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Optimization of the sensor network using genetic algorithm

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***Abstract*:** Recently, with the advancement of the aging society, robots that operate in homes and hospitals have attracted much attention, and robots that have flexible artificial skins have been developed. Usually, they have to touch human bodies while performing their jobs. So, many touch sensors are required for the surface of the whole body. However, it is difficult to allocate limited number of sensors to suitable positions, because frequency of stimulus applied to the body is different by the locations, and in addition necessary resolution is different by the locations. In this paper, we consider design of sensor networks for robots, and we distribute limited resources to the sensors and the communication channels by genetic algorithm. Simulations have been conducted, and as a result, in case of noisy environment, many resources have been distributed to communication channels for realizing enough rate of information throughput. And in case of noiseless environment, many resources have been distributed for sensors because each communication channel has enough speed in the noiseless environment. From the results we have confirmed that number of sensors and communication channels has been adjusted and optimal sensor networks have been obtained.
***Keywords*:** Genetic Algorithms, sensor network, touch sensor

I. INTRODUCTION

Recently, with the advancement of the aging society, robots that operate in homes and hospitals have attracted much attention, and robots that have flexible artificial skins have been developed [1]-[4]. Usually, the robots have to touch human bodies while performing their jobs. So, many touch sensors are required for the surface of the whole body. However, it is difficult to allocate limited number of sensors to suitable positions, because frequency of stimuli applied to the body are different by the locations, and necessary resolution is also different by the locations. Moreover, there is a trade-off between resolution and communication cost. By increasing the number of sensors, we can enhance the space resolution, but communication cost is also increased. So, even if we install large number of sensors to the robot, the robot can not utilize information from the sensors because of the lack of the rate of information throughput. So, we have to distribute limited resources adequately to the sensors and the communication channels.

On the other hand, animals have adequate touch sensors on their whole body, and the number of sensors is adjusted based on the locations. For example, human being has many touch sensors on their hand than their foot. It is considered that the distribution is designed by the evolution.

In this paper, we consider design of sensor networks for robots, and we distribute limited resources to the sensors and the communication channels, and in addition, we allocate sensors adequately based on the stimulus from the environment by Genetic Algorithms.

II. PROBLEM DOMAIN

In this paper, we consider the distribution of limited resources to sensors and their communication channels. We assume that there is noise in the environment, and positions of the stimuli are set randomly.

In the environment, amount of information that can be transmitted by a communication channel is given by equation (1), by Shannon− Hartley theorem.

$$C = \log_2(1 + \frac{S}{N}) \qquad \cdots(1)$$

Where, C is the communication channel capacity, S is the total signal power, N is the total noise power.

III. GENETIC ALGORITHM

To realize optimal distribution, we employ genetic algorithm [5]. Fig. 1 shows the flowchart of the genetic algorithm.

First, initial individuals are created randomly, and then, crossover and mutation are conducted and new population is produced. From the population, individuals that survive to the next generation are selected. By repeating this cycle, evolution is realized.

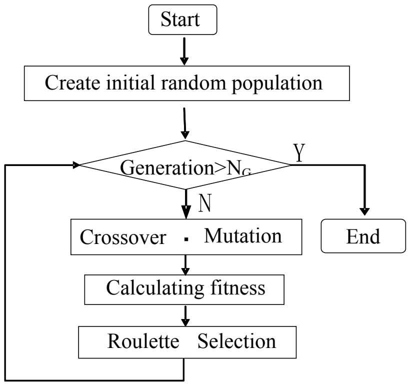

Fig. 1 Flow chart of Genetic Algorithm

IV. ENCODIN METHOD

Fig. 2 shows a sensor network that we consider in this paper. The circles show sensors, and lines are communication channels. Every sensor has own exclusive communication channel, and one communication channel is composed of multiple cables. Rate of information throughput of each communication channel is determined by the number of its cables and noise by equation (1) and (2). The position of the sensors and the number of the cables are given by genetic algorithm.

$$C_{ch}[i] = C \times N_c[i]$$

$$y[i] = \begin{cases} C_{ch}[i] & (C_{ch}[i] \le U) \\ U & (C_{ch}[i] > U) \end{cases} \qquad \cdots(2)$$

Where, C is information throughput of each cable and is given by equation (1). C_{ch}[i] is information throughput of i-th communication channel, N_c[i] is the number of cables of the i-th communication channel, U is input from each sensor, y[i] is output of the i-th communication channel.

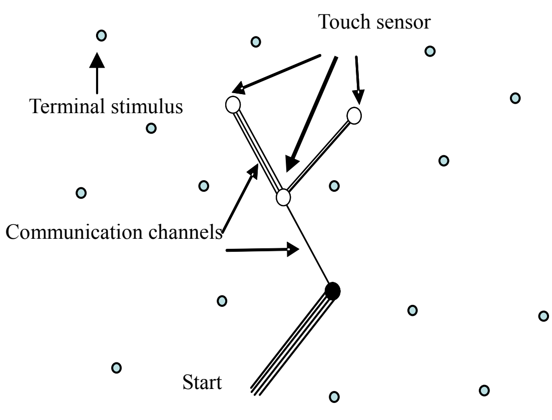

Fig.2 Sensors and communication channels

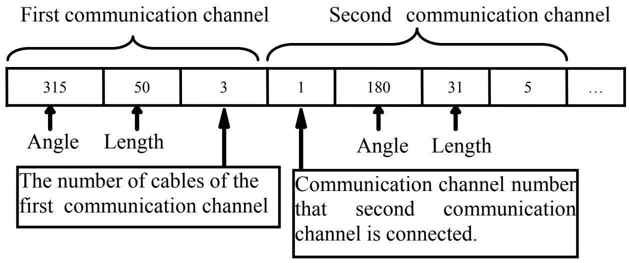

Fig.3 Encoding of sensor network

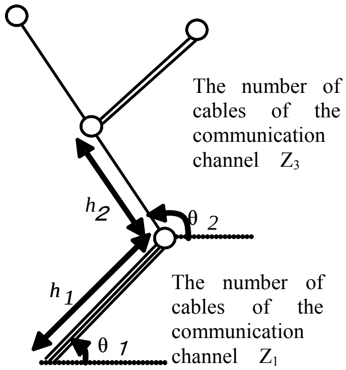

Fig.4 Phenotype

Fig. 3 shows the genotype of the sensor network and Fig. 4 shows the phenotype of that.

In Fig. 3, first gene means the angle from the horizontal axis to the first communication channel as shown in Fig. 4. The angle is selected from 0 to 360 degrees and its step size is one degree. The second gene means the length of the first communication channel. The value is selected from 0 to 50 and its step size is one. The third gene means the number of cables of the first communication channel. The value is selected from 1 to 10 and its step size is one. Fourth gene means communication channel number that second communication channel is connected. Fifth gene means the angle from the horizontal axis to the second communication channel.

By repeating this cycle, whole sensor network is described.

V. FITNESS

We calculate the fitness of the sensor network by total amount of transmitted information.

We input many stimuli to the sensor network. The positions of the stimuli are set randomly and are observed by the nearest sensor. The information of the stimulus is transmitted to the origin by its communication channel. The rate of information throughput of each communication channel is determined by the number of its cables and noise as shown section II and section IV.

From the amount of transmitted information, we calculate fitness as shown in equation (4).

$$fit = \frac{\sum_{i=1}^{n} y[i]}{\sum_{i=1}^{n} (Cs + Ct \times N_c[i])} \qquad \cdots(4)$$

Where, n is the number of communication channel, Cs is the cost of each sensor, Ct is the cost of each cables for the communication channel, $N_c[\mathrm{i}]$ is the number of cables of the i-th communication channel.

The numerator of the equation (4) means total amount of transmitted information, and the denominator means total cost.

In the setting that we consider in this paper, as the amount of the resources is limited, if rate of information throughput becomes high, the number of sensors becomes small. In this case, if amount of information that is sent from a sensor is smaller than its rate of information throughput, the communication channel is not utilized efficiently, and the value of the fitness becomes small.

By the same token, if the number of sensors becomes large, then the rate of information throughput becomes low, and it becomes impossible to send all information from the sensors to the origin, because of the lack of the rate of information throughput. So, in this case, the value of the fitness becomes small too.

Thus, by maximizing the fitness, the trade-off of the resolution and the communication cost is solved, and the optimal sensor network is realized.

VI. SIMULATION

We conduct simulations to demonstrate the effectiveness of the proposed approach. We employ three different cases. Table 1 shows the common setting of GA, and Table 2, 3and 4 show the setting of each case.

Table1.The setting of GA

Number of individuals	50
Number of generations	10000
Probability of crossover	50%
Probability of mutation	1%
Amount of information that is sent from each terminal stimulus	10
Cost of the sensor (Cs)	10
Cost of the communication channel (Ct)	1

Table2. The setting of case 1 (In Fig.7)

Gene length (the number of communication channel)	400 (100)
The number of terminal stimulus	100
Signal to noise ratio	2000

Table3. The setting of case 2 (In Fig.8)

Gene length (the number of communication channel)	400 (100)
The number of terminal stimulus	100
Signal to noise ratio	40

Table4. The setting of case 3 (In Fig.9)

Gene length (the number of communication channel)	1200 (300)
The number of terminal stimulus	100
Signal to noise ratio (0≦Y coordinate＜350)	2000
Signal to noise ratio (350≦Y coordinate≦700)	40

Fig. 6 shows the average and the maximum vale of the fitness. Fig. 7, 8 and 9 show examples of the acquired sensor networks.

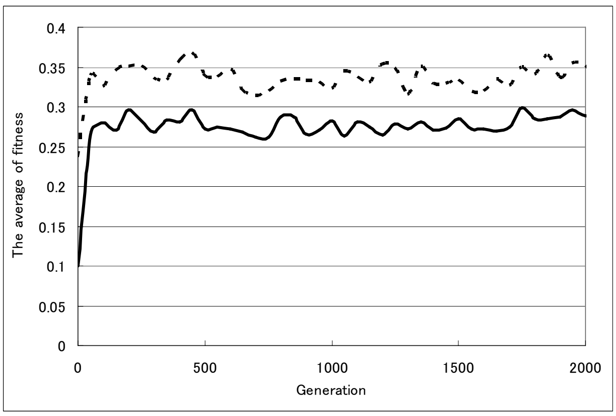

Fig. 6 The average and the maximum vale of the fitness

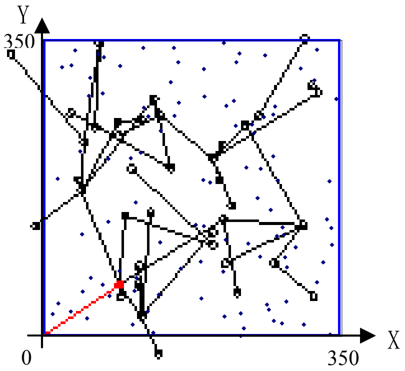

Fig. 7 Acquired sensor network (S/N=2000)

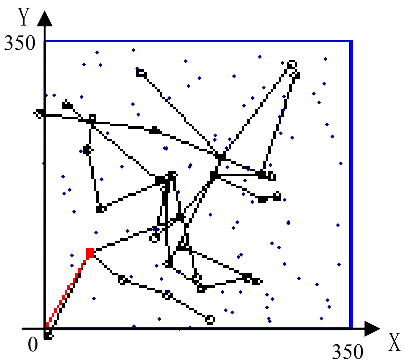

Fig. 8 Acquired sensor network (S/N=40)

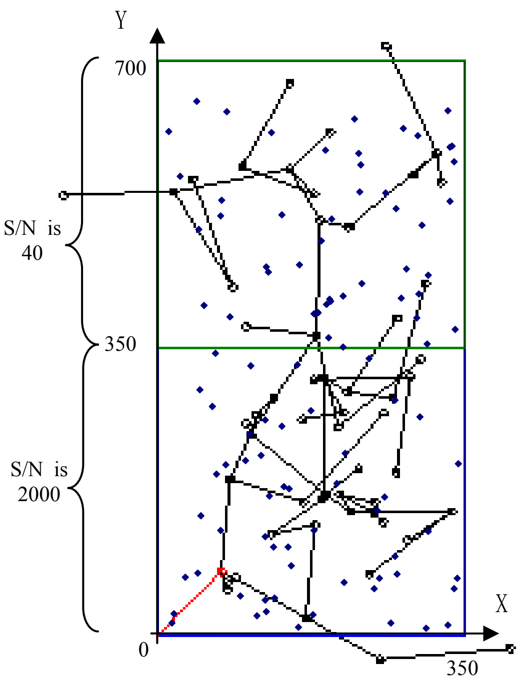

Fig. 9 Acquired sensor network

From Fig. 6, we can find that the fitness increases and evolution has been conducted successfully.

In case of noisy environment, many resources have been distributed for communication channels for acquiring enough rate of information throughput (Fig. 8). And in case of noiseless environment, many resources have been distributed for sensors, because each communication channel has enough rate of information throughput in the noiseless environment (Fig. 7).

From Fig. 9, we can find that even if there are different conditions in the environment, the sensor network is adapted for each condition adequately.

From the results, we can confirm that number of sensors and communication channels are adjusted and optimal sensor networks are obtained.

VII . CONCLUSION

In this paper, we consider design of sensor networks for robots and we distribute limited resources to the sensors and the communication channels. And in addition, we allocate sensors adequately based on the stimulus from the environment.

To demonstrate the effectiveness of the proposed approach, simulations in which noise is taken into consideration have been demonstrated. And as a result, in case of noisy environment, many resources have been distributed for communication channels to acquire enough rate of information throughput. And in case of noiseless environment, many resources have been distributed for the sensors because each communication channel has enough speed in the noiseless environment. From the results, we have confirmed that number of sensors and communication channels has been adjusted and optimal sensor networks have been obtained.

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