In case of the random data set, all fuzzy inferences can learn all equations except the proposed method with initial state (1) for eq. (6.23) without the knot addition / deletion process. From tables, MSE of the proposed method is smaller than others.

In case of the sequential data set, MSE of RBF does not converge under 1.0×10^{-4} for eqs. (6.18), (6.20), and (6.23) before 500 iterations. Carrying on learning till 1158 iterations, MSE converges under 1.0×10^{-4} in case of eq. (6.18). MSE of FNN dose not converge under 1.0×10^{-4} in case of eqs. (6.18), (6.19), and (6.21).

The proposed method can learn almost equations except eqs. (6.20) and (6.23) in case of initial state (1). The reason of eqs. (6.20) and (6.23) is that these equations are discontinuous output and the output changes very fast. The proposed method cannot learn these quick changes with only two rules. In case of initial state (2), the proposed method with the knot addition / deletion process can learn all equations before 100 iterations. Without the knot addition / deletion process, the method can learn them before 500 iterations except eq. (6.20). The method can learn eq. (6.20) at 915 iterations.

Figures 6.6 and 6.7 shows that MSE decreases with the knot addition / deletion process, and each table shows that iteration time of the proposed method with the knot addition / deletion process is smaller than others. Thus, the knot addition / deletion process is effective for improving the learning ability.

$$y = \frac{\sin(\pi x_1) + \cos(\pi x_2) + \sin(\pi x_1)\cos(\pi x_2) + 1}{4} \tag{6.15}$$

$$y = \frac{3x_1 - 2x_2 + 2}{5} \tag{6.16}$$

$$y = \frac{e^{(x_1 + x_2)}}{e^2} \tag{6.17}$$

$$y = \frac{1}{2}\left(1 + \cos\left(2\pi\sqrt{x_1^2 + x_2^2}\right)\right)e^{-\sqrt{x_1^2 + x_2^2}} \tag{6.18}$$

$$y = \frac{x_1^{0.3} + x_2^{1.7}}{2} \tag{6.19}$$

y = 1, if (x1 ≤ 0.5 and x2 ≤ 0.5) or (x1 ≥ 0.5 and x2 ≥ 0.5)

y = 0, otherwise (6.20)

$$y = \frac{1}{2}\left(1 + \cos\left(2\pi\sqrt{x_1^2 + x_2^2 + x_3^2}\right)\right)e^{-\sqrt{x_1^2 + x_2^2 + x_3^2}} \tag{6.21}$$

$$y = \frac{x_1^{0.3} + x_2 + x_3^{1.7}}{3} \tag{6.22}$$

y = 1, if (x1 ≤ 0.5 and x2 ≤ 0.5 and x3 ≤ 0.5) or (x1 ≥ 0.5 and x2 ≥ 0.5 and x3 ≥ 0.5)

y = 0, otherwise (6.23)

$$\text{AIC} = N\log_e E + 2(k+1) \tag{6.24}$$

6.4 Conclusions

In this chapter, we proposed a new fuzzy inference that consists of some membership function expressed by the cubic spline function. We showed it's structure, and it's learning methods as follows:

(1) Before learning, the value of the consequent is set to the operator's desired value, then fuzzy inference makes the shapes of membership function through the learning process.

(2) Before learning, the operator determines the shapes of each membership function. Then fuzzy inference modifies the consequent and the antecedent through the learning process.

We also show the effectiveness of the proposed method as follows:

(1) For the fuzzy inference with initial state (1), the number of rules is free from the number of input's dimension. The inference can learn an object quickly except discontinuous function as eq. (6.20) or (6.23).

(2) For the fuzzy inference with initial state (2), the operator can design the fuzzy inference based on his/her knowledge. The inference also can learn fast and its learning ability is higher than other fuzzy inference with the same number of rules.

(3) The knot addition / deletion process improves the learning ability, higher and more accurate.

We also showed a part of learning ability through the simulation experiments.

Table 6.1 Basic learning ability

Equation	Data set	Random						Sequential					
		RBF		FNN		Proposed		RBF		FNN		Proposed	
		MSE $\times 10^{-4}$	AIC	MSE $\times 10^{-4}$	AIC	MSE $\times 10^{-4}$	AIC	MSE $\times 10^{-4}$	AIC	MSE $\times 10^{-4}$	AIC	MSE $\times 10^{-4}$	AIC
6.15	Identify	72.4	-204.4	39.2	-227.1	40.9	-238.9	135	-169.0	64.2	-197.4	59.8	-214.8
6.16	Identify	1.84	-387.9	0.88	-416.9	0.65	-446.0	2.35	-367.4	0.00	-1755	0.88	-421.5
6.17	Identify	1.90	-386.4	0.67	-430.5	3.82	-357.5	2.44	-365.6	0.00	-1191	1.96	-382.2
6.15	Estimate	88.0	–	46.3	–	42.0	–	116	–	42.5	–	56.7	–
6.16	Estimate	2.24	–	3.67	–	0.70	–	2.00	–	4.07	–	0.55	–
6.17	Estimate	3.16	–	2.05	–	4.05	–	2.17	–	3.04	–	1.23	–

Table 6.2 Learning results of the proposed method for random data set

Equation	With knot addition/deletion						Without knot addition/deletion					
	Initial state (1)			Initial state (2)			Initial state (1)			Initial state (2)		
	Iterat-ions	MSE $\times 10^{-4}$	MAE	Iterat-ions	MSE $\times 10^{-4}$	MAE	Iterat-ions	MSE $\times 10^{-4}$	MAE	Iterat-ions	MSE $\times 10^{-4}$	MAE
6.18	54	9.92	0.0499	39	9.85	0.0413	68	9.75	0.0460	56	9.91	0.0504
6.19	32	9.14	0.0430	26	9.71	0.0536	32	9.47	0.0438	31	9.80	0.0521
6.20	112	9.92	0.0617	42	8.96	0.0706	206	9.95	0.0830	55	9.91	0.0967
6.21	45	9.99	0.0277	93	9.72	0.0338	72	9.90	0.0378	136	9.87	0.0369
6.22	35	9.72	0.0298	68	9.77	0.0397	41	9.92	0.0349	94	9.93	0.0459
6.23	118	9.57	0.0888	42	9.95	0.0642	500	-	-	42	9.95	0.0642

Table 6.3 Learning results of the proposed method for sequential data set

Equation	With knot addition/deletion						Without knot addition/deletion					
	Initial state (1)			Initial state (2)			Initial state (1)			Initial state (2)		
	Iterat-ions	MSE $\times 10^{-5}$	MAE	Iterat-ions	MSE $\times 10^{-5}$	MAE	Iterat-ions	MSE $\times 10^{-5}$	MAE	Iterat-ions	MSE $\times 10^{-5}$	MAE
6.18	38	9.60	0.0343	56	9.86	0.0223	65	9.98	0.0376	89	9.93	0.0244
6.19	36	9.96	0.0531	61	9.52	0.0336	51	9.94	0.0443	90	9.85	0.0410
6.20	500	-	-	98	8.99	0.0249	500	-	-	500	21.9	0.0344
6.21	22	9.61	0.1782	46	9.90	0.0294	23	8.89	0.1711	71	9.93	0.0469
6.22	46	6.43	0.0346	59	9.32	0.0358	48	9.92	0.0394	63	9.75	0.0355
6.23	500	-	-	96	9.86	0.1108	500	-	-	390	10.0	0.0421

Table 6.4 Learning results of RBF and FNN

Equation	Random data set						Sequential data set					
	RBF			FNN			RBF			FNN		
	Iterat-ions	MSE $\times 10^{-4}$	MAE	Iterat-ions	MSE $\times 10^{-4}$	MAE	Iterat-ions	MSE $\times 10^{-5}$	MAE	Iterat-ions	MSE $\times 10^{-5}$	MAE
6.18	14	9.91	0.0742	14	9.02	0.0497	500	32.6	0.0367	500	56.8	0.0559
6.19	9	9.82	0.0982	11	9.94	0.0937	462	9.99	0.0347	500	62.2	0.0677
6.20	281	9.66	0.0977	16	8.98	0.0898	500	-	-	62	9.27	0.0402
6.21	24	9.55	0.0836	26	9.66	0.0860	298	9.99	0.0279	500	26.5	0.0551
6.22	31	9.94	0.1105	17	9.98	0.1074	41	9.97	0.0303	27	9.87	0.0376
6.23	124	9.51	0.1028	16	8.38	0.0894	500	-	-	50	9.37	0.0477

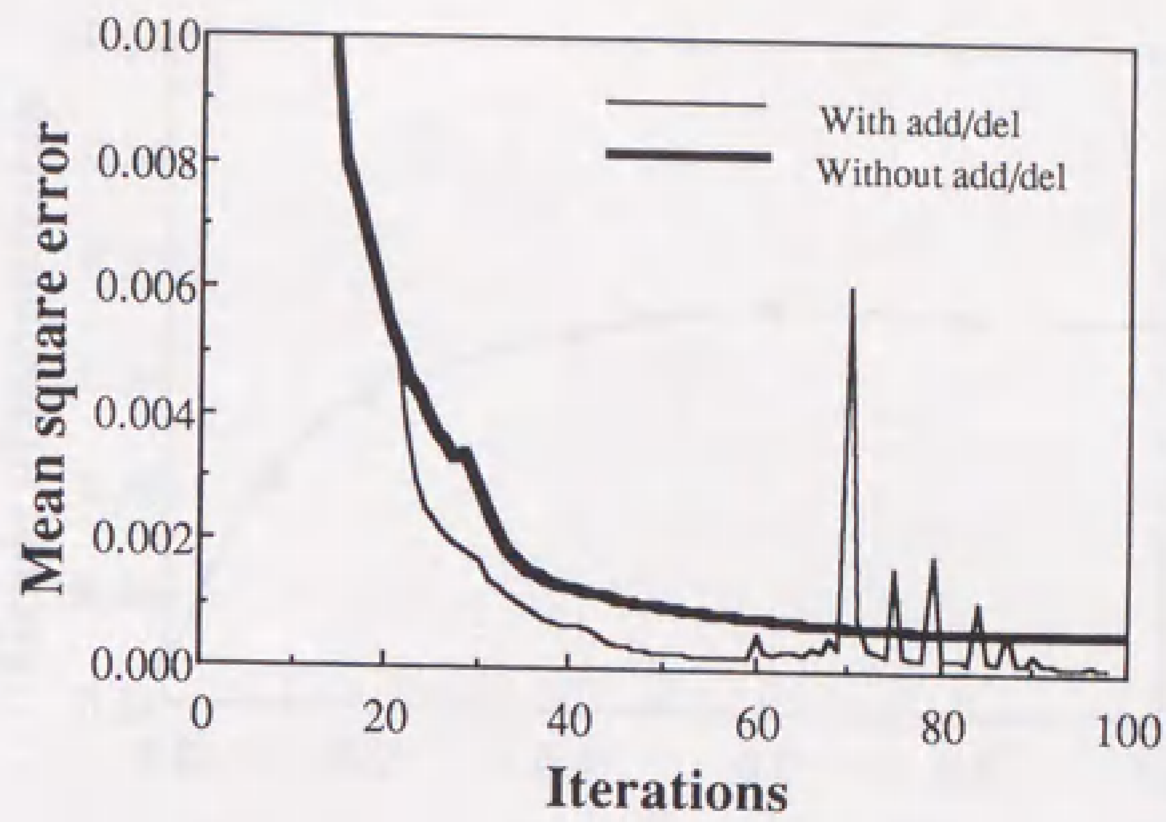


Fig. 6.6 Error curve in case of initial state (2), eq. (6.20), sequential data set

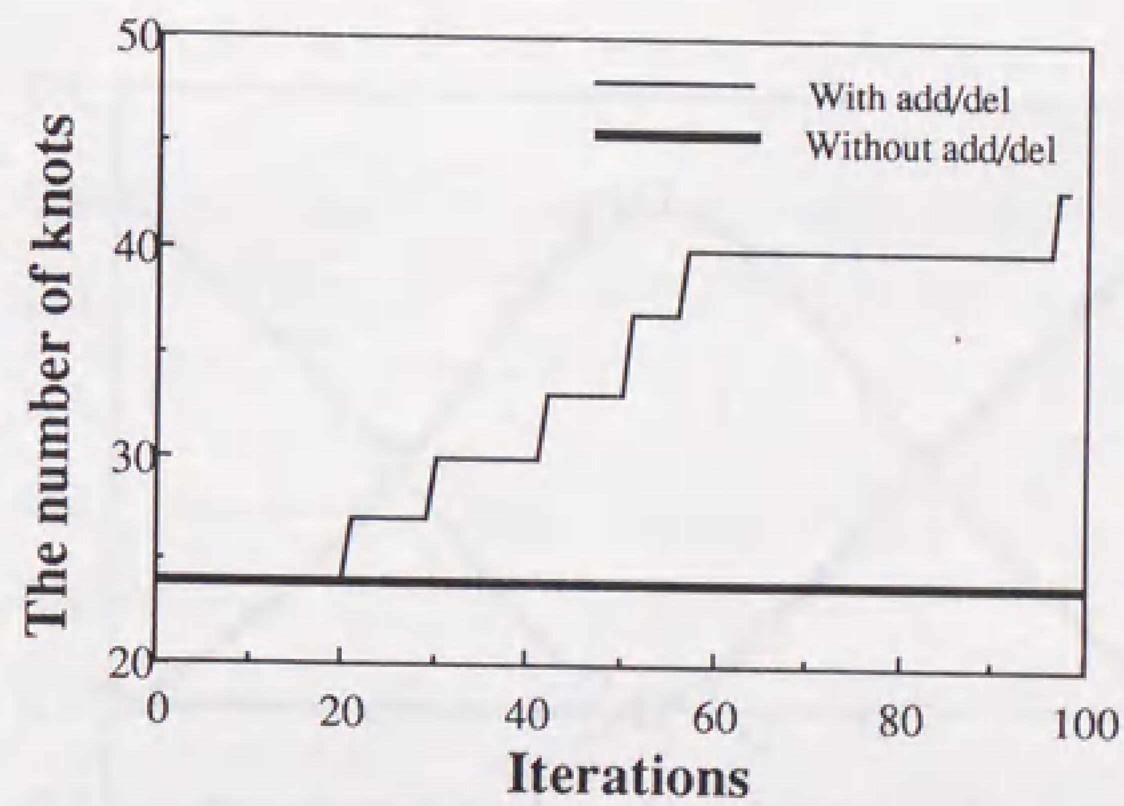


Fig. 6.7 number of knots in case of initial state(2), eq. (6.20), sequential data set

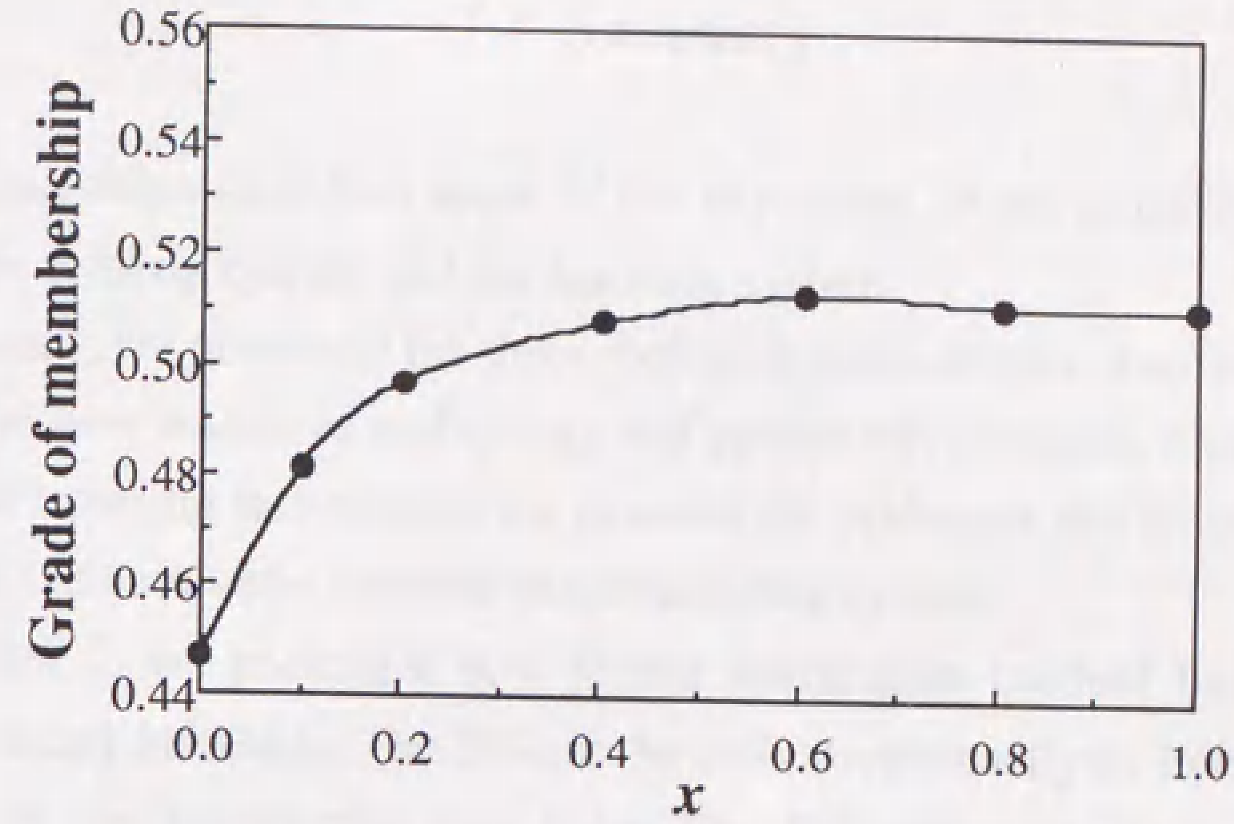


Fig. 6.8 Membership function after learning (initial state (1))

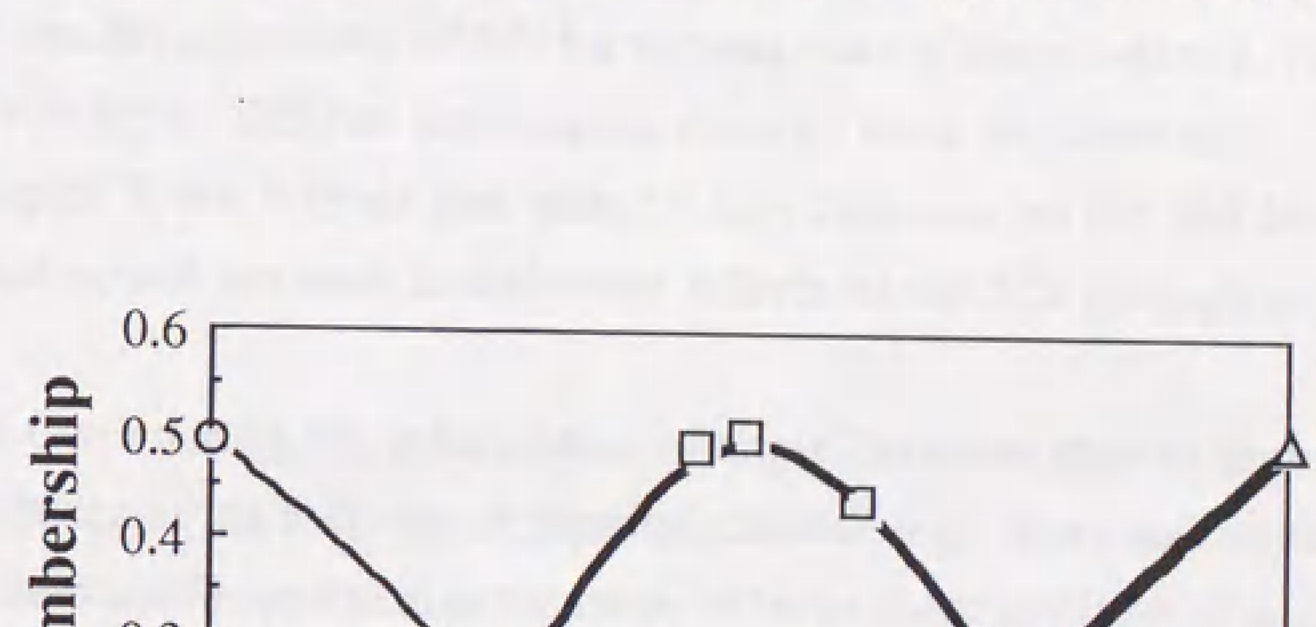


Fig. 6.9 Membership function (initial state (2))

7. Conclusions

7.1 Summary

This dissertation describes some of the key issues of the reusable technologies concerning the sensing system and the learning system.

In chapter 1, we presented the three recycling technologies, they become the key technologies to save resources and energy and protect environment. Especially for the reusable manufacturing technology, we denoted the problems and its solutions of the realization for the automatic reusable manufacturing system.

In chapter 2, we present a new sensor integration method based on neural networks and fuzzy inference. The SIS can be constructed easily by linking the sensor specification to the knowledge data base. The following results were shown by experiments using two different distance measurement sensors with the proposed SIS:

Using fuzzy inference, we can use sensors more efficiently, because we can get more information of sensors' state. Using NN, we can treat sensors more freely, because we can design outputs of NN for various state of sensors easily. The usefulness of the "NN+Fuzzy's" SIS has been shown through these experiments.

In chapter 3, we refined and added a new function on the SIS based on fuzzy inference and neural network and showed effects of the SIS through experiments as follows.

(1) Considering the information of angle between sensors and the target on each sensor as a factor of sensing condition in fuzzy inference, the sensor system could approach to the target effectively at any case of angle difference between sensors and the target.

(2) NN eliminated the failed data of sensors and the system could continue to work in safety even if some of sensors were failed.

We presented a 3-D measurement system that consists of the LED displacement sensor and the vision system and its integration method in chapter 4.

We showed effectiveness of the proposed SIS through some experiments as follows:

1) Utilizing outputs of the LED displacement sensor, camera parameters can be calibrated easily.

2) Using NN's compensator for the lens distortion and camera calibration's errors, the vision system can measure accurately.

3) Utilizing the fuzzy inference with moving data of the sensor system and environmental data of measurement, the measurement system can measure

accurately and is stable against variation of environments and internal parameters of sensors.

In chapter 5, we denoted the adaptive sensing strategy for the LED displacement sensor and the vision system that is proposed in chapter 4. We also showed effectiveness of the proposed SIS through some experiments as follows:

Utilizing the adaptive sensing strategy, the **SIS** uses the vision system which takes long time to measure when the **SIS** estimates the LED displacement sensor cannot measure the object, and then the system achieves fast and accurate measuring.

In chapter 6, we proposed a new fuzzy inference based on membership function expressed spline function. We showed the effectiveness of the proposed method as follows:

(1) The number of rules is free from the number of input keeping the learning ability..

(2) The operator can design the fuzzy inference based on his/her knowledge. The inference also can learn fast and its learning ability is higher than other fuzzy inference with the same number of rules.

(3) The knot addition / deletion process improves the learning ability, higher and more accurate.

7.2 Future works

We have been studying some of key issues of the automatic reusable technology, and investigated some technologies.

However, the problems that prevent us from realizing the automatic reusable manufacturing system:

(1) the recognition of the state of the object system whether a malfunction is occurred,

(2) the automatic planning of the fixing way/method,

(3) dexterous manipulator system like human hand,

(4) multi-manipulation system,

We would like to tackle and solve problems as follows:

(1) multi-sensor fusion system with multiple and various sensory system, such as vision, force, sound, color, and temperature,

(2) multi-sensor integration method for a number of sensors,

(3) the knowledge management system based on fuzzy reasoning and/or neural networks.

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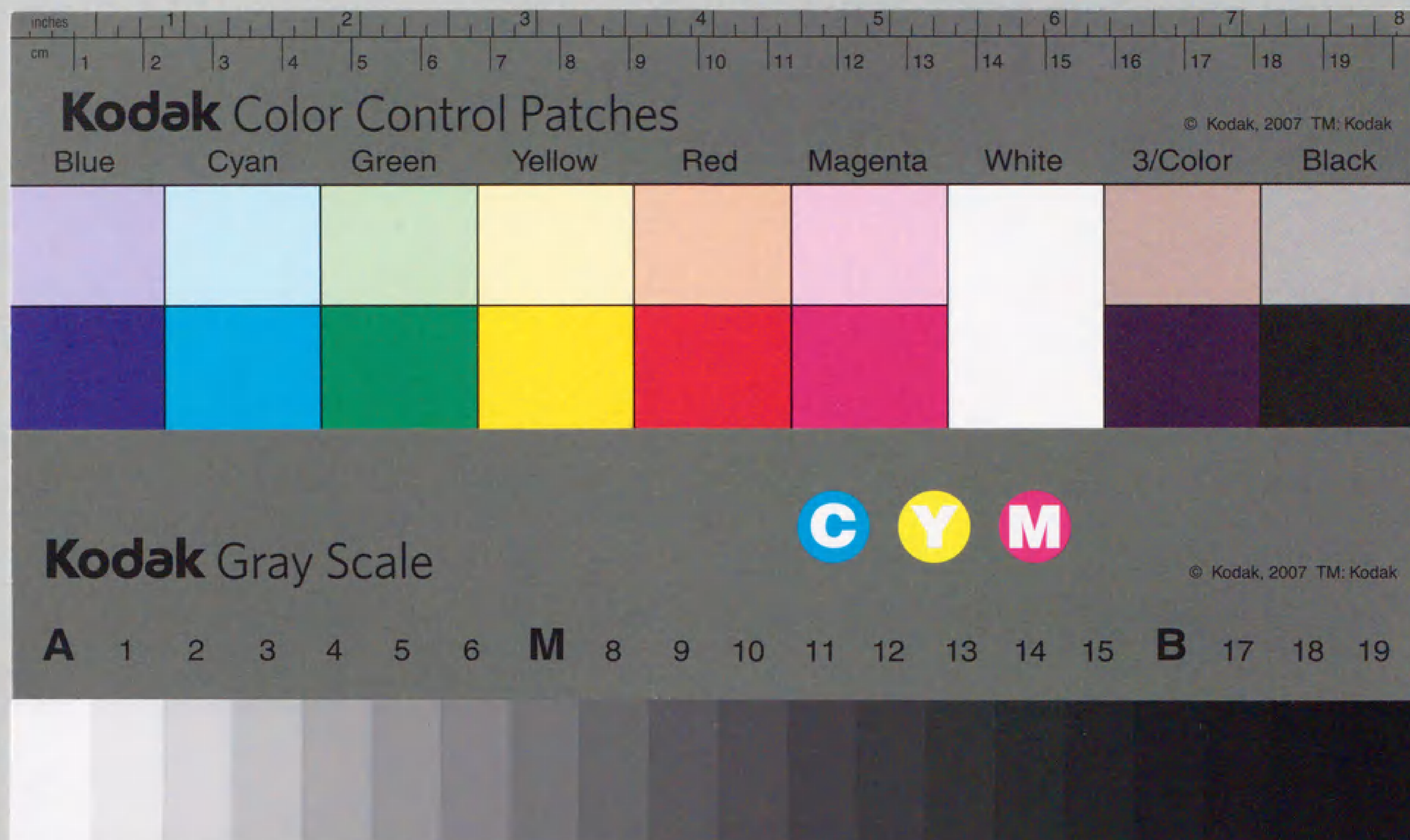
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