Haptic Communication between Humans and Robots

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Abstract

This paper introduces the haptic communication robots we developed and proposes a method for detecting human positions and postures based on haptic interaction between humanoid robots and humans. We have developed two types of humanoid robots that have tactile sensors embedded in a soft skin that covers the robot's entire body as tools for studying haptic communication. Tactile sensation could be used to detect a communication partner's position and posture even if the vision sensor did not observe the person. In the proposed method, the robot obtains a map that statistically describes relationships between its tactile information and human positions/postures from the records of haptic interaction taken by tactile sensors and a motion capturing system during communication. The robot can then estimate its communication partner's position/posture based on the tactile sensor outputs and the map. To verify the method's performance, we implemented it in the haptic communication robot. Results of experiments show that the robot can estimate a communication partner's position/posture statistically.

I. Introduction

Haptic communication is as important as vision and voice. It allows blind people to acquire a certain autonomy in their everyday life, since it is largely redundant with vision for the acquisition of spatial knowledge of the environment and object properties [1]. Moreover, people who are familiar with each other often pat each other's back or hug each other; such haptic interaction reinforces their familiarity.

If a communication robot equipped with tactile sensors over its entire body could have the same capability of haptic interaction as human do, we would feel greater familiarity with the robot, thus shortening its communicative distance from people. There has been much research on developing tactile sensors that cover the entire body of a robot [2], [3], [4], [5], [6]. Pan et al. [2] and Inaba et al. [4] proposed tactile sensor suits made of electrically conductive fabric. Hakozaki et al. [5] proposed telemetric robot skin based on sensor chips that consist of an LC resonance circuit. In particular, Inaba et al. developed a full-body sensor suit to detect binary touching information for their remote-brained small humanoid robot. Iwata et al. [3] also proposed force-detectable surface-cover systems for humanoid robots and developed an actual humanoid robot, named WENDY, with the systems. Their systems are based on a six-axis force torque sensor and force sensing registers (FSR sensors) used to measure the external force vector and contact positions on the cover accurately. Regarding haptic communication, Naya et al. collected data of tactile information from a pet-like robot and proposed a method that could classify several human touching motions based on the tactile sensor values [7]. By using that method, a robot can classify human touching motion and establish a relationship with a person by giving appropriate responses to the person.

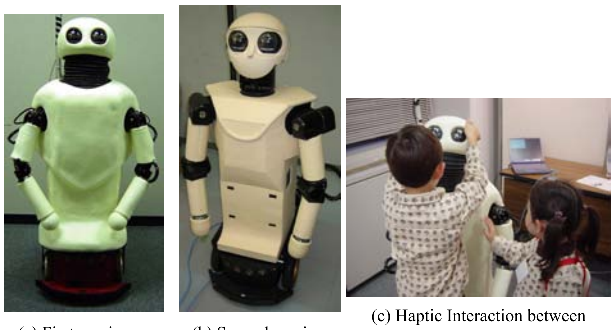
Let us consider some other aspects of haptic interaction. An infant is hugged by or plays with a caretaker. During that interaction, the caretaker acquires the infant's body geometry information in order to carefully control his or her motions. People often pat a communication partner on his/her body instead of calling him/her. In this case, since the partner is able to easily turn his/her face to the patting person directly, the partner can roughly estimate the position and the posture of the patting person without looking. This estimation makes human haptic interaction natural and safe. If we could realize such estimation for humanoid robots, the haptic interaction between humans and the robots would thus become more natural and safer. The previous researches, however, have focused on sensing the contact locations on the robot, and no method has been proposed to estimate position and posture by using only tactile information. In the field of computer vision, several methods have been developed to estimate position and posture [8], [9]. Under the situation of haptic interaction between a human and a robot, however, the distance between the human and the robot will be short, and images taken from the robot's cameras will only include a part of the human's body. Thus, it is difficult to use these methods for haptic interaction.

This paper proposes a method for a robot to detect human positions and postures by using tactile sensor data while the person is touching the robot. The key idea for handling tactile information is that the possible combinations of tactile information and human position/posture are quite limited in the above situations. In this method, the robot acquires a map that describes the correspondences between the tactile information and human positions/postures from the records of haptic interaction taken in situations of communication with humans. Using the map, it is possible to estimate position and posture based only on the information provided from the tactile sensors. We demonstrate the validity of the method in experiments on a robot covered with tactile sensors.

II. Tactile Sensors Covering an Entire Robot Body

A. Robovie-IIS

This section introduces the architecture of the tactile communication robot named Robovie-IIS. We have been developing communication robots, each named Robovie, for the study of communication between individual humans as well as between humans and robots. Robovie-IIS is designed to study tactile communication used in friendly relationships. This robot is based on Robovie-II [10], with tactile sensor elements embedded in a soft skin that covers the robot's entire body. Figure 1 shows overall views of two types of Robovie-IIS and scenes of its communication with a human.



(a) Fisrt version (b) Second version (c) Haptic Interaction between Robovie-IIS and chidren

Fig. 1. Two types of tactile communication robot "Robovie-IIS"

B. Tactile Sensor Elements embedded in Soft Skin

Figure 2 shows the hardware architecture of a tactile sensor element embedded in the soft skin. As the figure clearly illustrates, the soft skin consists of three layers. The outside layer is made of thin silicone rubber (thickness: 5 mm), and the middle layer is made of thick silicone rubber (thickness: 10 mm). We use these silicone rubber layers to achieve human-like softness. Moreover, the sense of touch and friction of the surface of the silicone rubber are similar to that of human skin. The thickness of the silicone rubber also absorbs the physical noise made by the robot's actuators. The inner layer is made of urethane foam, which insulates against heat from inside the robot and has a different surface friction from human skin. Its density is lower than that of the silicone rubber; the densities of the urethane foam and the silicone rubber are 0.03 g/cm^3 and 1.1 g/cm^3, respectively. The total density of the soft skin consisting of all layers is 0.6 g/cm^3. The tactile sensor elements are film-type piezoelectric polymer sensors inserted between the thin and thick silicone rubber layers. The film-type sensor, consisting of polyvinylidene fluoride (PVDF) and sputtered silver, outputs a high voltage proportionate to changes in applied pressure. Figure 3 shows the arrangement of the sensor elements for the

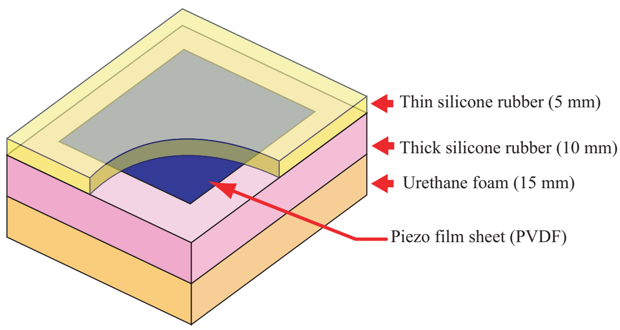


Fig. 2. Architecture of Soft Skin Sensor

first type of Robovie-IIS, of which there are 48 in its soft skin. The second type of Robovie-IIS has 276 sensor elements in the skin.

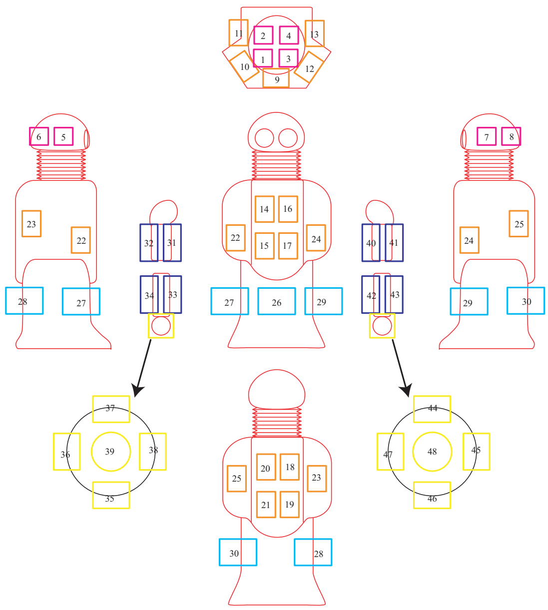


Fig. 3. Arrangement of sensor elements on Robovie-IIS

Although the sensor element outputs a high voltage, the signal is weak compared to electric noise disturbance since its electric current is weak.

Therefore, we distribute A/D converters (ADCs) with sensor-signal amplifiers to each body part. The ADCs are installed next to the sensor elements to convert the analog sensor signals to digital data. We developed two types of ADC, which are shown in Fig. 4. The dimensions of the first type of ADC are $23 \times 137 \times 8$ mm. On this board, there are four A/D converters (each channel has six bits) to obtain the outputs of four sensor elements. We also use a microcomputer (PIC) to convert the digital data to a serial signal (RS-232c). By adding other boards' serial signals to it, we can realize a daisy-chain connection between the boards, as shown in Fig. 5 (a). These boards allow us to sense all sensor elements embedded in the soft skin from a serial port of the host computer.

As for the second type of ADC, its dimensions are $22 \times 76 \times 10.2$ mm. This board has 16 A/D converters (each channel has 16 bits) and a micro-processor (SH2, Renesas Technology Corp.). We can connect 16 sensor elements to the board and preprocess the raw data of tactile sensor outputs, such as low-pass-filtering on the processor. The preprocessed data are converted to serial signals and sent to the host computer via a serial bus (RS-485), as shown in Fig. 5 (b).

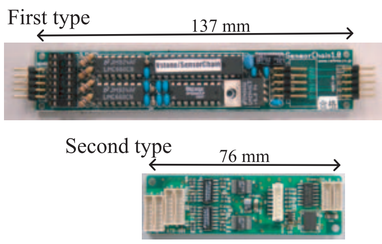
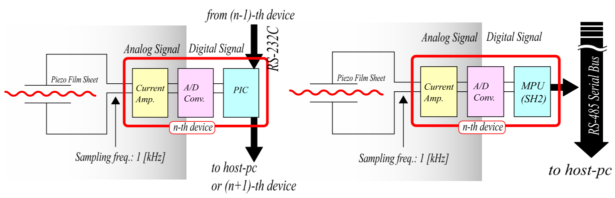


Fig. 4. Distributed A/D Converters



(a) First type (b) Second type

Fig. 5. Architecture of A/D Converters

III. Human Position and Posture Detection

In this section, we describe a method to estimate human position and posture from the tactile sensor outputs.

A. Measuring Position and Posture of Humans

We employed an optical motion capturing system (VICON, Vicon Motion Systems Ltd.) to measure body movements. The motion capturing system consists of 12 pairs of infrared cameras and infrared lights and markers that reflect infrared signals. These cameras were set around the environment of the experiment as shown in Figure 6 (a). The system calculates each marker's 3-D position from all of the camera images, and it features high resolution in both time (60 Hz) and space (accuracy is 1 mm in the room). In this paper, we use three markers to describe the position and the posture of humans with respect to the coordinates fixed to the robot. These markers are attached to the waist and the left and right fingertips of the human.

B. Mapping between Tactile Sensor Outputs and Probability Distribution of Human Positions/Postures

We calculate probability distributions of positions/postures of humans that correspond to tactile sensor outputs and build a map between them. The mapping process is carried out as follows. Figure 6 shows an outline of the process.

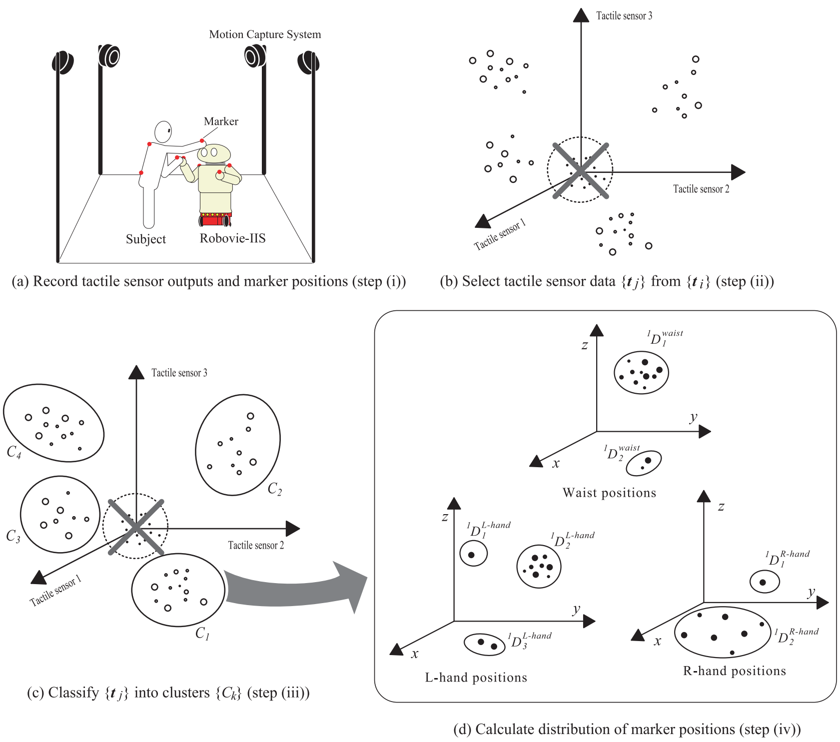
(i) Record time series data of the robot's tactile sensor outputs and positions/postures of subjects simultaneously while they communicate with each other. In this paper, we used 46 tactile sensors along with three markers that were attached to the waist and both hands of the subject for the motion capture system as positions/postures of the subject. Hence, the tactile sensor outputs and the marker positions of the waist, the left hand, and the right hand are described as $\boldsymbol{t}_i \in \Re^{46}$, $\boldsymbol{p}_i^{waist}$, $\boldsymbol{p}_i^{L-hand}$, $\boldsymbol{p}_i^{R-hand} \in \Re^3$, respectively, where i denotes time.

(ii) From all tactile sensor data $\{\boldsymbol{t}_i\}$, select the tactile sensor data $\{\boldsymbol{t}_j\}$ that are greater than a threshold for use while touching. The threshold is determined by preliminary experiments.

(iii) Classify selected data $\{\boldsymbol{t}_j\}$ into typical clusters $\{C_k\}$ by using the ISO-DATA clustering method [12].

(iv) Calculate distributions of marker positions $\{{}^k\boldsymbol{p}_j^*\}$ that correspond to the tactile sensor data $\{{}^k\boldsymbol{t}_j\}$ at each cluster C_k by the following steps.

  a) Classify the marker position data $\{{}^k\boldsymbol{p}_j^*\}$ into clusters $\{{}^kD_l^*\}$ by using the ISO-DATA. We first classify the waist marker position data $\{{}^k\boldsymbol{p}_j^{waist}\}$ into clusters $\{{}^kD_l^{waist}\}$. At each ${}^kD_l^{waist}$, we assume that the distribution of the marker position data



(a) Record tactile sensor outputs and marker positions (step (i))

(b) Select tactile sensor data $\{\boldsymbol{t}_j\}$ from $\{\boldsymbol{t}_i\}$ (step (ii))

(c) Classify $\{\boldsymbol{t}_j\}$ into clusters $\{C_k\}$ (step (iii))

(d) Calculate distribution of marker positions (step (iv))

Fig. 6. Outline of Mapping process

conforms to a normal distribution $N(\mu, \sigma^2)$. Under this assumption, we calculate a mean μ and a standard deviation σ of $\{{}^k_l\boldsymbol{p}_j^{waist}\}$, which are the elements of the cluster ${}^kD_l^{waist}$.

b) Calculate probabilities for the existence of the marker position at each cluster $\{{}^kD_l^*\}$ when the tactile sensor data belong to the cluster C_k. If the number of the elements $\{{}^k_l\boldsymbol{p}_j^{waist}\}$ is m, and the total number of the waist marker positions that correspond to the tactile sensor outputs in the cluster C_k is n, we obtain the probability, $P_{{}^kD_l^{waist}}$, as $\frac{m}{n}$.

c) Label the cluster ${}^kD_l^*$ effective if P_{D_l} becomes greater than threshold t_p and σ becomes less than threshold t_σ; t_p and t_σ are determined by premliminary experiments.

d) Iterate these steps from (iv)-a) to (iv)-c) for the data of the left- and right-hand marker positions, $\{{}^k\boldsymbol{p}_j^{L-hand}\}$ and $\{{}^k\boldsymbol{p}_j^{R-hand}\}$, respectively.

(v) Label the cluster C_k effective if the clusters $\{{}^kD_l^*\}$ that corresponded to C_k have more than one effective cluster.

C. Using the map

Once the map is obtained, the robot can use it as follows.

(i) Obtain tactile sensor data vector $\boldsymbol{t} \in \Re^{46}$ during communication with a human.

(ii) Calculate the distance between $\boldsymbol{t}$ and each cluster $\{C_k\}$ in the map, and select the cluster C_s for which the distance is shortest. Abandon the estimation if the distance is longer than a threshold.

(iii) Obtain the probability distributions of the waist, the left- and right-hand positions that correspond to C_s if the cluster is effective.

IV. Experiment

A. Acquiring Human Position and Posture

Figure 6(a) illustrates the system used to acquire the data of tactile sensor outputs and positions of the markers. The tactile sensor outputs were recorded on a hard-disk drive mounted on the robot's body. In this experiment, we used the first type of ADC described in Section II-B to obtain the outputs. The markers were attached to the waist and left/right fingertips of both the robot and a human subject. The motion capturing system was arranged to measure their motions representing haptic interaction. The sampling rate of the tactile sensor was 20 Hz, and the sampling rate of the positions of the markers was 60 Hz. In the experiments, Robovie-IIS continuously moved its joints, aside from its wheels, and communicated with the subject. The program used for its communication behavior was almost the same as that of Robovie-II [10], consisting of a behavior network based on situated modules that describe communication behaviors according to the situation. There are approximately 100 communication behaviors in Robovie's present behavior network.

The subjects of our experiment were 40 university students (males: 12, females: 28). An experimenter explained the purpose of the experiments as collecting haptic interaction data from the subjects and asked each of them to communicate with the robot for three minutes.

B. Results of mapping between tactile sensor outputs and probability distribution of human positions/postures

Table I shows the results of clustering the tactile sensor outputs and the evaluation of each cluster. The total number of data from the tactile sensor output, which was described as $\boldsymbol{t}_i \in \Re^{46}$ in section II-B, was 247,622. We used the first half of the data (123,811 data) for building the map between tactile sensor outputs and positions/postures of humans. The latter half of the data were used to verify the map.

First, we selected 14,265 touching data from the first-half data by employing the threshold of each tactile sensor. We then obtained 150 clusters using ISO-DATA. In this experiment, we set the threshold t_p to 0.1, t_σ for waist to 300 mm, and t_σ for both hands to 150 mm. Finally, we obtained 137 effective clusters for use in estimating human position and posture. Figure 7 describes in detail the number of effective clusters in a Venn diagram. We obtained 110 clusters for the waist position estimation, 90 clusters for left-hand position estimation, and 88 clusters for right-hand position estimation. As the figure shows, the robot can also estimate all positions, i.e. waist and both hand positions, from 54 clusters.

TABLE I
RESULTS OF CLUSTERING AND EVALUATION OF EACH CLUSTER

total # of skin sensor data	123,811
# of touching data	14,265
total # of clusters	150
# of effective clusters	137

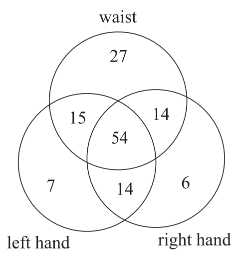
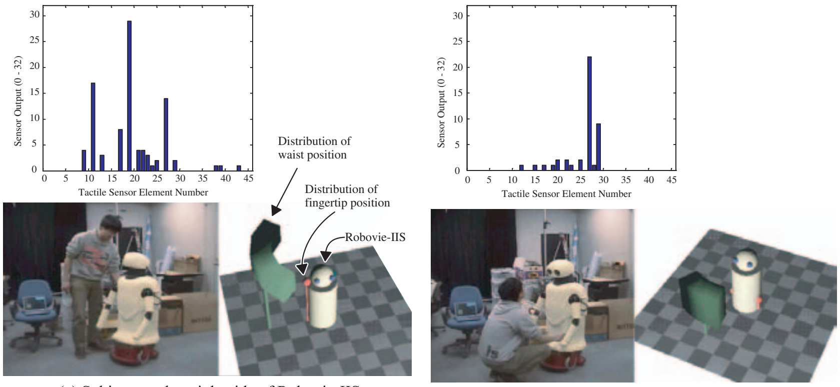


Fig. 7. Venn diagram of effective clusters

To verify the performance of the map, we used tactile sensor outputs of the latter-half data (123,811 data) as inputs of the robot and compared the estimation results of marker positions and the actual positions taken from the motion capturing system. In this paper, we decided that the estimation would be successful if the actual marker position fell within the area from $\mu - 2\sigma$ to $\mu + 2\sigma$ at the estimated distribution conforming to a normal distribution, $N(\mu, \sigma^2)$. We obtained 14,314 touching data from the latter-half data, and there were 12,711 data (89%) that belonged to the tactile sensor cluster in the map. Success rates of the estimations for the waist, the left hand, and the right hand were 87%, 63%, and 72%, respectively.

To verify the effectiveness of the estimation based on the map, we applied reflexive behaviors to the robot so that it would look at the subject's face based only on the tactile sensor outputs and the map. This behavior is difficult to achieve for robots that do not have such a map. The photographs in Figs. 8 (a), (b) and (c) show these reflexive behaviors. In these figures, the bar charts denote the tactile sensor outputs obtained during the haptic interaction shown in the photographs. The figures of the robot model show the distributions of waist and hand positions that correspond to the bar chart. As can be seen in these figures, the robot is able to estimate the positions of waist and hands statistically as information on human position and posture. The robot can look at the subject's face by utilizing the tactile sensor outputs, as the photographs indicate.



(a) Subject touches right side of Robovie-IIS

(b) Subject touches waist of Robovie-IIS

Fig. 8. Estimation results of human position and posture

V. Discussion and Conclusion

We proposed a method to estimate human position and posture by utilizing tactile information. In our method, the robot first acquires a relationship between its tactile information and human positions and postures from the history of haptic interaction. In our experiments, we obtained the success rates of the estimation for the waist, the left hand, and the right hand as marker positions. The success rate for the left hand turned out to be the lowest because almost all of the subjects were right-handed persons. They used mainly their right hand for touching the robot. Thus the position of the left hand became unstable while touching with the right hand. If the robot obtained more data of haptic interaction with left-handed persons, the success rate of the estimation for the left hand would increase. This implies that the success rates depend on the robot's experiences of haptic communications.

In this paper, we used the communication partner's position and posture based on a 3-D motion capture system. If the robot could sense more information from the partner by accessing its passive-type sensors and correlating their data to tactile information, it would estimate the partner's state more precisely based only on the tactile information. In future work, we will use the information described above to estimate the partner's state more precisely.

ACKNOWLEDGMENT

This research was supported by the Ministry of Internal Affairs and Communications.

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