A Novel Tactile Sensing System for Robotic Tactile Perception of Object Properties

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Abstract. Tactile sensing has become crucial in robotic applications such as teleoperation, as it gives information about the object properties that cannot be perceived by other senses. In fact, it is essential that robots are equipped with advanced touch sensing in order to be aware of their surroundings and give a feedback to an operator. Such sensing system are made of sensors and an elaboration unit that acquires tactile signals and process the data, retrieving information such as texture, hardness, and shape. In this paper, we propose a novel tactile sensing system made of flexible, high sensitive and high spatial resolution piezoelectric polyvinylidene fluoride-trifluoroethylene P(VDF-TrFE) sensors, and a low power and low cost Interface Electronics (IE) that can acquire data from 32 channels simultaneously with a sampling frequency of 2kSamples/s. We validate the system acquiring data from three different objects to classify their hardness using an artificial neural networks of one hidden layer with approximately 89% accuracy. The signal processing and the classifier will be hosted by the IE in the next future.

Keywords: Tactile sensing systems, Human–Robot interactions, Hardness recognition, Robot tactile sensors, Tactile sensors.

1 Introduction

In the last few decades, many research activities have been done to increase the effectiveness of robotic teleoperation. As teleoperation reflects mainly vision and force providing feedback on object shape and position, tactile sensing has been also considered important for teleoperation [1], which give information about object properties (i.e. texture, hardness, shape, etc.) by grasping, touching, or manipulating objects even with the absence of vision. Moreover, predicting object hardness also provides awareness. Tactile sensing in robots is essential for the exploration of object's properties and contact parameters such as position and size. Therefore, several methods were proposed to handle contact on robots using existing sensors and models [2].

Some tactile sensing systems are expensive and task specific [3], consisting of artificial tactile sensors (i.e. E-skin) that require high technology manufacturing. These types of systems could not be implemented in some applications due to design constraints. Therefore, a comprehensive design is needed to overcome this limitation.

Other constraints that face tactile sensing systems are related to the elaboration system required to measure, process and classify tactile data from a large number of sensors in real time. The elaboration system should be deployed on a low power and low cost embedded system [4].

In this paper, we present a novel tactile sensing system, that consists of a tactile sensing patch and Interface Electronics that overcomes many of the above mentioned problems, easily integrated to a Baxter robot gripper. We acquired data from three different objects to evaluate our proposed tactile sensors for object-hardness classification using an artificial neural networks of one hidden layer. We also present a simple pre-processing approach to reduce the signal noise and extract features that can be easily implemented on the embedded system (i.e. IE) with the predictor.

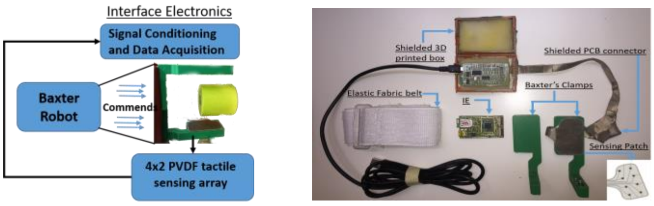
The paper is organized as follows: Section 2 presents the related work. Section 3 describes the tactile sensing system. Section 4 explains the experimental setup. Experimental evaluation and results are provided in Section 5. Finally, conclusions and future work are given in Section 6.

2 State of the Art

To this day, many of tactile sensing systems have been developed for robotics targeting different applications (e.g., manipulation, classification, teleoperation) [5]. These sensing systems are mainly composed of tactile sensors and a data acquisition circuitry. [6] implemented a flexible piezoresistive sensors into a two fingered robotic gripper. The sensors are capable of detecting forces up to 4.4N, and each circular sensor has a diameter of 9,5 mm. The authors used PIC32 Microcontroller in their system, and utilized the obtained data to classify objects based on their stiffness. On the other hand, some tactile systems are based on artificial sensing such as Biotac [3]. [7] proposed a tactile system based on capacitive transduction, which contains 25 sensing taxels in each unit. It performs spatial signal processing on the grid at each time step, and outputs a differentiating capacitive responses to a pressure event. The collected data are stored on a server and retrieved by the robot to control its arm movement in real-time. Nevertheless, one of the limitations is that multiplexing acquisition platform is required for full directional sensing capabilities in the robotic application. A different application was made by [8] where they demonstrated the efficiency of using tactile data for fruit-hardness classification using SVM and KNN classifiers. In order to increase the effectiveness of robot picking manipulators a WSG 50 two-finger manipulator and WTS0406-38 tactile sensor were used to grasp and collect data from fruits of different hardness. The authors also presented a methodology for preprocessing tactile data using PCA for feature extraction. In [9], authors employed the tactile data that were collected while doing a simple pupation procedure using a novel piezoresistive sensors to discriminate between rigid and deformable objects with k-NN classifier.

3 Description of the system

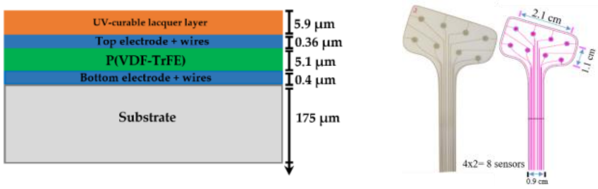
Our tactile sensing system, reported in Fig. 1a, is composed of tactile patches to sense dynamic contacts with objects, and an interface electronics (IE) to acquire and process the data. The tactile patches were integrated on the gripper of the Baxter's robot.



a) b)

Figure 1. a) Block diagram for the tactile sensing system. b) System components.

Fig. 2a shows the structure of the flexible tactile sensing patches fabricated by JOANNEUM RESEARCH [10]. The sensing patches (Fig. 2b) are screen-printed, made of piezoelectric polyvinylidene fluoride-trifluoroethylene P(VDF-TrFE), that generate charges proportional to the applied force and are highly sensitive for dynamic contacts. The patch, mounted on the Baxter's gripper, contains 8 taxels (4 × 2), total sensing area= 2.1 × 1.1 cm^2, center-to-center pitch= 1 cm, and a taxel diameter= 2 mm. It also provides a bandwidth in the range (1 Hz - 1 KHz). Therefore, it presents a high spatial resolution and a large bandwidth.



a) b)

Figure 2. a) Sketch for the structure of the sensing patch. b) Tactile sensing patch [10].

The second component in the tactile sensing system is the Interface Electronics (IE). The IE includes a BL600 module with an ARM-cortex M0 based microcontroller. The IE manages the charge-output of 32 sensors by employing a 32-channel analog-to-digital convertor (DDC232) with a current offset circuit. The DDC232 converts the 16-bit resolution data of 32 channels at 2 kSps. The power consumption of the IE during the data acquisition is about 300 mW. Other specifications are found in [11].

In this study, the Baxter robot is employed to assess the efficiency of integrating our tactile sensing system on the electric parallel gripper, to classify the hardness of three objects. More specifications of the Baxter robot are found in [12]. One of the drawbacks in this robot is the mechanical noises (i.e. vibration) caused by the backlash in gears, that may cause motion loss and vibrations. For this reason, a moving average filter is implemented inside IE.

4 Experimental Setup

To validate our tactile sensing system, we did some experiments on three objects of different hardness. In the following sections, we present the setup of the system, the data collection and the classifier.

4.1 Hardware Setup

Before starting with the integration process, we grounded the sensing patch, connector and the IE externally (Fig. 1b). The IE was set to provide continuous data transmission from 4 channels (4 sensors in the form of 2 × 2 matrix). In these experiments we used one of the Baxter's end effectors, which consist of an electric parallel gripper. We customized the supports of the gripper to fit our sensing patch and 3D printed them (Fig. 1b). To reduce uncertainties, and avoid any damage for the sensors, the gripper velocity was fixed at v=5cm/s and the applied force at $F = 0.03*F_{max}$ (F_{max} = 35N) [12]. During the experiments, the object was placed on the table as the gripper performs repeated grasps. We ran many tests, during each, the position of the gripper was changed having at least one sensor in contact, to simulate different grasps on the same object.

4.2 Construction of Datasets

For this study, 3 objects of cylindrical shape were used to record tactile data and create 3 bi-class datasets. One of the objects was rigid made of wood while the other two were more or less deformable rubber-like objects of different hardness. We applied 20 grasp/release sequential trials on each object 12 times, changing the position of the gripper, thus we obtained a total of 240 grasp/release sequences for each object. Each trial lasts for 3 s, 1 s of grasping followed by 2 s of release.

Illustrated in Fig. 3 an example of a tactile data from one sensor. The tactile data, acquired simultaneously from four sensors by the IE continues sampling at 2kSps, is composed of three main responses. First, when contact take place the charge decreases, creating a drop peak (referred to "Press" in Fig 3). Second, as the gripper continuous to hold the object the charge returns to its initial state. Third, when the gripper release the object, the charge increases and creates a peak (release peak). The acquisition process was controlled by a LabVIEW GUI. To build the datasets, we extracted only 150 samples that corresponds to the grasp (samples between the dotted lines Fig. 3) by taking 20 samples before the peak and 130 after. Data processing and feature extraction were done automatically using Matlab. The average values of the 150 samples from each sensor are taken as features. As a result, each dataset contained 480 data (240 per object) having 4 features (the average for each sensor). Eventually, the datasets included the Rigid-Soft (RS) objects, the Rigid-ExtraSoft (RES) objects, and the Soft-ExtraSoft (SES) objects.

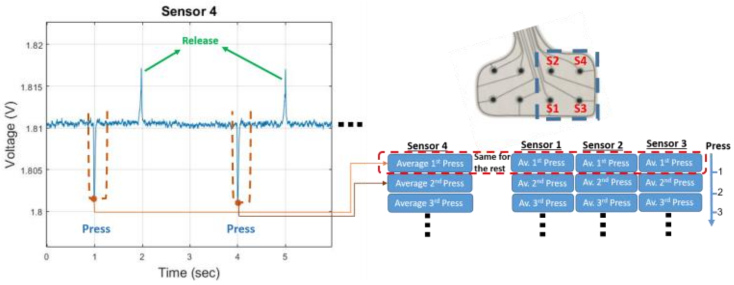


Figure 3. Pre-processing and feature extraction from tactile data.

4.3 Classifiers

The implemented classifier was the fully connected neural network (FCNN) with one hidden layer. We used Python with Keras library. The classifiers are designed to deal with 2-class classification problem. The activation function used in the hidden layer is the 'ReLU'. The hyper-parameters are defined as follows: number of hidden layer neurons N= {50, 100, 200, 300} ; regularization term λ= {10^i, i= −4, −3, ..., 4} to avoid overfitting; weights and biases are initialized randomly between [-1 1]. Datasets are normalized before feeding the FCNNs. Three types of normalization are tested: Minmax (M) between [0 1], modified Minmax (MM) between [-1 1], z-score (ZS, average=0 and standard deviation std=1). To define the hyper-parameters and estimate the generalization performances, the data were split into training, validation, and test sets. On each dataset, we performed 100 experiments that involved 10 runs and 10 rolls (used for different starts of the neural network weights). Each run has different training, validation, and test sets, which are divided as follows: 70% for training; 15% for validation (used to choose the best N and λ), and 15% for the test set. The batch size was 64 and the number of epochs was 200.

5 Results

Table 1 shows the performances of the classifier over the three dataset. The rows refer to the number of neurons in the FCNN, while the columns refer to the datasets and the type of normalization employed. In results, the classifier with ZS normalization performs the best in all datasets, especially when the number of neurons is 300. Moreover, results show that ZS normalization improved the accuracy 10% (± 2.46) more than with M. Finally, the low accuracies obtained by the SES dataset, compared with the results of the other datasets, are expected since both objects are soft.

6 Conclusion and Future work

This paper proposes a novel tactile sensing system, based on piezoelectric sensors and Interface Electronics, integrated to a Baxter robot and used for the recognition of object hardness. The experimental evaluation is done using the fully connected neural network on three two-class problems. Results demonstrate we are able to classify the hardness of objects with an accuracy of 88.9% between rigid and soft object, and 77.2%, between two soft objects of slight difference in hardness. Our future work is to extract more features and test multiclass classification on different object hardness, and implement the processing and classification of data to the IE.

Table 1. Algorithm's performance on different configurations and datasets.

Algorithm \ Datasets			RES			RS			SES		
			M	**MM**	**ZS**	**M**	**MM**	**ZS**	**M**	**MM**	**ZS**
FC	Neurons	50	.706	.732	.795	.775	.823	.860	.610	.676	.692
		100	.706	.770	.830	.780	.854	.876	.626	.686	.709
		200	.710	.827	.851	.802	.869	.883	.652	.709	.746
		300	.711	.836	.860	.814	.881	.889	.668	.728	.772

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