Using Machine Learning to Perform Force Calibration of Soft Triaxial Magnetic Sensors and Identify the Temperature of Grasped Objects

Yao-Wei Tian
Department of Institute of Mechatronic Engineering of NTUT
Taipei, Taiwan
Email: t109408014@ntut.edu.tw

Jung-Tang Huang
Department of Institute of Mechatronic Engineering of NTUT
Taipei, Taiwan
Email: jthuang@ntut.edu.tw

***Abstract*—The purpose of this research is to develop a low-cost and high-accuracy force sensor. The three-axis magnetic field change value and the surface temperature of the touch object can be obtained by using a magnet, a silicone block, and a Hall sensor. Through the self-developed automatic calibration machine and machine learning, the magnetic field value can be directly output as a three-axis force. Today's three-axis force sensors are bulky and expensive, even if the single-axis force sensors have been developed. However, it cannot provide precise tactile information like human beings, and we believe that multi-axial force perception is bound to provide more control information for robots. Therefore, this study designs a high-precision and low-cost triaxial force sensor by machine learning and an automatic calibration machine.**

Keywords- hall-sensor; Soft sensor; force and tactile sensor.

I. INTRODUCTION

In recent years, the ability of visual recognition and speech recognition has become stronger and stronger. Accurate portrait recognition and ubiquitous voice assistants have been integrated into our lives. However, the feedback of robots for touch is still insufficient [1], and cannot be like human fingers. It can accurately sense changes in the hardness, temperature, and weight of objects, so if the robot wants to grab objects that change in weight, it can usually only apply enough force. In case of plastic bottles that are filling water, excessive force can cause deformation of the bottle, so the force applied must be adjusted as the amount of water increases.

Most of the force sensors used in current automation equipment and robots are rigid materials, which are less able to withstand excessive impact and deformation [2]-[4], and sensors that can measure more than one axis are usually larger in size. Common tactile sensors, such as capacitive, optical and resistive types, have high measurement accuracy, but the disadvantage is that such sensors are relatively precise and large in size, and the disadvantages are as follows: (1) The shear force cannot be measured, (2) the scalability is poor, and (3) the temperature of the grasped object cannot be determined.

Usually, the body of the tactile sensor with higher resolution is more precise, so the expansibility will be poor, the number of circuits will be increased, and the measurement range will be sacrificed if the resolution is high. Therefore, the force sensor composed of soft materials, magnets, and Hall sensors in this study is expected to achieve the following goals: (1) Accurately measure normal force and shear force, (2) Accuracy less than 0.1N, (3) Identify temperature of touched items.

Different from the work done by Holgado et al. [5], since the sensor body is converted into the force value by the deformation of the soft material, the force can be accurately identified when the positive force is applied alone, but if the force of more than two axes is given, there will be a coupling situation, and the normal force value at this time will be affected by the lateral force, so it is difficult to accurately derive it with a general calculation formula. We collect data from our self-developed auto-calibration platform and use Neural Network and Recurrent Neural Network to convert sensor data to force.

In order to obtain a more anthropomorphic touch, we will identify the temperature of the object touched by the sensor, so that the mechanical gripper or other applications equipped with this sensor can obtain more sensing information.

II. SENSOR ARCHITECTURE

The main body of the sensor is shown in Fig.1, which includes a silicone block, a magnet, and a flexible circuit board. The Hall sensor MLX90393 is used on a 13 mm * 13 mm flexible circuit board to read the three-axis magnetic flux. The communication between the sensor and the host computer uses I2C to communicate because it can share a common data bus with more sensors to save wiring space.

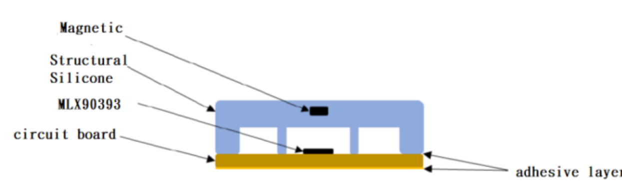

Figure 1. Sensor Schematic.

A. Flexible circuit board

Since the sensor body is composed of a silicone block, a magnet, and a sensor chip, and communicates through I2C, the circuit and wiring can be simplified, and the values of all sensors can be connected in series through a bus, and the assembly. When it is installed on the gripper, it can reduce the wiring on the equipment, and the host computer is also more convenient for control.

B. Silicone structure

The silicone structure uses TSE 221-4U, the specifications are shown in the Table I, a ø2*1mm N35 axial magnet is embedded in the center of the structure, as shown in Fig.2, a hole is designed in the silicone layer to accommodate the magnet, and ensure that the magnet is not under stress directly above the sensing wafer. TSE 221-4U silicone is suitable in the range of 30(N) in our designed structure.

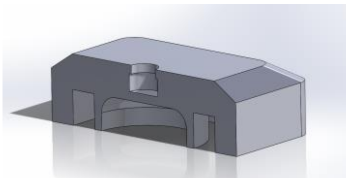

Figure 2. Silicone structure Schematic.

TABLE I. SILICONE RUBBER TYPICAL PROPERTY DATA

Specification	***TSE221-4U***	***unit***
Density	1.13	g/cm³
Hardness	40	°A
Tensile strength	8.4	MPa
Tear strength	23	N/mm
Elongation	500	%
Compression set	19	%

C. Magnetic

For the selection of magnets, we evaluated two types of magnets, N35 and N50, and observed the relationship between the magnetic field strengths of the magnets and the sensing chip at different positions. As shown in the Fig.3, when the N50 magnet is close to 1 mm or less, the measurement of the magnetic field is almost saturated, and the sensing range is also reduced. Therefore, the N35 magnet is used to make the sensor.

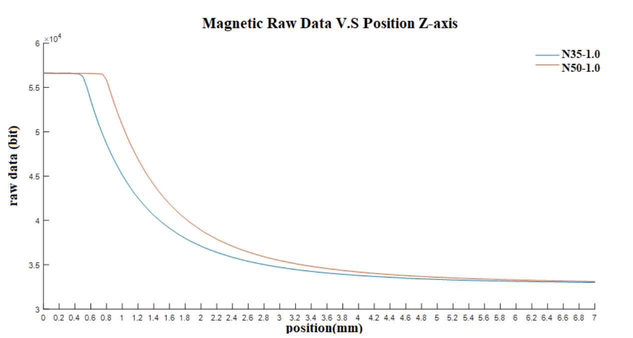

Figure 3. The relationship between the magnetic field and the position of the N35 and N50 magnets

III. AUTOMATIC CALIBRATION MACHINE

In order to identify the relationship between the real force and the magnetic field, we design an automatic calibration machine, which can perform force calibration in three axes. As shown in the Fig.4, using stepper motors, linear slides, and six-axis force-torque sensors, high-precision position and force control can be performed, and tactile sensors can be verified and analyzed.

The six-axis force and torque sensor use ATI Force/Torque Sensor Axia80-M20, which can measure the maximum 900(N) normal force and 500(N) lateral force with an accuracy of 0.1(N). Therefore, the 3D forces value and the magnitude of the magnetic field change can be obtained by using this automatic calibration machine and then the magnetic field can be converted into 3D forces through subsequent processing.

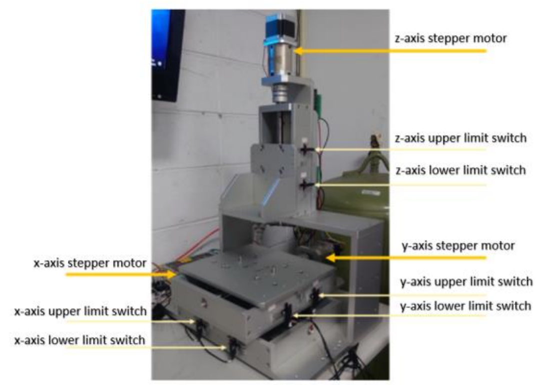

Figure 4. Automatic calibration machine

IV. MACHINE LEARNING MODELS

In recent years, the application of machine learning has developed vigorously. The most common ones are image recognition, speech recognition, and various applications. At present, most people use the Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), which can analyze and calculate many tasks with such neural network models, among which we found that neural network models related to time series are more suitable for use in calibrating sensor models. So we try to use this for sensor development.

Through the test of the sensor by the automatic calibration machine, we can obtain the original data of the sensor corresponding to the real 3D forces. When the normal force is applied alone, the accuracy is about 0.1 (N), but because of the relationship of the silicone structure, the multi-axis force will cause the signals to couple with each other, and it is difficult to calculate the relationship using general mathematical formulas. Therefore, we have tried a neural network model and a time series model to convert

 ISBN: 978-1-61208-987-4

data and power, and use this method to distinguish the two relationships between them.

A. Data format

During calibration, we use the Arduino Uno board as the host computer of the sensor and use the serial port monitoring window to read the sensor's three-axis data and temperature values (R_x, R_y, R_z, T). The automatic calibration machine obtains three-axis force values (F_x, F_y, F_z). Through the above data, our sensor data R_i is the input, and the force value F_i is the output. The temperature value does not need to be used since it does not need to be calibrated.

B. Data processing

The initial value of the sensor is read in before training, and we set the maximum value of the data to 57000 bits and normalize it. The collected initial data (input_min) and the upper limit data (input_max) are used as the maximum and minimum values of the formula. When performing calibration in the future, the initial state also needs to be read as the initial value of the sensor. Its purpose is to reduce the situation that the results will fail to converge during training.

C. Neural Networks force fitting model

Using machine learning to convert between magnetic field and force, we designed a four-layer model architecture, as shown in the Fig.5, using functions such as ReLU, Tanh, Linear, and BatchNorm1d, and each function has 500 neurons. This is the best model architecture we have tried so far.

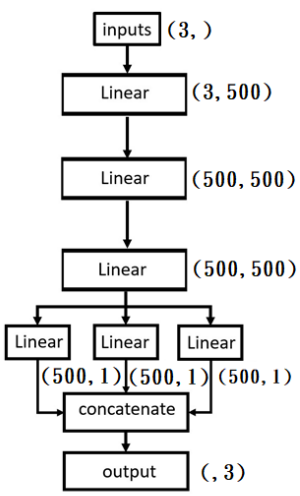

Figure 5. Neural Networks Model Architecture

D. Transformer force fitting model

Compared with neural networks, Transformer is a time series model (Sequence to Sequence model), which is similar to Recurrent Neural Networks (RNN), but RNN adopts a sequential structure, while Transformer adopts parallel training, which can make full use of all signal.

The special feature is the self-attention [6]. When we input three elements, the self-attention can simultaneously perform operations on these three elements related to each other. As shown in the Fig.6, the three axes of the sensor itself are affected by the silicone, and the three will be related to each other when the force is applied, so we think that using the Transformer will be very suitable for this project.

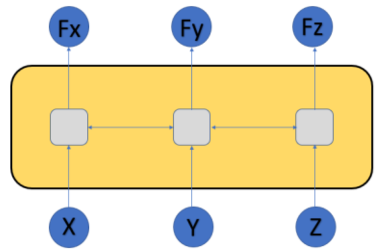

Figure 6. self-attention diagram

The data processing type is originally a two-dimensional matrix, but the time series model training must take into account the before and after the status of each data, so we will first reshape the data into a three-dimensional matrix. Each piece of data is the current data and the next 30 pieces of data as a unit for training.

The model architecture is designed with two layers. The first layer is the Transformer layer, including functions such as ReLU and Linear. The second layer uses functions such as ReLU, Tanh, Linear, and BatchNorm1d, and each layer is calculated by 64 neurons.

V. EXPERIMENT

From the reading value of the sensor to the pressure value, we divide the system structure into 5 layers, as shown in the Fig.7, from top to bottom are data reading, data processing, and power conversion. For the power conversion part, we use an automatic calibration machine to calibrate and store the data into the machine learning model for training.

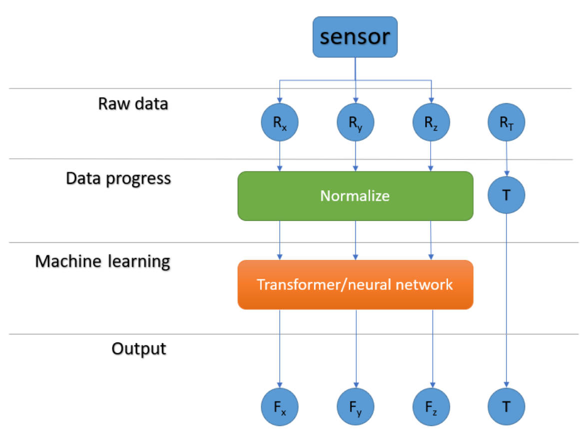

Figure 7. System Architecture Diagram

A. Temperature recognition

When we touch different objects, we can identify their temperature by the conduction of thermal energy. We use a heat gun to heat the sensor and use an infrared thermal imager as the ground truth of the thermal energy. As shown in Fig.8, when it is not heated, the ambient temperature is about 26 degrees C. After heating, we increase the temperature to 30 degrees C and identify its temperature value.

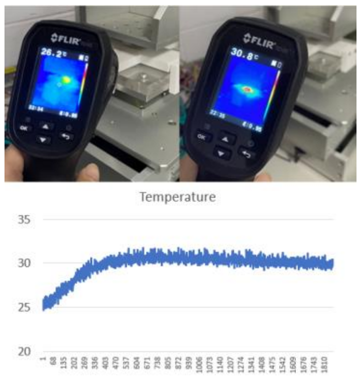

Figure 8. Comparison of sensor heating temperature and infrared thermal imager

B. Sensor Calibration

In order to convert the sensor data, we obtain the real pressure value through automatic machine calibration, and apply more than two axes of force for grasping objects. As shown in Fig.9, the first is the normal force applied to the object, and the second and third are the shear forces parallel to the sensor against gravity. Therefore, the calibration is also divided into two types: normal force correction and shear force correction. We record 5000 pieces of data every 5(N) for the sensor and record 7 groups from 0 to 30(N). The second part applies the lateral force of the X-axis for every 5(N) of the normal force, the third part applies a Y-axis lateral force for every 5(N) of the normal force.

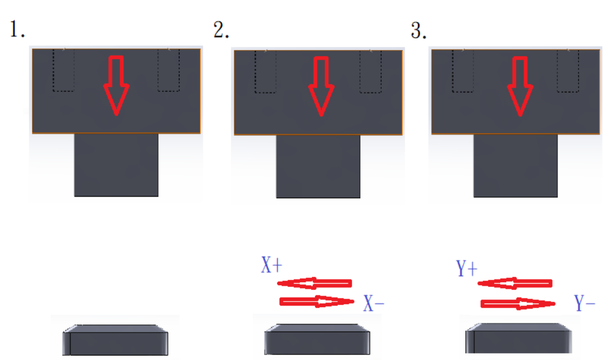

Figure 9. Sensor Calibration Diagram

As shown in Fig.10, a normal force of 10 (N) is applied. We can find that the accuracy of the automatic calibration machine is 0.1 (N). The actual measurement result increases with the increase of the normal force, and the sheer force also increases. By applying positive and negative X-axis shear force, you can see that the X-axis force value of the automatic calibration machine will follow the fluctuation. We repeat this method to collect normal force and shear force data, and then throw them into the neural network model training.

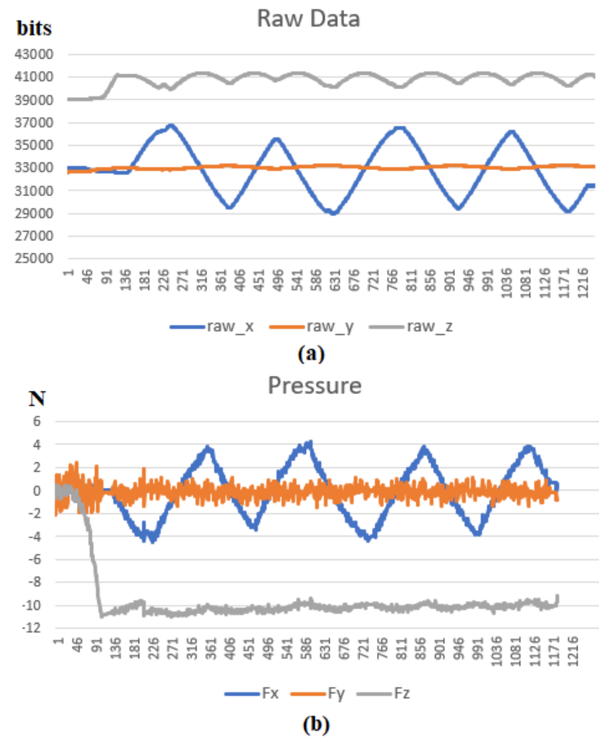

Figure 10. Sensor and calibration platform 10N force value(a) Magnetic force raw data measured by the sensor.(b) Triaxial force measured by automatic calibration machine.

C. Neural Network and Transformer comparison

In the first experiment, we use an automatic calibration machine to simulate grasping an object. As shown in Fig.11, a positive force and a gradually increasing lateral force will be applied at this time, and the middle will gradually increase by 1(N), so that the force of the Y-axis will gradually increase, and the positive force will be constant.

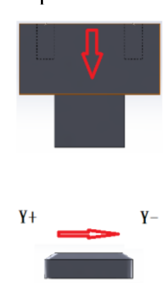

Figure 11. Automatic calibration machine pressure test chart

As shown in Fig.12, the vertical axis is the force value N, and the horizontal axis is the number of data strokes. We apply a normal force of 15(N) and gradually increase the force on the Y axis, the target is the ground truth, and pred is the force value predicted by the model. It can be seen that the results calculated by the model generally follow the trend of the real data. We use the same data to compare the differences between the two models. As shown in Table II, we compared the root mean square error and absolute value average error between the two models, and the difference in root mean square error is 1.06 (N), so it can be seen that using Transformer does get better results.

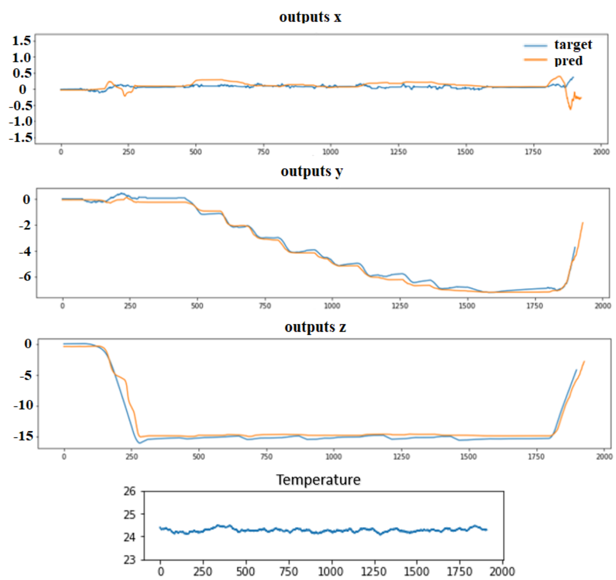

Figure 12. Three-axis force ground truth (target), force prediction value (pred)) and measured temperature value

TABLE II. NEURAL NETWORKS AND TRANSFORMER WITH OR WITHOUT TEMPERATURE COMPENSATED RMSE AND MAE

type	*RMSE*	*MAE*
NN	1.39	1.1
Transformer	0.33	0.22

D. Temperature Identification Test

This experiment is to place a water glass above the sensor and gradually add hot water to measure the temperature change while sensing the normal force. In the process, we first put a mug on the pressure and shear force sensor, and then gradually pour hot water. The temperature part is verified by an infrared thermal imager. The weight of the mug is 3.4 (N), and 180 ml of hot water at 50 degrees C is equivalent to 1.8 (N). As shown in Fig.13, in section 1, the weight of 3.4(N) is measured after placing the mug.

In section 2, the weight change gradually increases by 1.9(N) after adding hot water, and in section 3 is the shaking during the experiment. As a result, the fourth section is placed above the sensor stably, and the measured total weight is 5.31(N). As shown in Fig.14, the temperature of the cup was measured to be about 23 degrees C when the hot water was not poured, and the temperature of the cup rose to 37.1 degrees C after the hot water was poured. The temperature measured at the bottom of the cup is about 26.2 degrees C. In the graph of pressure and temperature change in Fig.13, it can be seen that the sensor can accurately measure the temperature of the bottom of the cup and the change in the weight of the item..

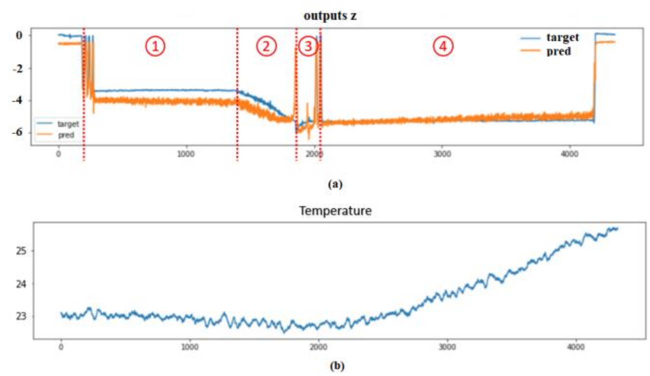

Figure 13. Normal force measurement and temperature measurement diagram: (a) normal force actual force curve and force prediction curve, (b) 3D force sensor surface temperature diagram

Figure 14. Infrared thermal imager temperature change

VI. CONCLUSION

This research was to design a tactile sensor, which could make the device have skin like the human body, and could know the weight and temperature of the object. We also used machine learning and a calibration machine to calculate the precise force value. Therefore, the tactile sensor designed in this research will be able to be used in the robot as a feedback signal for precise force control.

At present, the accuracy of the automatic calibration machine may not be high enough, so the corrected error was relatively large, and we continued to improve the machine learning model, hoping to reduce its error and consider the hysteresis of the sensor itself. Since the contact surface of the sensor body was a silicone structure, the heat conduction will be slightly delayed when sensing the temperature of the object. Therefore, in the future, graphite powder will be mixed into the silicone structure to increase the heat conduction speed, and the measured temperature value will be higher and more precise without long delay time.

In the future, we hope to design a sensor that can recognize the position of multiple points on this sensing surface, and improve the application range of 3D force. The application of multi-point recognition can improve the recognition of the outline of the grasped object, so it can provide more accurate information for robots with real tactile feedback.

REFERENCES

[1] R. Bhirangi, T. Hellebrekers, "ReSkin: versatile, replaceable, lasting tactile skins ", 5th Conference on Robot Learning (CoRL 2021), London, UK, 2021, pp. 1.

[2] W. H. Ko and Q. Wang, "Touch mode capacitive pressure sensors," Sensors and Actuators A: Physical, vol. 75, no. 3, 1999, pp. 242-251.

[3] S. Guo, J. Guo, and W. H. Ko, "A monolithically integrated surface micromachined touch mode capacitive pressure sensor," Sensors and Actuators A: Physical, vol. 80, no. 3, 2000, pp. 224-232.

[4] E. Hwang and Y. Kim, "A Polymer-based Flexible Tactile Sensor and Its Application to Robotics," in SENSORS, 2007, pp. 784-787.

[5] A C. Holgado, N. Piga, T P Tomo, G Vezzani, A. Schmitz, L. Natale, S. Sugano, "Magnetic 3-axis Soft and Sensitive Fingertip Sensors Integration for the iCub Humanoid Robot", IEEE Robotics and Automation Letters, VOL. 5, NO. 3, JULY 2020, pp. 2-3.

[6] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, I. Polosukhin," Attention Is All You Need" 31st Conference Neural Information Processing Systems, 2017, pp. 2-8.