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Neural Network Controller for Two-Dimensional Smart MEMS Conveyor

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Abstract

We study distributed micro system, which is called Smart MEMS(Micro Electro Mechanical System). We utilize neural network implemented in electrical circuit to control the MEMS device. In this paper, We aim to sort the object by the shape with a modified neocognitron. We apply this system to partsfeeder to sort electronic parts by the defect of the shape. We carried out the detection of deformation of rotated parts with our modified neocognitron. The accuracy rate of rotation pattern without and with deformation is 85.3% and 92.9%. Our modified neocognitron is useful for sorting the object.

1 Introduction

Today, the size of circuit and actuator has got smaller and smaller with advanced semiconductor manufacturing technology. Micro-machining technology provides us with the capability of integrating many devices and mass production. But, central control is not suitable for controlling many actuator.

Smart MEMS[1] is suggested to address this issue. Smart MEMS(Micro Electro Mechanical System) has distributed structure, which is composed of array of identical subsystems. Each subsystem has a processing unit, which is integrated with sensors and actuators. The subsystems communicate and exchange information for extracting valuable information from locally obtained data, by combining them in a larger area.

Our final goal is a micro system which conveys an object to different directions according to its shape using Smart MEMS. We utilize NN(Neural Network) implemented in electrical circuit to control the MEMS devices. The benefit of NN is, for example, (1)the study of pattern recognition is advanced, (2)parallel processing allows the system to recognize many objects and to convey them per unit time, (3) with chip architecture advanced, it is possible to make compact system. Analog circuit technology can reduce the size of NN, but, the drawback of analog circuit is instability caused by noise and the fluctuation of device. Thus, we adopt patten recognition using NN with digital circuit. We use neocognitron[2] for pattern recognition.

In our research, we apply this system to partsfeeder[5], which is used for conveying electronic parts[6] in manufacturing factory. Our goal is to sort electronic parts by the defect of the shape. Since the plastic mold of the electronic devices is easy to be distorted and to suffer from the defects, several degradations of the quality will be increased in the fabrication process[7]. We use NN for shape recognition to resolve this problem.

In this paper, we aim to sort one rotated electronic part and simplify neocognitron for circuit implementation. Because a rotation-invariant neocognitron[3] is more complicated than basic neocognitron, it is not very suitable for circuit implementation.

In section 2, we explain the architecture of Smart MEMS and MEMS conveyor. In section 3, we explain neocognitoron, which is used for pattern recognition, and Central Pattern Generator, which is used for controlling MEMS actuator. In section 4, we show the result for detecting deformation of electronic parts. In section 5, the conclusion is presented.

2 MEMS conveyor

Our final goal is the system that is composed of three layers of different function; i.e. a Mechanical layer, a sensing layer(PD layer) and a Neural Network layer (Fig.1). We use two-dimensional conveyance system with MEMS technology[4]. The mechanical layer composed of the array of thermally driven actuators is made by layers of polyimide on a Si or glass substrate, and is transparent with light. When an object to be conveyed is on the mechanical surface, light coming downward makes bright and dark(which is a shadow of the object) regions on the surface of photo sensitive device. The output of PD is input to the module of pattern recognition, which can recognize the shape of object. The information of the shape is input to the module of controlling actuator, which is Central Pattern Generator[8]. The actuator is controlled based on the shape of object detected the module of patten recognition (Fig. 2).

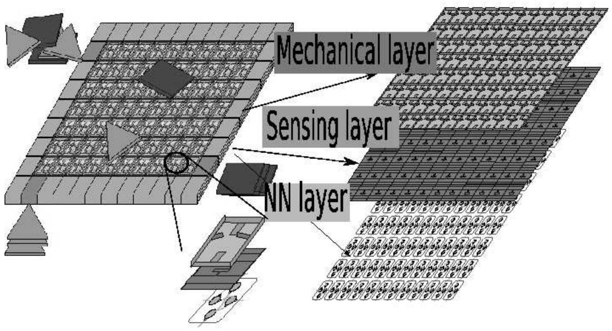

Figure 1: Our goal. This system composes three layers, which are actuator, sensor and NN.

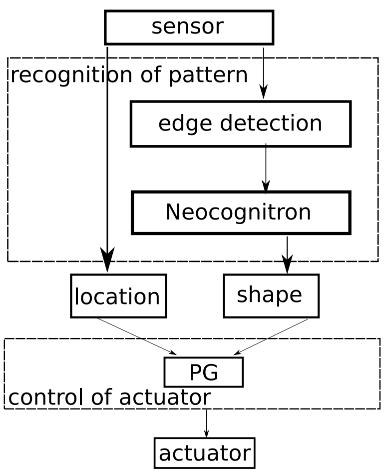

Figure 2: Flow of signal.

3 Neural network

3.1 Modified neocognitron

K.Fukushima et al. suggested the neocognitron[2] in 1982. It recognizes two-dimensional stimulus patterns correctly without being affected by shifts in position or even by considerable distortions in shape of the stimulus patterns. The neocogitron, however, cannot recognize rotated patterns because deformations by rotations are not considered.

So, we propose a method for detecting the deformation rotated parts for electrical circuits (Fig.3). The first layer is input layer. The degree θ is detected in the second layer. In the second layer, the rotated pattern by every 15° (which is the pattern of good parts) is learned, and θ is detected based on the output of the second layer. In the third layer, the input pattern is rotated by $-\theta$. In the forth layer, the deformation of input pattern is detected by the following method: we increase the number of input interconnections per S-cell and the value of threshold. The more deformed the object on the mechanical layer is, the less the output of the forth layer becomes. This modified neocognitron is simpler than a rotation-invariant neocognitron in terms of the number of planes and layers.

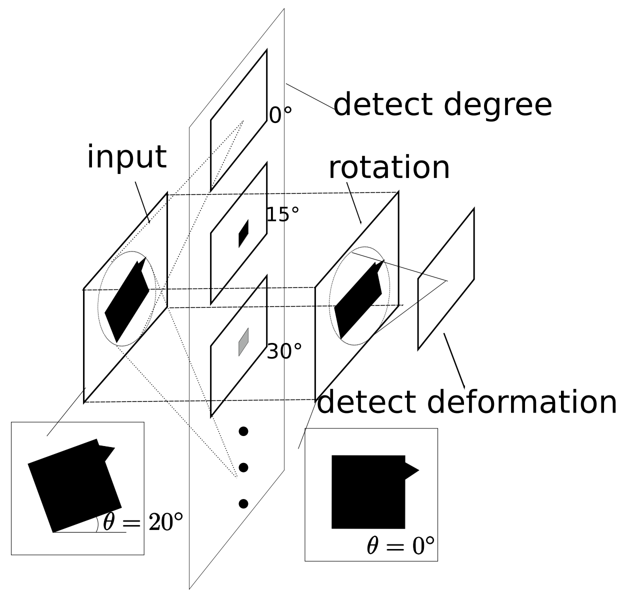

Figure 3: Modified neocognitron.

3.2 Conveyance system

This mechanical layer is composed of the array of thermally driven actuators. A bimorph thermal actuator using two types of polyimide with different thermal expansion coefficients and a metallic microheater in between them was fabricated. It moves downward when current is applied to the heater. The actuator can be controlled by two driving pulses with phase shift of 90 degree. In this way, the object is conveyed [4].

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3.3 Pattern generator

Biological rhythmic movements, such as walking, running and swimming, are believed to be driven by the biological neural network, called the central pattern generator(CPG)[8]. CPG is composed of sets of neural oscillators, situated in ganglion or spinal cord. Induced by inputs from command neurons, a CPG generates a rhythmic pattern in nerve activity automatically.

We are planning to set CPG under a cilium. One of CPG is connected with a cilium. Induced with the results of pattern recognition, different conveyance pattern is yielded. We are expecting that we will be able to generate firing pattern with phase shift of 90 degree by making many CPGs connected with proper weight. In this way, we convey the objects in different shape to different directions accordingly.

4 Results

We carried out detecting of the deformation of parts with the modified neocognitron. In our research, we used square as an example of electric parts such as capacitors. Fig.4 is the pattern of good parts for learning.

First, these patterns are learned. Next, we input the pattern with and without deformation (Fig.5) which was rotated by 1° from 0° to 30°. Finally, we estimate the output of the forth layer (Fig. 3).

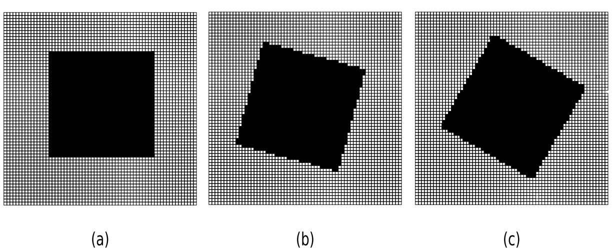

Figure 4: Learning pattern in 64×64. (a)0°, (b)15°, (c)30°.

In Fig.6, we show the results of the outputs of the modified neocognitron with input patterns (Fig.5(a)(b)). In Fig.5(a) the shadow of good parts is shown which is the learning pattern. Fig.5(b) is the shadow of bad parts, which has deformation. We applied as input these shadow patterns rotated by every 1° from 0° to 30°. The vertical axis in Fig.6 represents the output of the forth layer of the modified neocognitron. The larger the output of an input patten becomes, the similar to the learning pattern (the good part) the input pattern is. Therefore, we expect the input pattern which has larger output (more than 0.1) as good parts(Fig.5(a)), and the input pattern which has the smaller output (less than 0.1) as (Fig.5(b)).

In this way, we show the results of the modified recognition of rotated input pattern in Table.1. It shows the relationship between the degree and the detection. The accuracy rates of good and bad parts rotated were 85.3% and 92.9% respectively.

From table.1, we calculated the rate at which input pattern is really a bad part when the result of recognition is a bad part, and the rate at which input pattern is really a bad part although the result of recognition is a good part. We show these rate in the upper row and the lower row on table2 respectively. At the same time, we show these rate respectively when the proportion of the number of good parts and bad parts is 10:1, 100:1 and 1000:1. The larger the proportion becomes, the less these rate becomes.

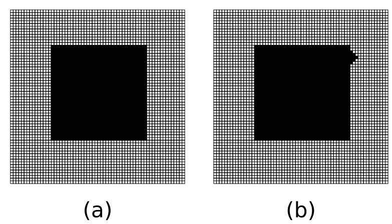

Figure 5: (a)the input pattern of good part which is rotated by 0°. (b) the input pattern of bad part which is rotated by 0°. the area of deformation occupies about 0.7% of the area of good part.

5 Conclusion

In this paper, we reported the result of recognizing task of deformation in electronic parts. real Fig.5(b) / expected (b) is small in the larger proportion(the lower row in Table.2). We suspect that it is caused by insufficient precision in detecting the degree in the second layer on Fig. 3 and inappropriate rotation of the input patten by $-\theta$ in the third layer. We need to improve the accuracy of detecting the degree and rotating the pattern by $-\theta$. We expect to resolve these problem by increasing the resolution of PD array.

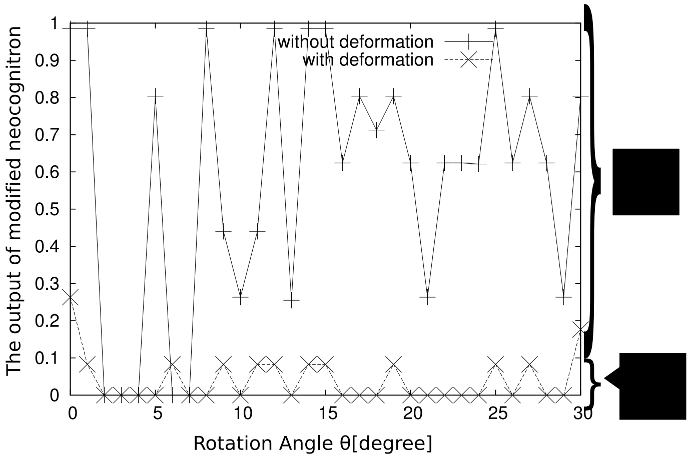

Figure 6: The result of the output of Fig.3 with input pattern(Fig.5(a)(b)) which is rotated by every 1°. X-axis is degree. Y-axis is the output of the forth layer of Fig.3. The larger output (more than 0.1) is expected Fig.5(a). The smaller output (less than 0.1) is expected Fig. 5(b).

Table 1: The relationship between the degree and the detection. (a) indicates that the recognition is Fig5(a). (b) indicates that the recognition is Fig.5(b). Accuracy rate is correct recognition rate.

	0°	1°	2°	3°	4°	5°	6°
Fig5.(a)	(a)	(a)	(b)	(b)	(b)	(a)	(b)
Fig5.(b)	(a)	(b)	(b)	(b)	(b)	(b)	(b)
	7°	8°	9°	10°	11°	12°	13°
Fig5.(a)	(b)	(a)	(a)	(a)	(a)	(a)	(a)
Fig5.(b)	(b)	(b)	(b)	(b)	(b)	(b)	(a)
	14°	15°	16°	17°	18°	19°	20°
Fig5.(a)	(a)	(a)	(a)	(a)	(a)	(a)	(a)
Fig5.(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)
	21°	22°	23°	24°	25°	26°	27°
Fig5.(a)	(a)	(a)	(a)	(a)	(a)	(a)	(a)
Fig5.(b)	(b)	(b)	(b)	(b)	(b)	(b)	(b)
	28°	29°	30°	accuracy rate			
Fig5.(a)	(a)	(a)	(a)	85.3%			
Fig5.(b)	(b)	(b)	(a)	92.9%			

Table 2: 10:1, 100:1 and 1000:1 are the proportion of good parts and bad parts. The rate of Fig.5(b) recognized (b) and the rate of Fig.5(b) recognized (a) .

	10:1	100:1	1000:1
$\frac{real(b)}{expected(b)}(\%)$	36.7	5.48	0.576
$\frac{real(b)}{expected(a)}(\%)$	0.763	7.69×10^{-2}	7.69×10^{-3}

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