3D shape recognition system by ultrasonic sensor array and genetic algorithms

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3D Shape Recognition System by Ultrasonic Sensor Array and Genetic Algorithms

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Abstract *– This paper describes 3D shape recognition system using ultrasound pressure data and a Genetic Algorithm. The ultrasonic 3D shape recognition system using has commonly used a Neural Network (NN). 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 recognition system using the GA are higher than that of a conventional 3D shape recognition system using a NN. Therefore, it is shown that our ultrasonic 3D shape recognition system is effective for many industrial applications.*

Keywords *– Ultrasonic sensor, 3D shape recognition, Genetic Algorithms*

I. INTRODUCTION

From the viewpoint of industrial applications, 3D shape recognition methods using ultrasound have the following advantages over those using a light[1]-[5]:

1. The method is effective under many different conditions, including a dark or underwater environment, as well as for a variety of objects including those made of transparent materials, which cannot be recognized by optical sensors.
2. Signal processing of ultrasonic sensors is simpler and less expensive than that of optical or image sensors because ultrasonic sensors do not require expensive image processing circuitry.
3. An ultrasonic signal includes many types of information which are not included in a light signal, such as information about the materials of which the measured object is composed.

On the other hand, shape recognition using ultrasound has the following disadvantages over light shape recognition systems:

1. The resolution of the measured values acquired by ultrasonic sensors is relatively low.
2. Color information is not included in the ultrasonic signal.
3. An ultrasonic signal is sensitive to changes in temperature, humidity, atmospheric pressure, and external noise.

We here propose a new ultrasonic shape recognition system using Genetic Algorithms (GAs)[6] in consideration of the characteristics of ultrasonic signals. Our system has many practical applications, including use in the handling system of industrial parts by robots in situations in which cameras cannot be used or in an on-line identification system of glass bottles in the factory.

Conventional ultrasonic shape recognition has usually employed Neural Networks (NNs) [7] as the recognition algorithm, but NNs cannot fully identify the shape of unlearned objects. Thus, in order to resolve this problem, we employ GAs rather than NNs.

Many problems remain to be solved in shape recognition using ultrasound. At the present stage of the research, for example, it is more difficult with ultrasound than with light to identify objects with complex shapes. We therefore started by creating an ultrasonic identification approach for objects with primitive shapes such as cylinders, rectangle prisms, rectangle pyramids and cones.

II. OUTLINE OF THE PROPOSED SYSTEM

Fig. 1 shows a schematic drawing of the proposed recognition system. The system is composed of two ultrasonic transmitters, ultrasonic receivers, signal processing circuitry, and a recognition unit that is equipped with the GAs. The two transmitters are positioned orthogonally to a horizontal surface, and project the ultrasound toward an object. The receivers consist of three sensor arrays with 16

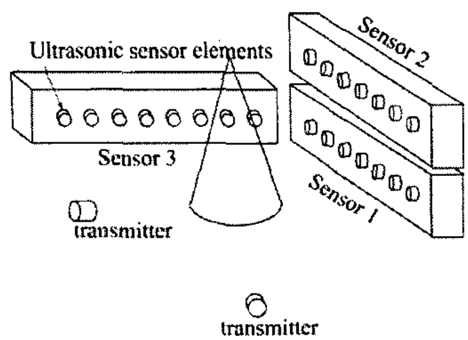

Fig. 1. Outline of the proposed recognition system.

ultrasonic sensor elements in total. The sensor elements are arrayed in linear form. Two of the three sensor arrays (Sensors 1 and 2) are aligned vertically, the other (Sensor 3) is placed at the position orthogonal to the first two sensor arrays. Sensor 1 and Sensor 3 are located at the same vertical position. The sensor 1 and sensor 2 are arranged at the same horizontal position. The space between each sensor and the interval between the sensor elements are dependent on the size of a measured object.

The system identifies the shape of an object using information from the transmitted ultrasonic wave which is distorted by the presence of the object. We conducted experiments using 18 kinds of objects. In this system, the objects under study are symmetrical.

III. CHARACTERISTICS OF ULTRASONIC DISTRIBUTION

This section describes the relationship between the transmitted ultrasound pressure distributions and the shapes of the objects.

Fig. 2 shows the difference between a rectangle prism and a cylinder in the transmitted ultrasonic pressure distribution of Sensor 1. In this case, the side view of both objects is the same, but the cross section is different. The distribution in this figure was drawn by first plotting and then connecting the peak values of the outputs of each sensor element. The concavity of the distribution indicates the position of the object. This distribution has three peaks due to ultrasonic diffraction. The interval between the two peak positions at each end of the cylinder is smaller than that of rectangle prism, as shown in Fig. 2.

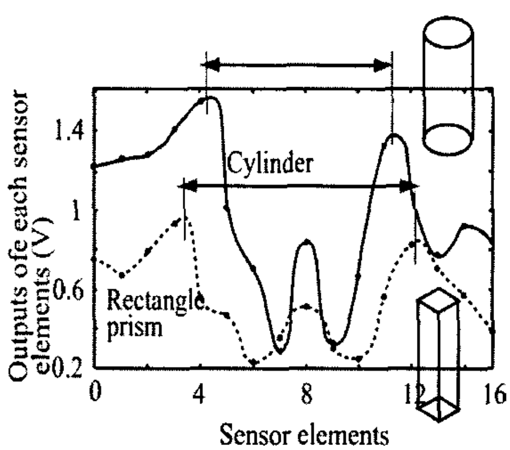

Fig. 2. The difference of the ultrasound distribution between cylinder and rectangle prism.

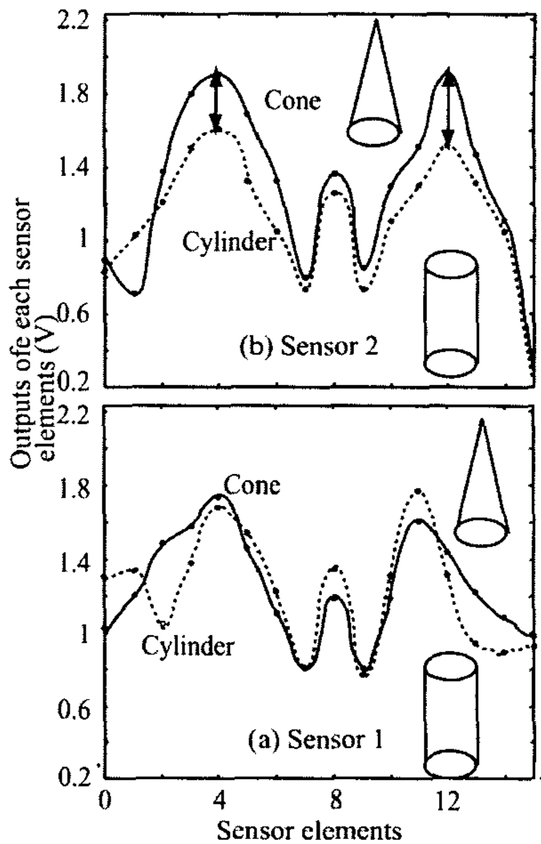

Fig. 3. The difference of the ultrasound distribution between rectangle cylinder and cone.

Fig. 3 shows the ultrasonic pressure distributions of Sensors 1 and 2 for a cylinder and a cone, which are similar figures in the cross section, but whose side view differs. In this figure, the areas of the cross section of the cylinder and the cone at the position of Sensor 1 are equal, but those at Sensor 2 are different. Based on this figure, the distributions of the cylinder and the cone at Sensor 1 are almost the same, but the peak value of the cone at Sensor 2 is larger than that of the cylinder.

Fig. 4 shows the distributions of Sensors 1 and 3 for a rectangle prism and a triangle prism. In this case, the two distributions at Sensor 1 are equal, but those at Sensor 3 are different.

In this system, the features of objects under consideration as determined by the transmitted ultrasound pressure distributions from the three sensor arrays are used as identifying parameters for shape recognition.

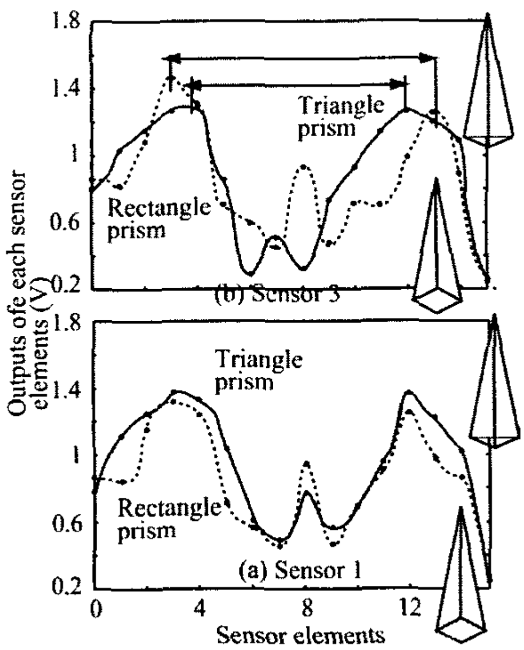

Fig. 4. The difference of the ultrasound distribution between rectangle cylinder and rectangle prism.

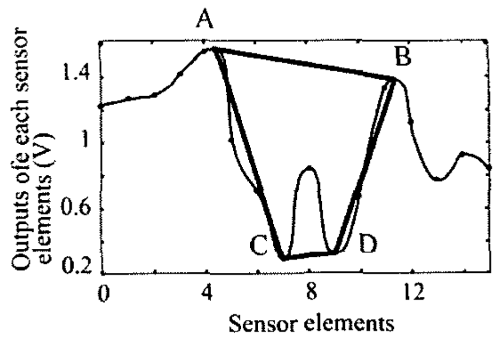

Fig. 5. Quadrangle using four points for recognition.

IV. PRINCIPLES OF SHAPE RECOGNITION USING GA

This section describes the new recognition approach we propose.

Fig. 5 shows the feature values that we employed for ultrasonic shape recognition. As shown in this figure, a quadrangle that consists of four points (two end side peak points, A and B, and two bottom points, C and D) of the ultrasound pressure distribution is generated by the three ultrasonic sensor arrays. The specific shape of this quadrangle is generated differently for different objects.

These quadrangles extracted from each sensor array reflect changes in shapes according to changes in the conditions under which the reading is conducted, including temperature, humidity, and the position of the object. However, changes in shapes have a certain geometrical similarity. Specifically, as confirmed in our preliminary experiments, even if the above quadrangles of an object are acquired under different conditions, their shapes become similar by geometrically similar expansion or reduction , and/or rotating them.

In the present study, we carried out advance measurements of ultrasound pressure for 18 "reference objects", and generated the above quadrangles as "reference quadrangles" for Sensors 1, 2 and 3. Next, we measured the ultrasonic signal for a "trial object" subjected to ultrasonic identification, and generated the "trial quadrangles" for this object. We sought objects which would coincide geometrically with the trial quadrangles of our 18 reference quadrangles, in order to identify the trial object. However, since a trial quadrangle does not always coincide with a reference quadrangle except when the two quadrangles are determined under exactly the same conditions, we then manipulate the trial quadrangle by geometrically similar expansion or reduction, rotation, reversal to make it coincide geometrically with one of reference quadrangles. And, after repeating these operations, we identify the trial object. This process of identification is carried out through the genetic operation of GAs.

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

As shown in Fig. 6, we first generate a quadrangle composed of the four points of the ultrasound pressure distribution acquired from the ultrasonic sensor arrays. The shapes of this quadrangle are different according to the specific trial object and the measuring conditions.

The quadrangle of the trial object is transformed by using

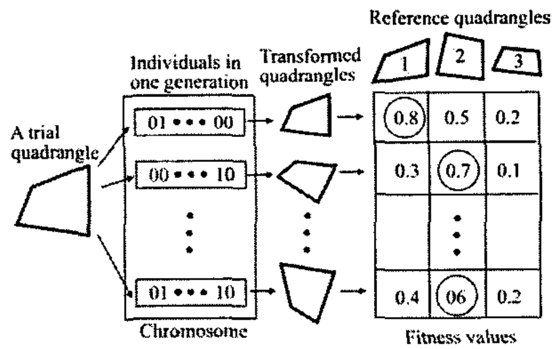

Fig. 6. Principle of the shape recognition using GA.

the operators by the GAs, which are selection, crossover and mutation, as shown in Fig. 6. The fitness values are calculated between the trial quadrangle and the reference quadrangles using spatial information, and the distance between vertices are calculated. The fitness value f is defined as the following equation in which S is the difference in the area between the trial quadrangle and the reference quadrangles, and D is the total distance between the vertices of the reference quadrangles and those of the trial quadrangle:

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

Using GA operations, chromosomes that have information on expansion or reduction, rotation, and reversal are generated. Some chromosomes are applied to the trial quadrangle, the majority of each fitness value is utilized, and the solution of the generation is determined. In the case shown in Fig. 6, the solution is the object featured as reference quadrangle No. 2.

Fig. 7 shows the genotype of an individual which is binary data of 80-bit length. The binary data is comprised of the rate of expansion 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.

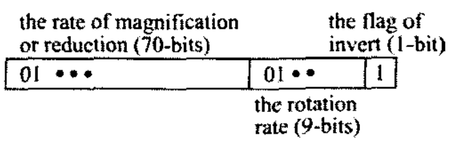

Fig. 7. Genotype and phenotype of an individual.

V. EXPERIMENT

A. Experimental setup

Fig. 8 shows a photograph of a prototype recognition system embodying the proposed principle for shape recognition. The transmitters are located at the left and right sides of the figure, and the three receivers (ultrasonic sensor arrays), which are composed of 16 ultrasonic sensors, are located at the left and in the center. The measured object (a cone in this photograph) is located between the transmitters and the receivers. The space between Sensor 1 and Sensor 2 is 40mm. The interval between sensor elements is 16mm. The distance between the transmitter and Sensor 1 (Sensor 2) is about 250mm.

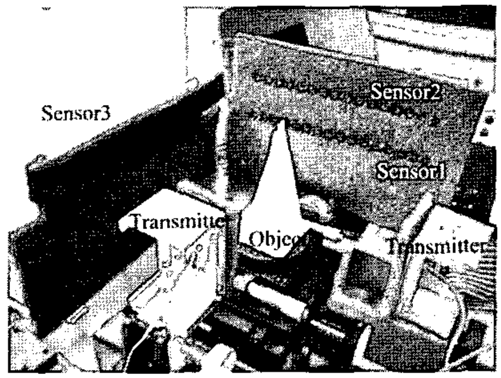

Fig. 8. Photograph of experimental setup.

B. Measured objects

Fig. 9 shows the six kinds of measured objects: cylinder, cone, rectangle prism, rectangle pyramid, triangle prism, and triangle pyramid. Each type of object was tested in three sizes: large, medium and small.

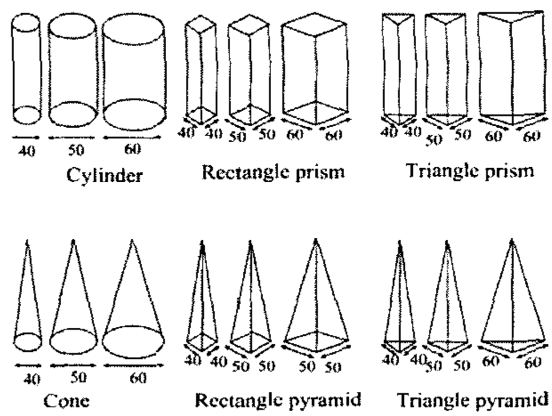

Fig. 9. Measured objects.

C. Procedure

We conducted two kinds of experiments to verify the effectiveness of our method of shape recognition by GAs, and compared our method to the method by NNs.

In the first experiment, we selected one of the 18 objects, acquired the ultrasound pressure data under different conditions from the reference quadrangle, and generated a trial quadrangle of the trial object, which was then identified as one of the 18 trial objects.

The second experiment reduced the number of reference quadrangles that were compared with the trial quadrangle. This experiment used only reference quadrangles of the medium size of each of the 6 kinds of objects. As each trial object was selected, its trial quadrangle was compared to the reference quadrangle of the all and only the medium-sized objects. Identification was achieved by matching the trial quadrangle with its respective medium-sized reference quadrangle. This method of identification is more difficult than that used in the first experiment because of the paucity of reference quadrangles.

In the recognition process, the GAs repeated the calculation for evolution 100 times. As a result, the solution of the recognition unit was deteremined by majority. We set the number of generation changes in the GAs for 100 times.

NNs used for comparison with GAs employed a five layer construction. The number of units in the input layer was 24 and the number in the output layer was 24 for the first experiment and 6 for the second experiment. The NN system employed the error back propagation algorithm.

D. Results

In first experiment, the recognition ratio achieved by the GA system was 100% for all objects; the recognition ratio by the NN system was also 100%.

Table 1 shows the results of the second experiment. As in the first experiment, the recognition ratio achieved by the GA system was 100%, indicating that the proposed approach is capable of identifying objects which are geometrically similar using a single reference quadrangle regardless of the size of the trial object. On the other hand, in the second experiment, although the NN system was able to identify objects it had learned in advance, it had difficulty identifying objects that had not previously been learned.

These experimental results show that the recognition ratios of the proposed ultrasonic shape recognition system using GAs are higher than those of a conventional ultrasonic shape recognition method using NNs. We therefore believe that our] proposed shape recognition system will be effective for many industrial applications.

Table I. Experimental results for second experiment.

Object	Size	GAs			NNs		
		Number of trial	Number of success	Recog-nition ratio	Number of trial	Number of success	Recog-nition ratio
Cylinder	small	10	10	100	10	0	0
	middle	10	10	100	10	10	100
	large	10	10	100	10	1	1
Rectangle prism	small	10	10	100	10	0	0
	middle	10	10	100	10	10	100
	large	10	10	100	10	0	0
Triangle prism	small	10	10	100	10	0	0
	middle	10	10	100	10	10	100
	large	10	10	100	10	0	0
Cone	small	10	10	100	10	0	0
	middle	10	10	100	10	10	100
	large	10	10	100	10	1	1
Rectangle pyramid	small	10	10	100	10	0	0
	middle	10	10	100	10	10	100
	large	10	10	100	10	0	0
Triangle pyramid	small	10	10	100	10	2	2
	middle	10	10	100	10	10	100
	large	10	10	100	10	1	1

VI. CONCLUSIONS

We here described a new 3D shape recognition system 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 recognition system using the GA are higher than that of a conventional ultrasonic recognition system using a NN. Therefore, it is shown that our ultrasonic recognition system is effective for many industrial applications.

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