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Ultrasonic Robot Eye for Shape Recognition Employing a Genetic Algorithm

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Abstract – This paper describes an ultrasonic robot eye for shape recognition using ultrasound pressure data and a Genetic Algorithm. This type of robot eye has commonly used a Neural Network (NN) for shape recognition. However, a NN perform poorly when lacking learned data. In order to overcome this problem when using a NN, we here attempt to replace the NN with a Genetic Algorithm (GA). Unlike a NN, the GA can recognize shapes without depending on learned data. Experimental results demonstrate that the recognition ratios of the proposed ultrasonic robot eye using the GA are higher than that of a conventional ultrasonic robot eye using a NN. Therefore, it is shown that our robot eye is effective for many robotic applications.

Keywords: Ultrasonic robot eye, Genetic Algorithm, Shape Recognition.

1. INTRODUCTION

Robot eyes utilizing ultrasonic sensors are often used for shape recognition in situations in which optical sensors cannot be used, such as in dark environments or under water [1].

In the field of shape recognition, several recognition methods have been proposed which use a neural network (NN) based on the image range determined by time of flight, holographic image, and ultrasound pressure data which are acquired using an ultrasonic sensor array [2]-[5]. In the previous paper [5], we proposed the method using NN and the ultrasound pressure data. In the paper, it is true that the method using NN has the ability to extract shape information from ultrasonic data, but it has some severe drawbacks: an unavoidably long leaning time for accomplishing high accuracy recognition, and a decline in the recognition ratio for non-learned objects. Thus, we try to construct the robot eye that overcomes the drawbacks by using Genetic Algorithm (GA) [6].

In this paper, we propose to replace the recognition algorithm using the NN with that using the Genetic Algorithm (GA). The GA is based upon the principle of biological evolution. Unlike the NN, it can be expected that the GA will achieve shape recognition without depending on learned data. Thus, it is possible for the ultrasonic robot eye using the GA to improve its recognition ratio for non-learned objects compared to that of the system using the NN.

However, systems using GA have not yet been developed. In this paper we examine the feasibility of the ultrasonic robot eye for shape recognition using the GA.

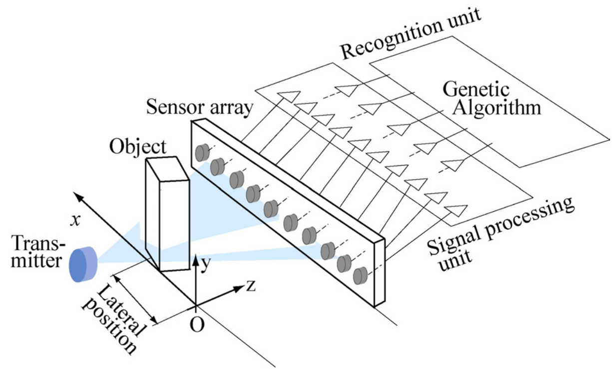

Fig. 1 Outline of the propose robot eye

2. PRINCIPLE FOR SHAPE RECOGNITION

Fig.1 shows a schematic drawing of the outline of the proposed robot eye. The robot eye is composed of a transmitter, an ultrasonic sensor array comprised of a small number of ultrasonic sensor elements, a signal processing unit, and a recognition unit that is equipped with the GA. The robot eye identifies the shape of an object using information from the distorted ultrasonic wave produced by the presence of the object. The experiment was carried out using six kinds of objects, including cylinders, right rectangular prisms.

Fig.2 shows a schematic diagram for explaining the object recognition mechanism utilizing the ultrasound pressure. The left side of Fig.2 shows the diffused condition of the ultrasonic wave generated by the transmitter. The right side of the figure shows the ultrasonic wave distribution received by the sensor array. In this figure, the cross section of the top view is shown. In designing the system, we referred to preliminary experimental results showing that the inflection points differed among differently shaped objects.

The sharper the angle made by the edge of the object, the wider the interval between the two inflection points becomes, as a result of the wide diffusion of the ultrasonic wave caused by the sharp edge, as shown in Fig.2(a). For example, the interval between two inflection points in a wave transmitted over a prism having square corners is wider than that for a cylinder having a curved surface.

Fig.2(b) shows the received ultrasonic wave distribution in the case of similarly shaped objects. These two objects

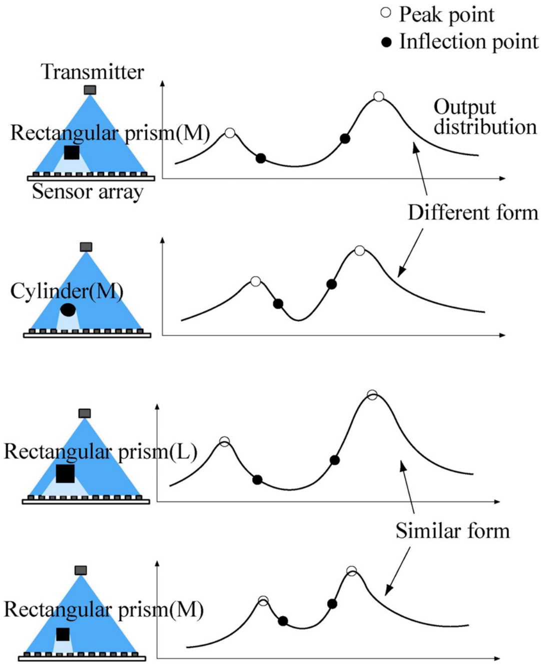

Fig.2 Mechanism for shape recognition

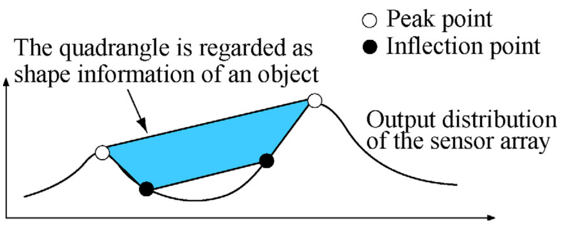

Fig.3 Quadrangle using four points

differ from each other only in size. In this case, their received ultrasonic distributions are similar to each other.

We found out that the difference in the ultrasound pressures based on shape and size are distinguished by two peak points and two inflection points. We here propose the method that relates the difference of the ultrasound pressure distribution to the difference of the shape of a object by GA.

The outline of the recognition algorithm using the GA is as follows:

(1) As shown in Fig.3, a quadrangle consists of the these four points (two peak points and two inflection points) of the ultrasound pressure data acquired from the ultrasonic sensor array. The shapes of this quadrangle are different from those of the trial objects.

(2) The quadrangle of the trial object is transformed by using the operators by GA, which is selection, crossover, and mutation, as shown in Fig.4. The fitness values are calculated between the trial quadrangles and the reference quadrangles using the space information, and the distance between vertices are calculated. The fitness value f is defined as the following equation:

$$f = \frac{1}{S + D + 1}$$

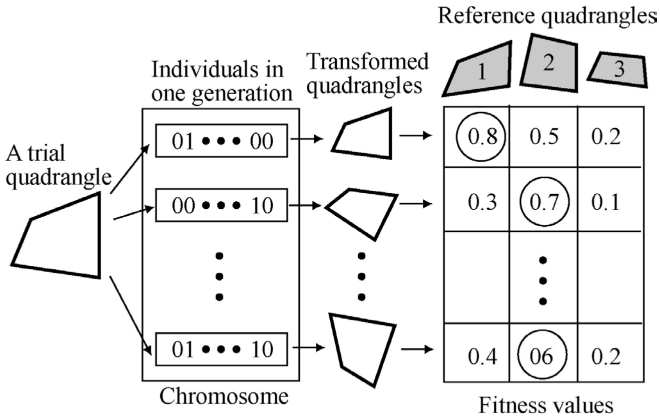

Fig.4 Principle of the shape recognition using GA

Here, S is the difference in the area between the trial quadrangle and the reference quadrangle, and D is the total distance between the vertices of the reference quadrangle and the trial quadrangle.

(3) Using GA operations, chromosomes that have information on expansion, rotation, and reversal are generated. Some chromosomes are applied to trial quadrangle, the majority of each fitness value is utilized, and the generation's solution is determined. In the case shown in Fig.3, the generation's solution is the object featured as the reference quadrangle No.2.

Fig.5 shows the genotype of an individual which is binary data of 80-bit length. The binary data is comprised of the rate of magnification or reduction with 70 bits at the beginning, the rotation rate with the next 9 bits, and whether the quadrangle inverts in line symmetry with the last 1 bit.

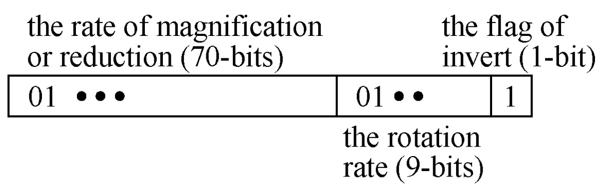

Fig. 5 Genotype and phenotype an individual

3. COFIGURATION OF THE PROPOSED ROBOT EYE

Fig.6 shows a block diagram of the proposed robot eye. The robot eye consists of an ultrasonic transmitter, an ultrasonic sensor array, a signal processing unit, which detects the peak values and their positions, and the positions of the inflection points and their values, and a computer that is used for the calculation based on a GA. The system, at present, can identify only pillar-like objects such as a cylinder, a prism, and so on.

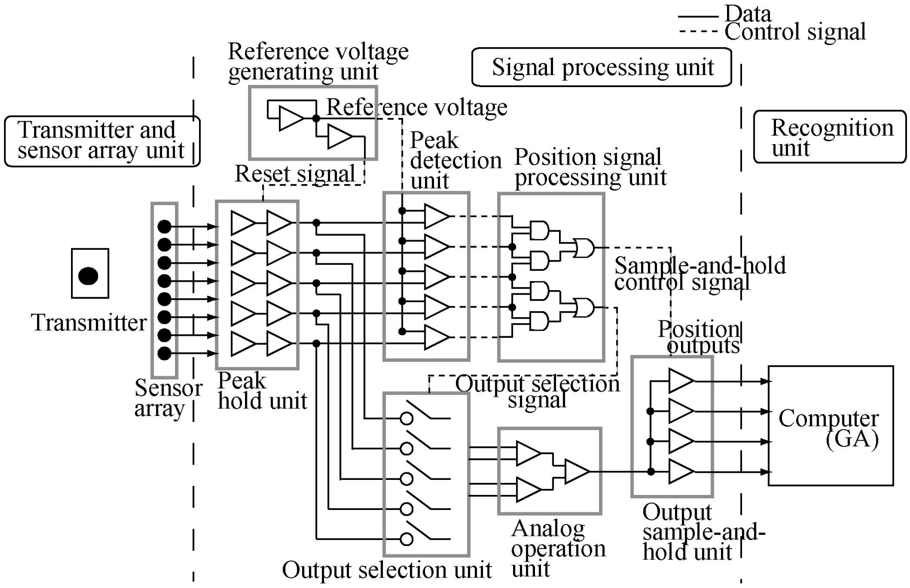

Fig. 6 Circuit configuration of the prototype robot eye

The sensor array unit is made up of multiple ultrasonic sensor elements. It consists of 16 ultrasonic sensor elements that are arranged linearly at about 20.1 mm intervals. The peak-hold circuit is conected to the output terminal of each ultrasonic sensor element, and the amplitude of the sinusoidal wave of the ultrasonic sensor output is held and transmitted to the signal processing circuit.

Fig.7 shows the process used by the sensor array for detecting the peak values and the peak positions. The process of the operation is as follows.

(1) The reference voltage is set to a value larger than the maximum value of the ultrasonic sensors, as shown in Fig.7(a).

(2) The reference voltage is reduced, and is compared with the output voltages of the ultrasonic sensors. When the reference voltage coincides with the voltage of one ultrasonic sensor, the actual peak value and the actual peak position are determined by interpolating an approximated second-order polynomial, which is generated from the peak value and the values of the two ultrasonic sensors adjacent to the sensor outputting the peak value, as shown in Fig.7 (b). The reference voltage is reduced to detect the next peak value of the ultrasonic sensors without stopping the descent of the voltage.

(3) When the next peak is detected, the actual peak values and the peak positions are determined using the same method as described in steps (1)-(3).

(4) These steps are repeated until the reference voltage reaches zero. All actual peak values and the peak positions can be determined in this manner.

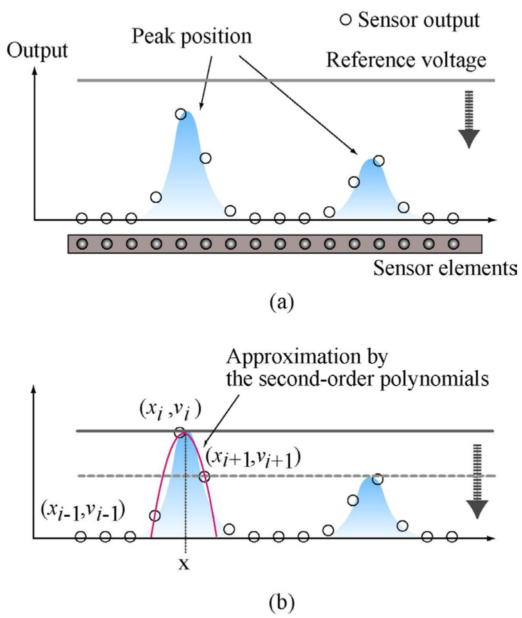

Fig.7 Detecting process of the peaks.

Fig.8 shows the detection of the inflection points from the distribution of the sensor array. The distribution is differentiated with respect to x by an analogue circuit, and the positions of the inflection points are determined as the

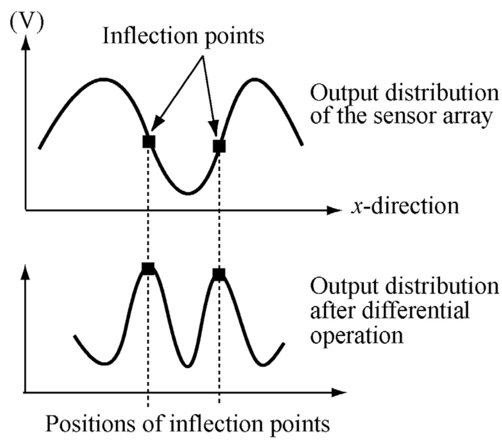

Fig.8 Detections of the inflection points

peak positions of the differential wave. The circuit performs the differential calculation by the digital differential method using numerical operations, not by the ordinary analog differential method using capacitors and registers. The circuit calculates the differential value with the following equation.

$$f' = \frac{1}{2h}\{f(x_{i-1}) - f(x_{i+1})\}$$

where f' is the differential value, f is the output voltage of the ultrasonic sensor, and h is the interval between the ultrasonic sensors.

As above mentioned, this circuit detects the peak values, the peak positions, and the positions of the inflection points and their values. This circuit is mounted mainly by using the analogue circuits. The essential components of this circuit include a sensor element signal processing unit, a peak detection unit, a position signal processing unit, and an output sample-and-hold unit.

4. EXPERIMETAL RESULTS AND DISCUSSION

4.1 Experimental setup

We designed and built a prototype ultrasonic robot eye using the GA. Fig.9 shows the photograph of a prototype robot eye embodying the proposed principle for the shape recognition. The transmitter locates at the left-side of the figure, and the receiver (ultrasonic sensor array), which is composed of 16 ultrasonic sensors is located at the right side. The measured object is located between the transmitter and the receiver.

Fig.9 Photograph of the prototype robot eye

4.2 Measured objects

This paper shows the experimental results of the recognition of both cylinders and rectangle prisms. Fig. 10 shows the measured objects. The diameters of these cylinders were 30mm(LC), 24mm(MC), 12mm(SC), respectively. The length of the pairs of sides of these rectangular prisms were 24mm(LP), 17mm(MP) and 12mm(SP), respectively.

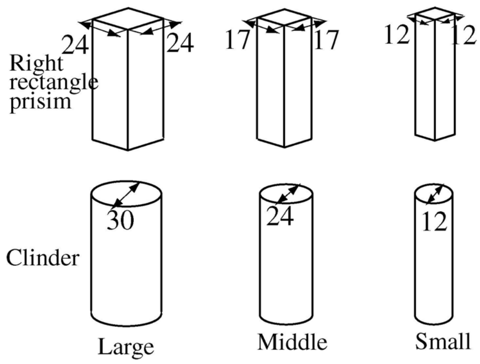

Fig. 10 Measured objects

4.3 Procedure

We made four kinds of experiments to verify the effectiveness of our method for shape recognition by GA, and compared our method to the method by NN: Case A1, Case A2, Case B1, and Case B2.

Table 1 shows the experimental conditions. In the Case A1 and the Case A2, the measured objects are fixed position. On the contrary, in the Case B1 and the Case B2, the measured objects are free position. In the Case A1 and the Case B1, GA used the 6 reference objects corresponding to 6 trial objects, and NN also used 6 learned objects corresponding to 6 trial objects. On the other hand, In the Case A2 and the Case B2, GA used exclusively two reference objects, which are the large cylinder and the large rectangle prism, for 6 trial objects, and NN also used exclusively two learned objects for 6 trial objects. the Case A2 and the Case B2 are the experiments to examine whether the GA and NN have the able to recognize similar objects. For example, this means that even if a reference object is exclusively large cylinder in GA, the robot eye can recognize all kinds of cylinders as a cylinder. The NN is a five-layered feed-forward structure, and learns by an error back-propagation algorithm.

Table 1 Experimental conditons

Case	Object position	GA (NN)	
		trial	reference (learned)
A1	fix	SC,MC,LC, SP,MP,LP	SC,MC,LC, SP,MP,LP
A2	fix	SC,MC,LC, SP,MP,LP	LC, ,LP
B1	free	SC,MC,LC, SP,MP,LP	SC,MC,LC, SP,MP,LP
B2	free	SC,MC,LC, SP,MP,LP	LC, ,LP

The experimental procedure was as follows.

(1) One Object was placed between the transmitter and the ultrasonic sensor array. The distance between the transmitter and the object was about 80mm, and the distance between the object and the ultrasonic sensor array was about 70mm.

(2) We moved the reference object in the x-direction in 5mm increments in order to acquire the pattern data to be used in the recognition unit. In this experiment, we used the cylinder (LC) and the rectangular prism (LP) as the reference objects. We acquired 7 patterns of data from each object.
(3) We acquired the pattern data of the trial object placed at the any position in x-direction. The recognition unit, into which the data was inputted, arrives at the solution based on the GA. In this experiment, we tested 28 patterns of data per each object.
(4) In the recognition unit, the GA repeats the calculation for evolution 100 times. As a result, the solution of the recognition unit is decided by majority vote. We set the number of generation changes in the GA for 100 times.

4.4 Results

Table 2 shows the results of the Case A1 and the Case A2, which used both the GA and the NN for objects in a fixed position. In this case, the recognition ratio achieved by the GA was 100 percent for all conditions. This shows that our method by GA has the ability to recognize similar objects. On the other hand, although the NN was able to identify the object it had learned in advance, it had difficulty identifying the objects that were not learned.

Table 2 Experimental results in a fixed position

Object		Trial	Success			
			A1		A2	
			GA	NN	GA	NN
Cylinder	SC	4	4	4	4	0
	MC	4	4	4	4	0
	LC	4	4	4	4	4
Rectangle prism	SP	4	4	4	4	2
	MP	4	4	4	4	0
	LP	4	4	4	4	4

Table 3 Experimental results in a free position

Object		Trial	Success			
			B1		B2	
			GA	NN	GA	NN
Cylinder	SC	28	21	21	23	12
	MC	28	22	15	16	16
	LC	28	21	19	24	21
Rectangle prism	SP	28	28	18	26	16
	MP	28	27	21	24	10
	LP	228	23	20	21	21

Table 3 shows the recognition results the Case B1 and the Case B2, which used both the GA and the NN for objects in a free positions. In this case, the recognition ratio achieved by the GA was lower than that shown in Table 1. However, compared to that of the NN, the recognition ratio achieved by the GA was higher due to its ability to recognize similarly shaped objects

5. CONCLUSIONS

We here described a new shape-recognizing robot eye that uses a GA. Unlike a NN, the GA can recognize shapes without depending on learned data. Experimental results demonstrate that the recognition ratios of the proposed ultrasonic robot eye using the GA are higher than that of a conventional ultrasonic robot eye using a NN. Therefore, it is shown that our robot eye is effective for many robotic applications.

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