2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 14-18, 2024. Abu Dhabi, UAE

Magnetic tactile sensor with load tolerance and flexibility using frame structures for estimating triaxial contact force distribution of humanoid

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***Abstract*— For humanoid whole body contact motions, it is important to recognize the existence of whole body contacts and the contact forces. The challenges in recognizing the existence of whole body contacts and the contact forces in life-size humanoids are: 1) the measurement part with low mechanical strength must be tolerant of high load and 2) it is difficult to model thick elastic bodies with high impact tolerance and uneven sensor placements when applied to various shapes of the whole body. This paper proposes a method of constructing a load tolerant tactile sensor by separating the loaded part from the measuring part with magnetism and protecting the measuring part inside the frame of the robot. For modeling difficulties, this paper proposes learning the relationship between the change in the detected physical quantity due to deformation of the elastic body and the contact force distribution. This paper shows through experiments that the proposed tactile sensor based on a robot frame is load tolerant enough to support the weight of a life-sized humanoid, and that it can acquire contact force distribution and the robot is able to acclimate to external forces.**

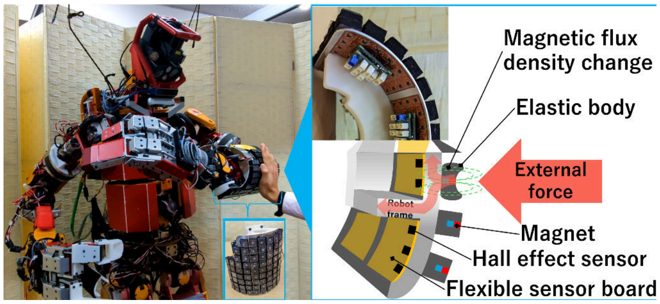

Fig. 1: The Flexible Magnetic Tactile Sensor with the humanoid frame structure. The proposed sensor separates the elastic body from the sensor element for load tolerance. To address the deformation of thick elastic bodies for impact tolerance and the uneven placement of sensor elements due to frame structures, the proposed sensor uses a neural network to infer tri-axial forces.

I. INTRODUCTION

Humanoid robots are expected to work in human living environments in place of humans, and in order to achieve this it is important that they effectively use their whole body to make contact with the environment and manipulated objects. For humanoid whole body contact motions, it is necessary to recognize the existence of whole body contacts and contact forces. A tactile sensor consists of a measuring part and an elastic body. The elastic body is changed by a force, and the measuring part detects the change in physical quantity resulting from the change and converts it into an electrical signal. The challenges in recognizing the existence of whole body contacts and the contact forces in life-sized humanoids are: 1) although humanoid motion requires a small area with high load tolerance, such as supporting the body with the elbow, the measurement part with low mechanical strength must be tolerant of high load, and 2) it is difficult to model thick elastic bodies with high impact tolerance, uneven sensor placements when applied to various shapes of the whole body and influence of nearby electric motors.

This paper proposes a method of constructing a load tolerant tactile sensor by separating the loaded part from the measuring part with magnetism and flexible printed boards capable of placing sensor elements on various shapes. The tactile sensor protects the measuring part inside the frame of the robot. For modeling difficulties, this paper proposes learning the relationship between the change in the detected physical quantity due to deformation of the elastic body and the contact force distribution. As shown in Fig. 1, the structure of the proposed tactile sensor consists of a sponge with embedded magnets as an elastic body outside a high-strength non-magnetic body such as the robot's aluminum frame, and a flexible sensor circuit board that measures the magnetic flux density inside as the measuring part. The change in magnetic flux density caused by the deformation of the sponge due to an applied force is converted into a force by inference with neural networks. This mechanical structure provides high load tolerance because the frame protects the measuring part. As long as the robot frame is non-magnetic, it can be used as a support structure, so tactile sensing is possible simply by attaching a sponge and a sensor substrate that reads magnetic flux density. Even in locations where sensor boards are difficult to place and sensors are unevenly distributed, where there is noise from nearby motors, or where the elastic material is thick for impact tolerance and changes in magnetic flux density are difficult to model, it is expected that inference will be possible as long as changes in magnetic flux density can be measured.

A. Related Works

Studies on whole-body contact distribution sensors that can measure the existence of contacts and contact forces have been conducted for a long time. Ohmura et al. developed a

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tactile sensor using light that can be cut and pasted [1] and performed a lifting motion of a humanoid [2]. Cheng et al. [3] developed a hexagonal sensor module with a proximity sensor, a uniaxial force sensor, a triaxial accelerometer, and a temperature sensor, and Rogelio et al. used it to detect the foot support area [4]. These sensors have a thin structure and are highly durable against compressive loads, but they are vulnerable to impacts and cannot detect shear forces. Kadowaki et al. [5] developed a triaxial tactile force sensor that uses light to recognize deformation in urethane, and Kumagai et al. [6] showed that it can classify applied forces into compression, shear, and torsion. However, this sensor cannot achieve high durability because the elastic body and measuring parts are integrated, so the load applied to the elastic body is also applied to the substrate and sensor element.

We focus on tactile sensing methods that are load and impact tolerant and capable of shear force detection. Tactile sensing methods can be classified into electrical resistance, capacitance, magnetic, pneumatic, and optical methods [7][8]. Only magnetic and optical methods can improve tolerance by placing the measuring part inside the robot frame and the elastic body outside such as the proposed method. The optical method is difficult to achieve because the frame must be light-transparent and free from any scratches. When tactile sensors use magnetism, one of the important issues is interference between magnets for nearby sensors. To increase tolerance against impacts such as landing impacts during walking, the elastic body needs to be thicker [9]. The issue is that it is necessary to use strong magnets whose magnetic force is proportional to the thickness of the elastic body, and interference between nearby magnets makes it difficult to model the deformation of the elastic body.

Most studies that use magnetism have the measuring part and the elastic body on the same side of the frame. Tomo et al. [10] developed a 3-axis tactile sensor that uses magnetic flux density to measure changes in the position of a magnet fixed to silicon. Youssefian et al. [11] also developed a tactile sensor that measures changes in the position of a magnet fixed to hemispherical silicon in terms of magnetic flux density. Hellebrekers et al. [12] developed a tactile sensor that contains tiny magnetic particles in an elastic body and is integrated with a flexible board to detect contact position and vertical force. These tactile sensors estimate the contact force by modeling the deformation of an elastic body, and the thickness of the elastic body is made thin to facilitate modeling. It is difficult to increase the thickness of the elastic body with these methods based on the model. Therefore, in addition to the tolerance problem due to the measuring part and the elastic body being on the same side, there is also a problem with impact tolerance.

Few studies have used magnetism and placed the measuring part and the elastic body on different sides of the frame as in this study. Goka et al. [13] proposed a sensor that estimates triaxial force by measuring changes in magnetic flux density with an elastic body and a magnet mounted on the outside of the frame and a GMR (giant magneto resistance) element on the inside. However, it focuses only on structural simplicity and low cost, and does not focus on load tolerance and no verification of tolerance was conducted. Kawasetsu et al. [14] focused on load tolerance and proposed a tactile sensor that detects contact by changes in magnetic flux density, with a magnet also attached inside and a sheet of elastic and magnetic material outside. He also proposed a tactile sensor with a magnetic elastomer sheet attached to the outside and a coil attached to the inside to estimate triaxial forces [15]. However, the changes that can be detected when force is applied are very small, and when multiple sensors are distributed, they may be strongly affected by interference of magnetic forces between sensors or by the magnets of nearby motors. When a magnet is used as in the proposed method, the sensor can relatively ignore the influence of nearby magnetic forces by using a strong magnet. In addition, these studies model deformation. However, it is difficult to accurately model the deformation of the above-mentioned elastic body with increased thickness or the interference of the magnetic forces of nearby sensors when distributed in multiple places.

Some previous studies have used neural networks to estimate the force from the magnetic flux density [16][17]. However, it is used for thin structures that can also be estimated by the model-based approach, or only vertical forces are estimated. This paper uses magnetism to place measuring parts and elastic bodies on different sides of the frame for load tolerance and uses neural networks to estimate triaxial forces for magnetic changes that are difficult to model for whole body distribution, including thick elastic elements for impact tolerance and nearby sensors.

B. Contribution

The contributions of this paper are as follows.

- We propose a method of constructing a load and impact tolerant tactile sensor by separating the loaded part from the measuring part and protecting the measuring part inside the frame of the robot by using a flexible board on which sensor elements can be arranged in various shapes and strong magnets, so that the sensor can detect contacts even under magnetic force from an external motor.
- We propose to use neural networks to estimate triaxial forces for modeling difficulties due to thick elastic bodies for impact tolerance and interference from nearby magnets.
- We show that the proposed method works in the operation of a life-sized humanoid with multiple sensors attached, even under the influence of magnetic interference between sensors and nearby motors.

The paper is organized as follows. Section II describes mechanical structures of the proposed tactile sensor. Section III describes triaxial forces learning of the tactile sensor. Section IV shows the verification of the performance of the tactile sensor using an real life-sized humanoid robot. Section V concludes this paper.

II. TACTILE SENSOR USING FRAME STRUCTURE WITH MECHANICAL TOLERANCE

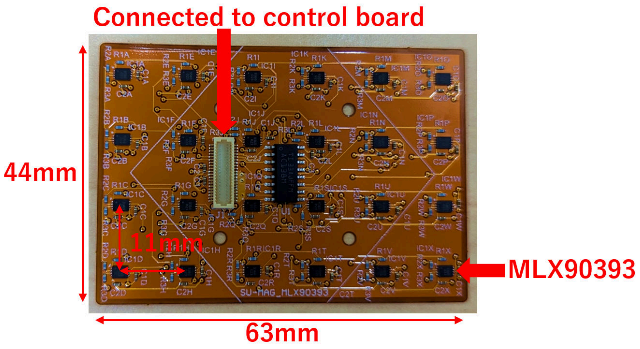
We propose the load tolerant tactile sensor structure that separates the loaded part from the measuring part using magnetism and protects the measuring part inside the frame of the robot. For clarity, we explain using the elbow-tactile-sensor shown in Fig. 1.

A. Overview of Flexible Magnetic Tactile Sensor

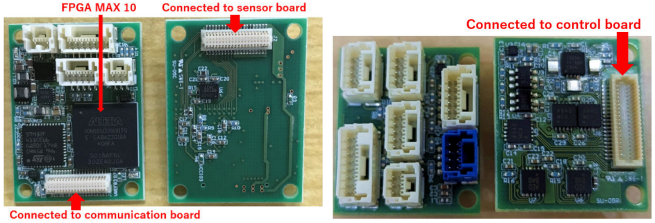
The proposed tactile sensor places an elastic body with embedded magnets on the outside of the frame and a sensor that measures the magnetic flux density on the inside. When the contact with the environment occurs, the elastic body is deformed by the force and the sensor measures the change in magnetic flux density due to the change in the position of the magnet. External contact forces are received by the elastic body and frame, so no load is applied to the measuring part such as the sensor element. The sensor substrate was designed using a flexible circuit board to allow flexible placement of sensor elements for curved shapes such as arms. The designed flexible board is shown in Fig. 2(a). The size of the flexible circuit board is 63 × 44, in which 6 × 4 triaxial Hall effect sensors (MLX90393 [18]) are mounted at 11mm intervals. The sensor element is capable of obtaining 16-bit triaxial magnetic flux density values. The resolution of this sensor can be specified. In this study, the resolution was set to -50mT∼+50mT in the shear direction (x,y axis) and -80mT∼+80mT in the vertical direction (z axis). The board that measures the sensor values is shown in Fig. 2(b). This board is equipped with an FPGA, which acquires the values of the magnetic sensor via SPI communication and sends the measured values to the PC via RS422 at 80 Mbps through the connector board of the Fig. 2(c). Each board is connected in daisy chain. The flexible cables allow space between the communication board and the sensor board. In this paper, the communication board is directly attached to the curved surface. The elastic body consists of two layers of 5mm-thick natural rubber sponges separated by 15mm squares. Holes are drilled in the sponge on the top surface. Cylindrical neodymium magnet of 3mm diameter and 4mm height is contained in a sponge. The surface flux density of this neodymium magnet is 0.35T. A transparent tape and a non-slip sheet are applied from its top surface.

B. The Exterior of the Elbow with Magnetic Tactile Sensor

The shape of the elbow-tactile-sensor is shown in Fig. 1. The elbow-tactile-sensor is an exterior, designed as a semi-cylinder with a radius of 72 mm and a thickness of 1.5 mm, made of aluminum sheet metal. The supports for the exterior are printed with a 3D printer. Although it is not possible to attach a circuit board to the mounting surface of the support and exterior, it is possible to estimate the force by measuring the change in the magnet on the support from a sensor on a nearby board. As shown in Fig. 1, 8 flexible boards are mounted. 105 sponge and magnet units are mounted for every 17 mm. The difference in appearance before and after installation is shown in Fig. 3.



(a) The flexible magnetic sensor board.



(b) The control board. (c) The communication board.

Fig. 2: The boards in the Flexible Magnetic Tactile Sensor. There are magnetic sensors and a multiplexer in the flexible magnetic sensor board (a). Also, there is an FPGA in the control board (b).

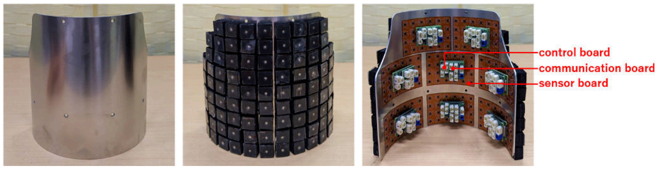


Fig. 3: The middle and right image show the flexible magnet sensor mounted on the inside and the magnets and sponge on the outside of the robot frame shown in the left image.

C. The Exterior of the Wrist with Magnetic Tactile Sensor

The proposed structure can easily be applied to structures other than elbow-tactile-sensor. For example, it can be applied to the wrist-tactile-sensor shown in Fig. 4 and the sole shown in Fig. 8, mentioned later. The wrist-tactile-sensor is an exterior, designed as a semi-cylinder with a radius of 72 m and a thickness of 1.5 mm, made of aluminum sheet metal. As shown in Fig. 4, 4 flexible boards are mounted. 57 sponge and magnet units are mounted for every 17 mm.

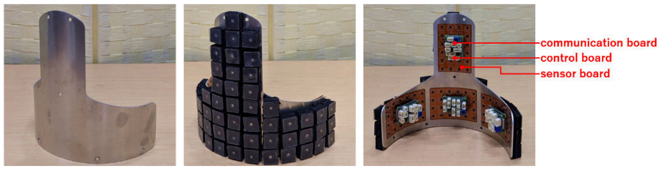
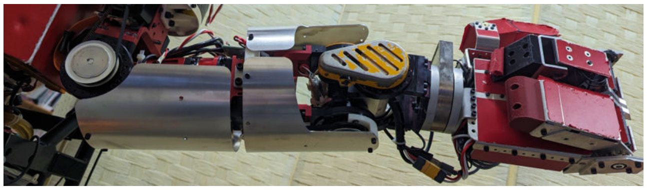


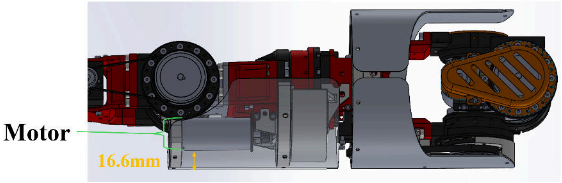
Fig. 4: Wrist-tactile-sensor appearance.

The difference of the arm in appearance is shown in Fig. 5(a), (b). In particular, the brushless motor is mounted about $16mm$ from the elbow-tactile-sensor as shown in Fig. 5(c), and the noise from the rotation of the magnet of the motor affects the magnetic sensor. Since this method of measuring changes in magnetic flux density due to changes in the position of the magnet, it is possible to relatively reduce the influence of the motor magnet on the contact force estimation by using a strong magnet. In fact, the rotation of the motor generates about 100 uT of noise to the closest sensor. On the other hand, when a neodymium magnet is pressed, a magnetic flux density of more than 1000 uT is measured, and the difference between contact and noise is of the order of magnitude.



(a) Without tactile sensor.

(b) With tactile sensor.



(c) The placements of the tactile sensor and the motor.

Fig. 5: The left arm of the robot is equipped with the proposed tactile sensor. The brushless motor is located at a distance of 16.6 mm from the elbow-tactile-sensor.

III. TRIAXIAL FORCE LEARNING SYSTEM

A. Learning Data Collection by a Robot

To estimate contact forces from deformation of elastic bodies under nonlinear magnetic flux densities and a variety of positional relationships of tactile sensors and magnets, this paper uses Neural Network-based learning. The attachment was mounted on the right arm of the HRP2W [19] for training data generation. As shown in Fig. 6, the exterior with a tactile sensor is attached to the right arm of the HRP2W and pressed against a projection fixed to the pedestal. The robot collects 3-axis force and magnetic flux density values from the force sensor on the right arm for each of the 105 contact points where the magnet and elastic body are placed. From 0 mm between the elastic body and the projection, the elastic body is pressed against the projection every 1 mm up to 12 mm. At 3 mm to 6 mm, the shear force is also generated by moving it 1 mm in each of the eight horizontal directions.

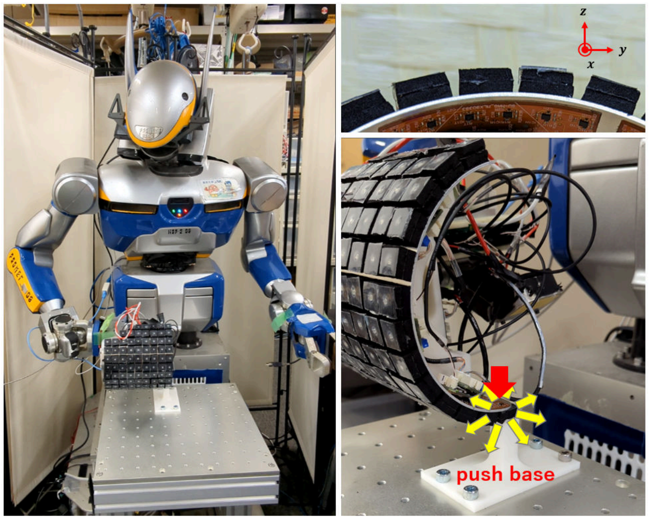


Fig. 6: The motion for collecting the learning data. The red arrow indicates the indentation direction and the yellow arrows indicate the shear direction.

B. Setting of learning

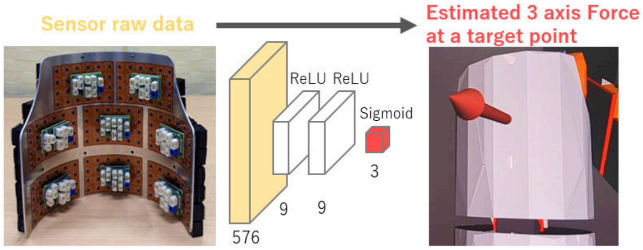


Fig. 7: Network structure for force inference. For each contact point, different models are created as the same structure.

The total number of magnetic flux density values is $3 \times 24 \times 8 = 576$ for 8 sensor boards with 24 sensor elements on 3 axes. To account for the influence of any magnet, the forces at each contact point are learned using all magnetic sensors measurements. The trained network structure is shown in Fig. 7. The network structure consists of four layers, with an input layer of 576 magnetic flux density, two intermediate layers of 9 elements, and an output that is the triaxial force at the relevant contact point. We create this network for each contact point, 105 contact points, and train on each of them.

We describe the preprocessing before the learning. The resolution of the magnetic sensor is 16 bits, but due to the positional relationship between the magnet and the magnetic sensor, the magnetic flux density changes only about 13 bits when the sponge is deformed, so it is divided by 2^{13} as preprocessing. The output forces are normalized as follows.

$$o_z = \begin{cases} \frac{f_z}{45}(0.93 - 0.07) + 0.07 & (f_z > 0) \\ 0 & (f_z = 0) \end{cases} \tag{1}$$

$$o_{x/y} = \frac{f_{x/y} + 10}{20}. \tag{2}$$

The f denotes the contact force and the o denotes the force normalized for learning. The output force is $0 \sim 0.93$ in the z direction corresponding to $0 \sim 45$N, and $0 \sim 1$ in the x,y direction corresponding to $-10 \sim 10$N. As a tactile sensor for a robot, it is important to be able to clearly determine the existence of contact. To increase accuracy, a force of about 3N or greater is inferred when touching even slightly. We use the mean squared error as the loss function and Adam [20] to update the weights.

We validate the accuracy of the learned model. Since the training data acquired by the robot consists only of data from pressing a single point, we randomly select contact points and add the training data together to create the test data. With 50 randomly generated data for each of the 10,000 contact points combinations and the training data, we compute the Mean Absolute Error of the inferred value and the force sensor value. The average results for all contact points are shown in Table I. All of them can estimate with an error of about $1 \sim 1.5$N. There is no difference in accuracy depending on the location of the contact point.

TABLE I: Results of accuracy evaluation

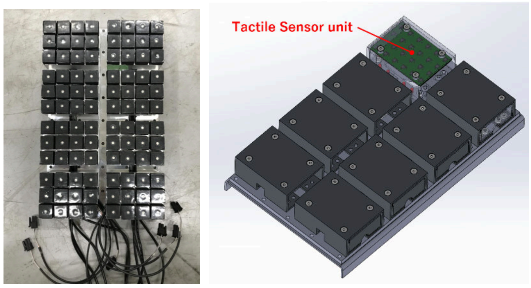
MAE of x-axis force [N]	MAE of y-axis force [N]	MAE of z-axis force [N]
0.8275	0.6744	1.4399

IV. EXPERIMENT

We conducted several experiments to verify the load tolerance of the proposed tactile sensor structure and the accuracy of the contact force inference.

A. *Mechanical Tolerance*

1) Tolerance of the Self-weight of a Life-size Humanoid: First, we verify the tolerance of the structure. The proposed structure can be placed in any part of the robot frame by placing the sensor circuit board inside and the elastic body outside. However, for verification of load tolerance, we need to take a ground truth of the force. For this reason, a proposed tactile sensor is attached to the sole where the FT sensor is pre-installed. As a tactile sensor for the sole, we developed a tactile sensor sole shown in Fig. 8. The tactile sensor sole consists of 8 tactile sensors shown in Fig. 9. Since the sole is flat, there is no need to use a flexible structure as shown in Fig. 1, and we developed a rectangular module as shown in Fig. 9. Also, by keeping the distance between modules on a wide surface, we use a common inference model in each module.



(a) The sensor sole. (b) The CAD design of the sole.

Fig. 8: The sole with the Magnetic Tactile Sensors.

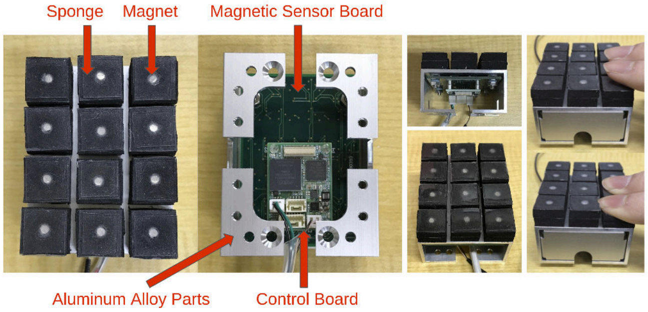
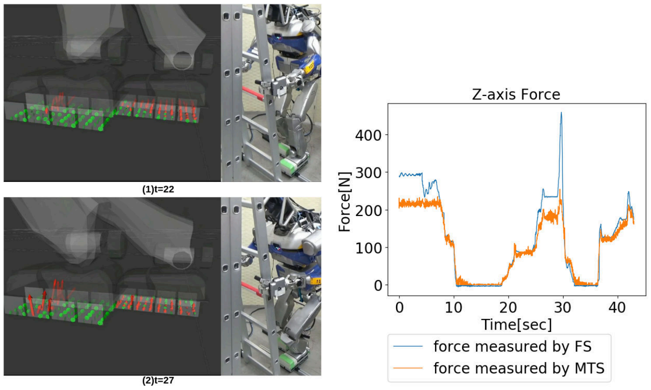


Fig. 9: The Tactile Sensor unit for the flat shape.

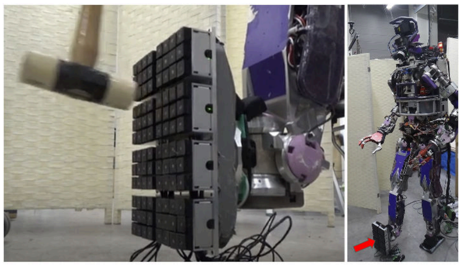
To verify the load tolerance of the tactile sensor, we conducted an experiment using HRP2-JSKNT to support its own weight. HRP2-JSKNT is an improved version of HRP-2 [21]. Since the proposed structure uses the frame as it is, the measuring part will not be destroyed unless the frame is destroyed. Assuming that the frame is designed with sufficient load tolerance, we examined the tolerance of the elastic bodies and magnets outside the frame and the inference of forces using them. The experiment is shown in Fig. 10(a), where the HRP2-JSKNT steps on an aluminum frame. The graphs of the vertical resultant force (MTS) of each tactile sensor module of the left foot and the vertical force (FT) of the FT sensor of the ankle are shown in Fig. 10(b). About $300N$ was applied to the left foot as a resultant force, and the contact area was about $5.2 \times 10^{-3} m^2$. Therefore, the sensor was subjected to a pressure of about $5.77 \times 10kPa$, but the sensor did not break during the experiment. The contact force can be detected even after pressure is applied, indicating that the proposed method is effective for contact detection even under high loads.



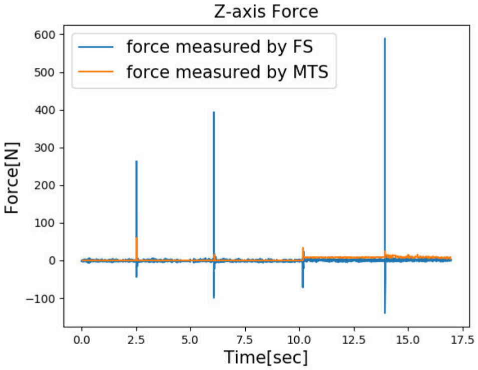
(a) Stepping motion. (b) Z-axis force

Fig. 10: Experiment of stepping on an aluminum frame. The tactile sensor was able to detect the shape of the aluminum frame. A pressure of $5.77 \times 10kPa$ was applied to the sensor, but the sensor did not break during the experiment.

2) Impact Tolerance: We conducted an experiment to determine the impact tolerance of the proposed sensor. As shown in Fig. 11(a), the tactile sensor sole was attached to the right foot of the JAXON [22] and hit with a hammer. The



(a) Hitting the right sole of JAXON with a hammer.



(b) Z-axis force.

Fig. 11: Impact tolerant experiment. A pressure of up to $6.11 \times 10^2 kPa$ was applied, but the sensor was not destroyed during the experiment.

measured force itself is relaxed owing to the elastic body with a thickness of about $10mm$. As shown in Fig. 11(b), a maximum striking force of about $600N$ was measured. The contact area was about $9.82 \times 10^{-4} m^2$, meaning that a maximum of $6.11 \times 10^2 kPa$ was applied. The sensor was not destroyed during the experiment. On the other hand, it was not possible to correctly measure the striking force.

B. Contact Detection

We conducted an experiment to verify the detection of contact using the elbow-tactile-sensor and the wrist-tactile-sensor. We verified the pushed position and the estimated force, as shown in Fig. 12. The contact was correctly recognized at each point.

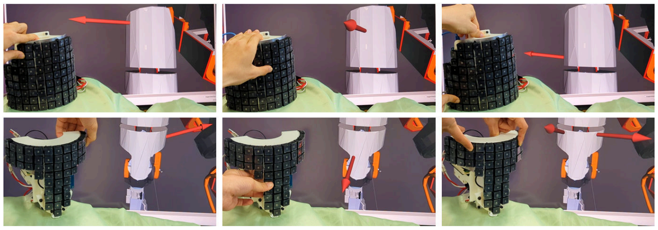
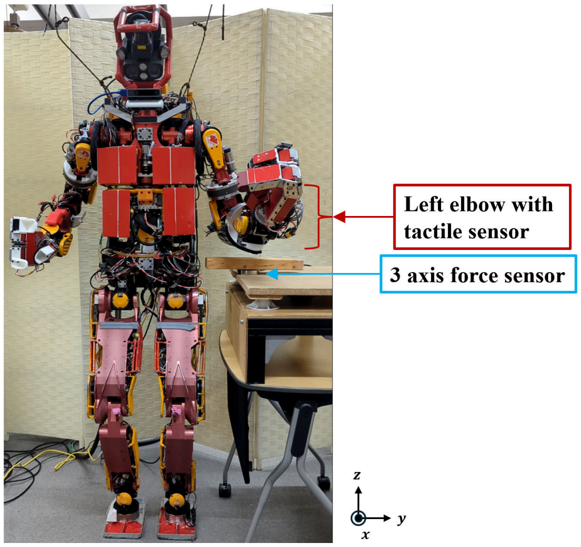


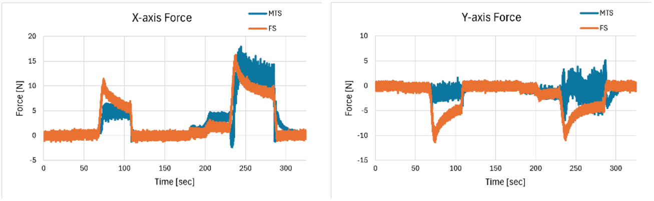
Fig. 12: The tactile sensor is on the left and the red arrow on the screen represents the estimated force. The contact point is correctly estimated.

C. Accuracy

We conducted experiments to evaluate the accuracy of force inference with the proposed sensor. We used the elbow-tactile-sensor to press the sensor part against an FT sensor fixed to the environment as shown in Fig. 13(a). The estimated resultant force and the external FT sensor values are shown in Fig. 13(b), (c), (d). The estimated force was obtained by converting the triaxial forces estimated by each tactile sensor into a force applied to the link and adding them together.

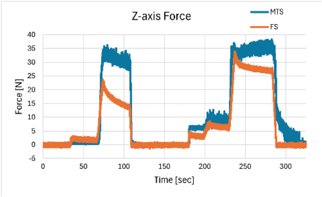


(a) Contact motion using JAXON.



(b) X-axis force

(c) Y-axis force



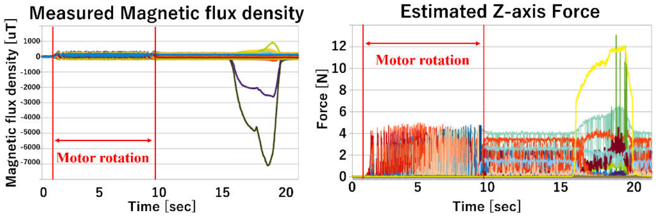
(d) Z-axis force

Fig. 13: Verification of force accuracy of tactile sensor. The sensor is able to correctly estimate relatively small forces in X-axis and Z-axis. On the other hand, as the load increases, the estimation accuracy becomes worse.

For the x and z directions, the difference between the measured and estimated values is small while the external force is about $0 \sim 10$N, but the larger the external force, the larger the difference. Especially in the z direction, the pressing direction is the direction that compresses the elastic body, and the elastic body is almost fully deformed under a large external force. When elastic bodies are fully deformed, the change in shape of elastic bodies becomes small in relation to the change in external force, and the error in the estimated value is considered to be large. For the y direction, the estimates changed with changes in the external force, but the differences in the estimates were large. This would be because the deformation of elastic bodies was different from the training data. When applying a vertical force to an elastic body, the measured magnetic flux density depends on where on the sponge the force is applied, although when the training data was generated, only one point on the sponge was pressed in this paper. For example, if we press directly above the magnet, the posture of the magnet does not change, only the distance from the magnetic sensor changes. On the other hand, if we press on the edge of the sponge, the orientation of the magnet will also change due to the deformation of the sponge, even if the applied force is the same. Because the elbow-tactile-sensor is cylindrical, the above effects are large in the y-direction, which is the tangential direction, and the difference in estimated values is considered to be particularly large when a high load is applied in the z-direction. On the other hand, the x direction along the cylinder axis was almost parallel to the pressing surface, so the difference in values was small even at high loads.

D. Tactile Sensing under the Magnetic Force of the Motor

We conducted an experiment using the elbow-tactile-sensor to investigate the effect of the rotation of the magnet of the motor on the sensor. The positions of the motor and the elbow-tactile-sensor are shown in Fig. 5(c). The experiment was conducted by turning a nearby motor and then pushing an elastic body near the motor. The measured magnetic flux density and the inferred force are shown in Fig. 14. As shown in Fig. 14(a), the change in magnetic flux density was about 100uT when the brushless motor rotated. On the other hand, the change in magnetic flux density when pressed with a force of about 10N reached nearly 7000uT at the nearest neighbor point. Owing to powerful magnets, the change in flux density due to contact is large compared to the effect caused by nearby motors. As shown in Fig. 14(b), the inferred force was dependent on the rotation of the magnet with a maximum error of about 5N. If the threshold is set to about 5N, the contact detection is possible even under the influence of motor magnets. However, it is difficult to estimate a force of about 0 $\sim$ 5N under the influence of the magnet of the motor. Since the change in magnetic flux density itself causes a large difference between the motor magnet and the contact, it is expected that the more accurate estimation can be achieved by improving the learning method.



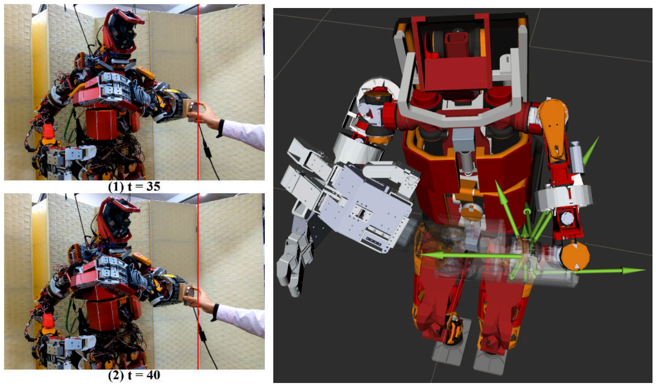
(a) Magnetic flux density.

(b) Estimated Z-axis force

Fig. 14: Investigation of the influence of magnets on nearby motors. The noise is measured to be about 100uT when the motor is rotating. The dark green and purple lines in (a) represent the measurements of the tactile sensor close to the pressed position and the measured value changes by several thousands uT when the elastic body is pushed.

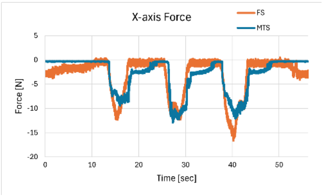
E. Admittance Control

We conducted an experiment using the elbow-tactile-sensor to feed back contact reaction forces. As shown in Fig. 15(a), the robot performs admittance control to acclimate to the external force estimated by the tactile sensor. A human holds the force sensor and presses it against the tactile sensor. The distribution of the force during pushing is shown in Fig. 15(b), and the measured resultant force in the direction of pushing is shown in Fig. 15(c). It can be seen that it is possible to obtain the distribution of contact and to estimate and acclimate the external force.



(a) Acclimation of the left elbow.

(b) Force distribution.



(c) X-axis force.

Fig. 15: Admittance control of the left elbow.

V. CONCLUSIONS

The challenges in recognizing the existence of whole body contacts and the contact forces in life-sized humanoids are: 1) The measurement part with low mechanical strength must be tolerant of high load, and 2) it is difficult to model thick elastic materials with high impact tolerance, uneven sensor placements when applied to various shapes of the whole body and influence of nearby electric motors. This paper proposes a method of constructing a load tolerant tactile sensor by separating the loaded part from the measuring part with magnetism and flexible circuit boards capable of placing sensor elements on various shapes. The tactile sensor protects the measuring part inside the frame of the robot. For modeling difficulties, this paper proposes learning the relationship between the change in the detected physical quantity due to deformation of the elastic body and the contact force distribution.

The proposed method is highly shape-applicable because it uses the robot frame as it is. Experimental results show that the sensor is load tolerant enough to continue functioning even under pressure of about $5.77 \times 10kPa$, which is equivalent to supporting the self-weight of a life-sized humanoid, and that it is impact tolerant enough not to be destroyed even when $6.11 \times 10^2 kPa$ is measured as the striking force. The triaxial force estimation by learning is effective for force estimation in the low contact force range of about $0 \sim 10$N and can be used for contact detection. On the other hand, force estimation had problems for force estimation against striking force and high load, although it is load tolerant. In addition, estimation accuracy was worse when force was applied differently from the way force was applied during training. The experimental result shows that proposed senser can detect contacts even under the influence of magnets from nearby motors owing to the strong magnets. This sensor is not suitable for manipulation of magnetic materials because it uses magnetism. With respect to the accuracy of force estimation, improvements are expected in the materials and structure of elastic bodies and in the generation of richer deformation of elastic bodies training data.

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