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A Survey on Real-Time Learning Robot for Shape Recognition for Objects using Multi-Fingered Robot Hands

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Abstract: *Robots with the help of wearable tactile sensing arrays as a primary source can have human like sensitive sense of touch, which helps them to response to environmental objects. This paper gives an overall review the optimal grasp planning of multi-fingered hands. In order to analyze multi-fingered grasp qualitatively, the contact models in common use are introduced and form closure and force closure are analyzed, then stable operation conditions of grasping are also proposed. This paper introduces three aspects of planning, which serves the purpose of how to make the optimal planning. The methods about the planning of grasping point location are presented, including geometric analysis based method, knowledge rules based method and optimization based method. The planning of grasping force is divided into optimization of grasping force in contact force space and optimization of grasping force in joint torque space. The planning of fingers gate is also analyzed. At the end of the paper, a few research comparison results are highlighted and discussed.*

Keywords: Bio-inspired design, artificial muscles, robotic fingers, MEMS tactile sensor

I. INTRODUCTION

Humans have sense of touch from which it is possible for them to recognize the object. Whereas robots don't have such senses. Typically, robotic systems use visual sensors to acquire outside information, such as the location, size, and shape of the object. One of main faults of visual sensors is that they are difficult to use without proper lighting. To make up for this defect, it is necessary to find another way for robots to be able to work in the dark. Hence tactile sensing arrays are used on robots fingertips which give power to robots to sense any object. Therefore tactile sensors are one of the essential sensors for robots, due to its ability to determine object pose and recognizing gesture. For instance, the flexible tactile sensor arrays were used to achieve the accurate grasping movement of robotic hands, the MEMS tactile sensor arrays were used to detect the fabric of objects being touched, and the slip-tactile sensors and the tactile sensor arrays were used to detect the slippery movements of objects. Tactile sensor is frequently used to analyze the pressure distribution on the surface of a robotic hand while the hand performs grasping movements. The collected tactile array data was directly feature-extracted and sent to SVMs without building the 3D models of objects. In this way, the time for the additional process can be saved; and less information will be lost during processing. The main concern for the path planning of a robotic hand depends upon the collecting of tactile data. In contrast to the hard sensor, the soft and flexible tactile sensor arrays can be attached freely and used in many experiments. The benefits of the flexible tactile sensor arrays are that it can easily be attached to the surface of a robotic hand, even on curved fingertips, and it does not occupy a large area. To analyze tactile sensor array data and build a grasping database, a classifier should be used to classify the collected data from tests of grasping known objects. Typical classifier is SVMs that can project data to a high dimensional space and find a hyper plane to separate and categorize the data. SVMs have been widely applied to many different fields. With proper extraction of data features, the applications of tactile sensor arrays can be extended and the results can be furthered. If enough training data is fed into the SVM, its classification accuracy can be higher than that of other kinds of classifiers. The standard deviations of tactile array data were used as the feature data for a modified SVM algorithm, which was applied to perform multi-classification with high accuracy. Objects with like size but different shapes (including balls, square cubes, and columns) were identified by five-finger hand equipped with the tactile sensor arrays. Soft and flexible tactile skin can be used for shape recognition. Without building 3D models of the objects, the extracted features from the tactile array data were directly fed into the SVM for classification. Fig. 1 provides the outline of the whole process.

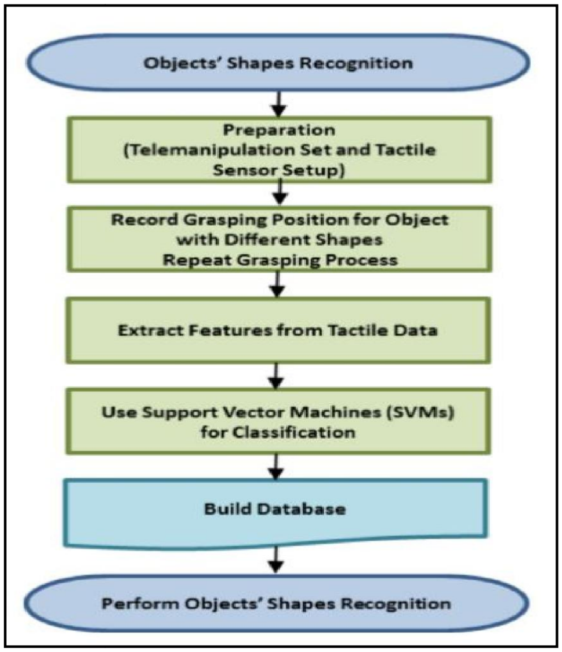

Fig 1. Flow diagram of objects' shape recognition.

First, a telemanipulation module is developed and equipped with flexible tactile sensor arrays. In this step, the proper way to grasp of the objects used will be learned. Second, the robotic hand repeats the grasping process to grasp the objects. The flexible degrees of all finger joints and the tactile array data are recorded at the same time. Third, the tactile array data analysis is added to obtain critical information that helped to effectively classify the data afterwards. Finally, the SVM is applied to perform the classifications and build the database. In particular, this paper studies the effects of different sensory streams on stable classification of grasping objects. These include the object's information (such as shape), grasp information (such as approach vector), tactile sensor arrays measurements from the surface of the robotic hand, and the joints' configuration of the robotic hand. Fig. 2 shows the overview of the control. The path planning makes the robotic hand movement consistent and stabilizes the collection of tactile array data. By creating an offline database for SVMs, real-time classification can be achieved in the future.

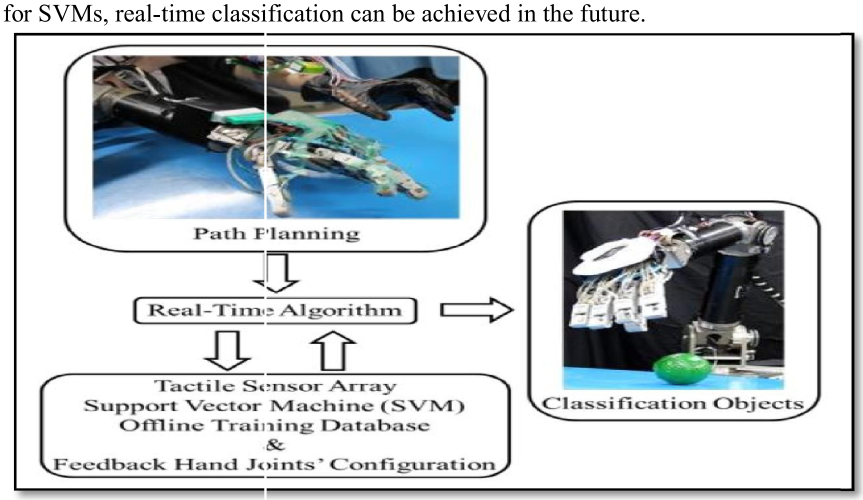

Fig 2. Overview of the control algorithm.

II. THEORIES AND METHODOLOGY

Grasping Position

Three kinds of objects with similar sizes but different shapes, including balls, square cubes, and columns, will be manipulated separately. To ensure that the
tactile array data are collected under the same conditions for all three objects, a proper grasping position that can successfully grasp all of the objects must be learned.

Features of Tactile Array Data and feature extraction

15 patches with 233 total points of tactile sensor arrays were used. The decision of what kinds of features to be extracted depends upon the property of tactile sensor arrays. Since the feedback of tactile sensor arrays can be shown in a 2D form with digits representing the forces, it seems feasible to use the pressure distributions of different rows and columns. Namely, standard deviations of digital sequences are chosen to be as the features to train SVMs.

Standard deviations help represent the pressure distribution of each row (along the X direction) of the tactile sensor arrays, it is feasible to use them as the feature variables in later classification. To represent the features of every set of tactile array data, 22 standard deviations (from every row) of the data were calculated and composed of a feature set. The standard deviation function is

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=n}^{n}(\chi_i - \mu)^2}$$

where, σ is the standard deviation, n represents the total number of variables to be calculated, X is the variable, and μ is the mean of all variables. The actual classifier used in the experiment was the modified SVM algorithm called SVC. SVC uses the same theory as SVM, but it can do multi-classification work.

Support Vector Machine (SVM)

A proper classifier will be trained and a database will be built from the training data. In this paper, SVMs were chosen to be applied. The illustration of the SVM is shown in Fig. 3. SVMs are a type of supervised learning model with associated learning algorithms that analyze data used for classification and regression analysis. Usually, SVMs are used to classify data into two groups and to find a Hyperplane to separate them. Since three kinds of objects will be classified in the experiment of this paper, the SVM algorithm is redesigned to fit the purpose of multi-classification. When using the SVM, the extracted features (22 standard deviations) from the tactile array data are the input training set, and the shape label is the output classification. The main function of the SVM is to build a tactile database for the five-finger hand to follow in the future. This database should contain enough information to help classify objects.

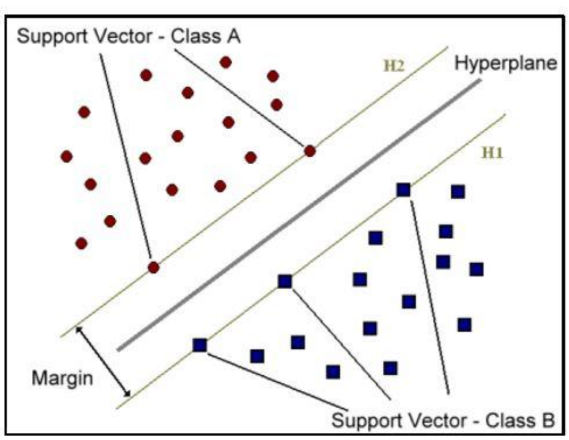

Fig 2. Support Vector Machine (SVM)

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III. SYSTEM OVERVIEW

Robotic System

The robots used in this paper are the NTU (National Taiwan University) five-finger hand and the NTU articulated six degrees of freedom (DOF) robot arm. To prevent the NTU five-finger hand from hurting itself and the objects being manipulated, an intelligent humanoid robotic hand with 12 DOF and 19 joints was designed. A series elastic actuator (SEA) and under-actuated mechanism were also applied to give the robotic hand a compliant property and high dexterity; hence, a humanoid robotic hand was devised. To obtain the proper path for the NTU five-finger hand to grasp objects, a telemanipulation module was developed to learn the best grasping position. The flexible tactile array skin was attached to the NTU five-finger hand with a layer of hydrocolloid dressing added over the top surface.

Telemanipulation module

The telemanipulation module includes a pair of control gloves and each one is composed of ten flex sensors and an Arduino Mega. A flex sensor is a kind of variable resistance sensor that detects the flex degree of each finger joint. The Arduino Mega detects and transfers the flex sensor values to the computer. Control gloves measure the human finger joint angles for mapping the human-to-robot hand motions. These angles are used to set the values for the motor joint angles of the NTU five-finger hand. Fig. 3.1 shows the corresponding finger joints of human hand measured by the flex sensors on the control gloves. In total, ten flex sensors are used (two for each finger).

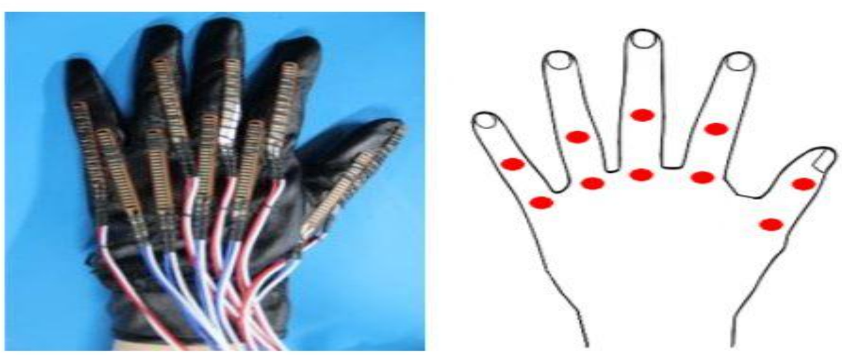

Fig 3.1. Indication of corresponding finger joints.

Tactile Sensors

The flexible tactile sensor arrays were used to achieve the accurate grasping movement of robotic hands, the MEMS tactile sensor arrays were used to detect the fabric of objects being touched, and the slip-tactile sensors and the tactile sensor arrays were used to detect the slippery movements of objects. Tactile sensor is frequently used to analyze the pressure distribution on the surface of a robotic hand while the hand performs grasping movements.

In contrast to the hard sensor, the soft and flexible tactile sensor arrays can be attached freely and used in many experiments. The benefits of the flexible tactile sensor arrays are that it can easily be attached to the surface of a robotic hand, even on curved fingertips, and it does not occupy a large area. Fig 3.2 shows structure of flexible tactile sensor and Fig 3.3 shows tactile multiarray sensor design.

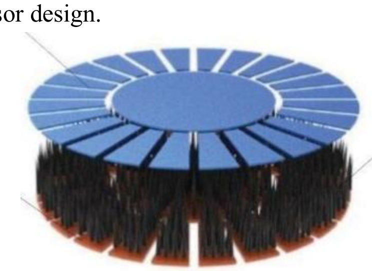

Fig 3.2. Structure of flexible tactile sensor.

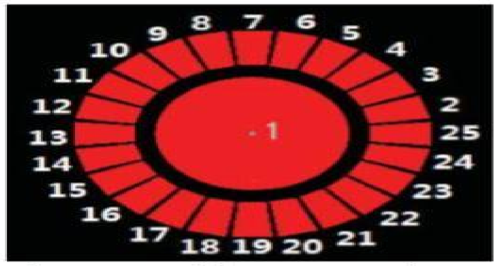

Fig 3.3. Multiarray sensor design

Installment of tactile sensor arrays

The tactile sensor arrays set used in this experiment is a flexible tactile skin, which is a distributed tactile sensor arrays with 376 detecting points on its surface. It can detect the pressure of the separate parts of the NTU five-finger hand and convert the pressure into force with a high temporal resolution of more than 100 Hz. Therefore, the pressure change can be detected immediately during any movement. Before being installed on the NTU five-finger hand, the flexible tactile skin is calibrated with counterweights for each separate tactile sensor arrays patch. The tactile array data from 15 patches of sensors were used. A layer of thick hydrocolloid dressing was added on the top surface of the tactile sensor arrays to improve sensing ability, softness, and friction. The thick hydrocolloid dressing is about 2 mms thick, composed of 1 mm of hydrocolloid material and 1 mm of a soft sponge. The final appearance of the NTU five-finger hand is shown in Fig. 3.4.

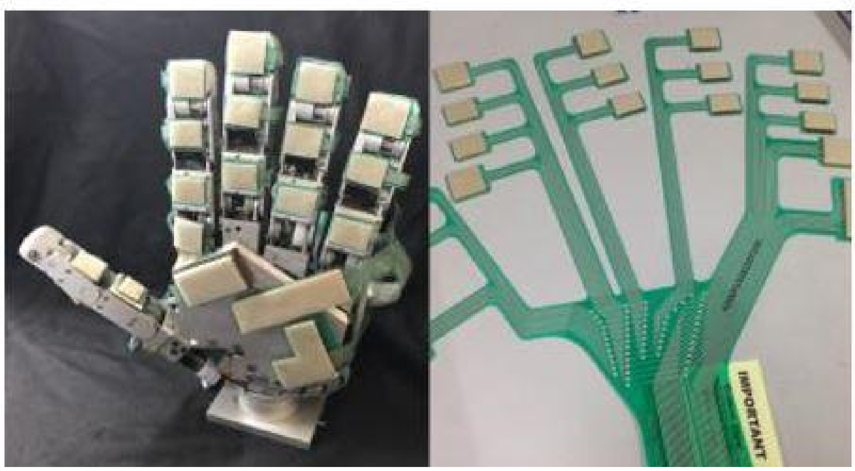

Fig 3.4 NTU five-finger hand with tactile sensor arrays and hydrocolloid dressing.

IV. FEATURE EXTRACTION

Fig. 4(a) shows the arrangement of tactile sensor arrays on the NTU five-finger hand. The pressure values can be displayed directly on the computer with color blocks in gradient labeling different values. Fig. 4(b), (c), and (d) show the approximate pressure distributions when grasping column, ball, and square cube, respectively. As shown in Fig. 7, the pressure distributions for different objects are quite different.

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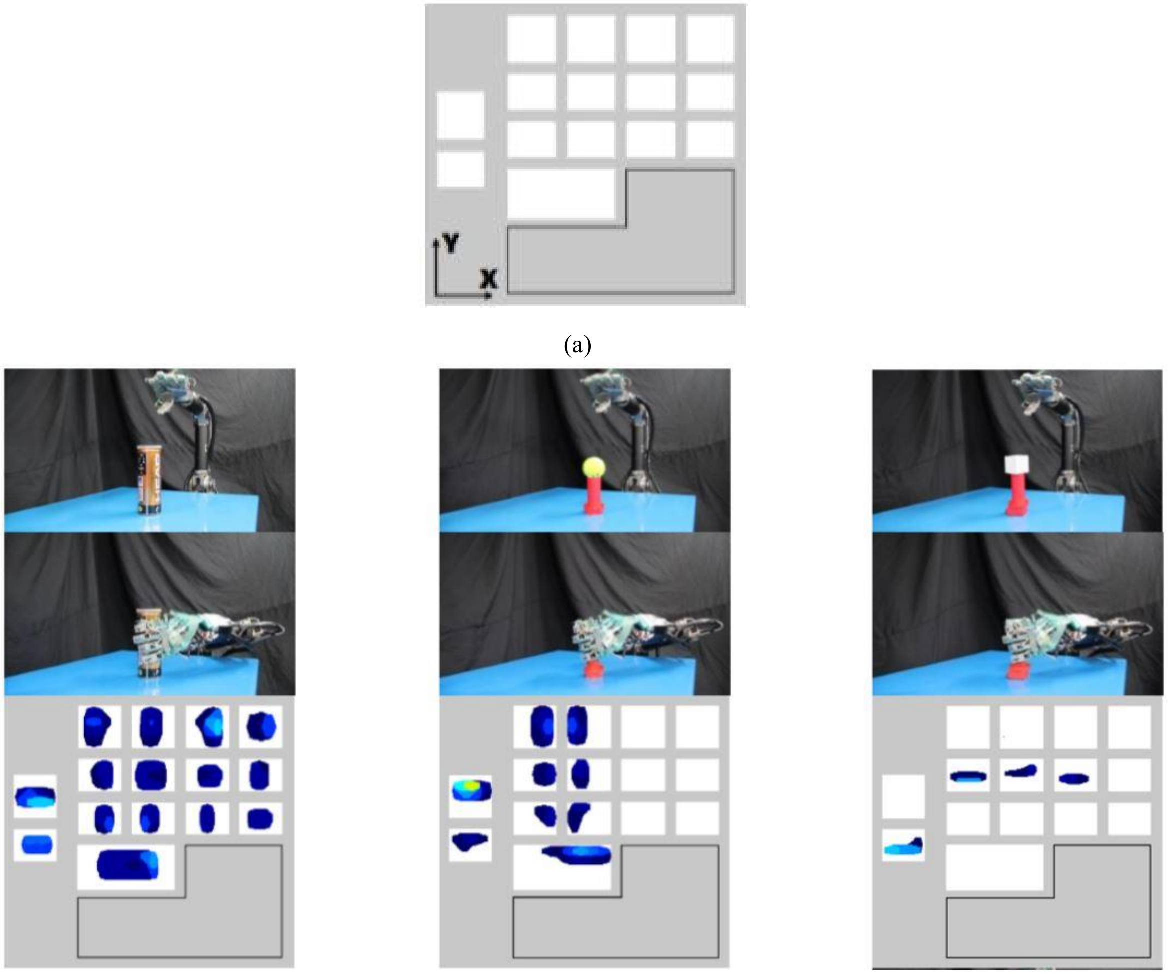

(a)

(b) Column (c) ball (d) square

Fig 4. Arrangement of tactile sensor arrays and the grasping gestures and approximate pressure distribution for three objects (a) (b) (c).

V. GRASPING POSITIONS USED IN THE EXPERIMENT

There are two grasping positions used in the experiment. To show the availability of the methods proposed in this paper, two sets of results are shown in Table I and Table II, respectively. Table I shows the results of the classification that only uses the data from single grasping position, and Table II shows the results of the classification that uses the data from two grasping positions.

		Tactile array data	
		Raw	Feature-Extracted
Added	Finger joints' configuration of the NTU five-finger hand	55%	76.67%
Non-Added		93.33%	96.67%

Table I. CLASSIFICATION ACCURACIES WITH SINGLE GRASPING POSITION

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		Tactile array data	
		Raw	Feature-Extracted
Added	Finger joints' configuration of the NTU five-finger hand	50.83%	81.67%
Non-Added		93.33%	96.67%

Table II. CLASSIFICATION ACCURACIES WITH TWO GRASPING POSITIONS

VI. CONCLUSION

The grasping operation of dexterous multi-finger hand is the emphasis and difficulty. It involves contact type, friction characteristics, the adaptability of grasping, stability, the feature modeling of grasping purpose, the quality modeling of grasping and so on. The primary challenge s that how the multi-fingered hands manipulate objects flexibly as human hands by learning from human hands or analyzing its movement [4]. So it is particularly important for the grasp planning of multi-finger hand. The problems of grasp planning have been extensively studied by scholars and a lot of planning methods and algorithms were put forward. The progress of multifingered grasping was presented and discussed in this paper. But because of the uncertainty of the environment and the multiplicity of grasping information, planning method need to be further improved.

REFERENCES

[1]. Learning Robot Tactile Sensing of Object for Shape Recognition Using Multi-Fingered Robot Hands. https://ieeexplore.ieee.org/document/8172474/

[2]. A novel wearable tactile sensor array designed for fingertip motion recognition https://ieeexplore.ieee.org/document/8324412/

[3]. Yu, C. and Wang, P., 2022. Dexterous manipulation for multi-fingered robotic hands with reinforcement learning: A review. *Frontiers in Neurorobotics*, *16*, p.861825.

[4]. Miao, W., Li, G., Jiang, G., Fang, Y., Ju, Z. and Liu, H., 2015. Optimal grasp planning of multi-fingered robotic hands: a review. *Applied and Computational Mathematics: An International Journal*, *14*(3), pp.238-247.

[5]. Suthar, B., Abdulrahman, Y. and Zweiri, Y., 2024. Robotic Fingers: Advancements, Challenges, and Future Directions-A Comprehensive Review. *IEEE Access*.

[6]. Ozawa, R. and Tahara, K., 2017. Grasp and dexterous manipulation of multi-fingered robotic hands: a review from a control view point. *Advanced Robotics*, *31*(19-20), pp.1030-1050.

[7]. Yu, Z. and Gu, J., 2008, May. A survey on real-time controlled multi-fingered robotic hand. In *2008 Canadian Conference on Electrical and Computer Engineering* (pp. 000975-000980). IEEE.