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Intelligent Haptic Sensor System for Robotic Manipulation

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Abstract – The paper discusses an intelligent sensor system developed for the haptic-control of the robotic manipulation of 3D objects. Based on a 16x16 array of Force Sensing Resistor (FSR) elements, the sensor system is able to provide an estimate of the object's surface orientation along with a fine description of features located within the sensing area.

I. INTRODUCTION

Haptic sensing technologies have experienced significant development over the last two decades that resulted in the identification of the best transduction methods and configurations [1]. This brought interesting results in haptic perception for virtual environments [2]. As haptic perception essentially emulates biological haptic perception mechanisms [3], it integrates two distinct sensing modalities: (i) *cutaneous* tactile sensing provides information about contact force, contact geometric profile and eventually the temperature of the touched object [4], and (ii) *kinesthetic* sensing provides information about the position and velocity of the structure carrying the tactile sensor [5].

A recent trend in haptic/tactile sensing focuses on the application of this technology in robotics and automation with various applications in industrial assembly, assisted surgery where palpation is important [6], or in safe human-robot cooperation [7, 8]. More specifically, a strong interest has been put in the development of articulated hands made of a few tactile sensitive fingers for dexterous manipulation [9, 10, 11]. Germagnoli *et al*. [12] present an approach to drive a robot gripper during the exploration of unknown objects based on the recognition of a limited set of tactile primitives and the interpretation of stress maps with neural networks to locate and follow edges on the object. Pedreno-Molina *et al*. [13] propose a neural-network based approach that uses artificial skins in guiding grasping operations to ensure stable grasp of object with a two-finger robot hand. Even though relatively good performances can now be achieved with this technology [14], the area and the complexity of the space that can be explored is limited due to the small size of the tactile sensors (mostly single point) and the fact that they are usually mounted inside the gripper fingertips [15].

On the other hand, the merge of haptic information with 3D models obtained from optical data for telerobotic manipulation of complex objects has not yet been widely explored in spite of the numerous new possibilities that it might open. As vision-based modeling is highly sensitive to object's surface reflection characteristics, tactile sensors can be advantageously integrated to complement 3D models. Canepa *et al.* [16] propose to extend computer vision approaches to tactile data in order to extract cutaneous primitives. Taking advantage of the fact that tactile sensors are directly in contact with the object surface allows to precisely identify fine shape primitives that remain invisible to vision systems.

Since a detailed representation of surface shape clearly revealed to be critical in controlling fine interactions between a robot manipulator and complex objects, these examples demonstrate the necessity for the development of haptic sensing systems targeted to robotic manipulation operations.

This paper describes a compliant haptic sensing system that is able to provide an estimate of the object's surface orientation along with a fine description of features located within the sensing area. A multilayer feedforward neural network operating directly on the raw data provided by the haptic sensor is also introduced to achieve the orientation-independent recognition of fine features detected on the surfaces. These features take the form of geometric symbols defining a pseudo-random encoding scheme that is meant to facilitate the recognition and the localization of each object in a complex scene. Being able not only to model the objects in the scene but also to precisely segment them in the representation brings a strategic advantage in guiding the robot during the manipulation phase.

II. KINESTHETIC SENSING SYSTEM

The robotic haptic sensing system consists of a commercial manipulator, a custom designed instrumented passive-compliant wrist and a tactile array sensor [5] as shown in Figure 1. The compliant wrist allows the tactile sensor to accommodate the constraints of the explored object surface and thus to increase the information acquired by the tactile sensor. Position sensors placed in the robot's joints and on the instrumented passive-compliant wrist provide the *kinesthetic* information.

The amount of information acquired by haptic exploration depends on how well the probing tactile sensor accommodates the constraints of the local geometry of the object. The instrumented passive-compliant wrist shown in Figure 2 allows the tactile sensor to better accommodate the object surface. It consists of two planar plates having three relative degrees of freedom: two rotations about the x and y axes of the tactile probe's plane and one displacement along the z axis (normal to the tactile sensor's plane). A set of four linear displacement transducers allows one to measure the distances between the two plates of the wrist, enabling the calculation of the relative orientation and distance between the wrist's plates.

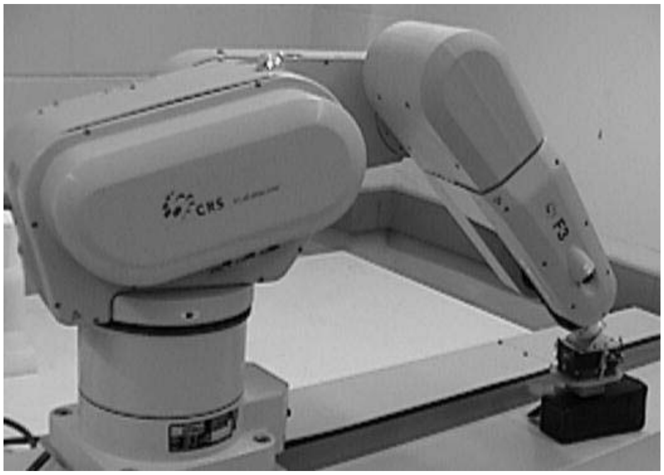

Fig. 1. Robotic haptic perception system.

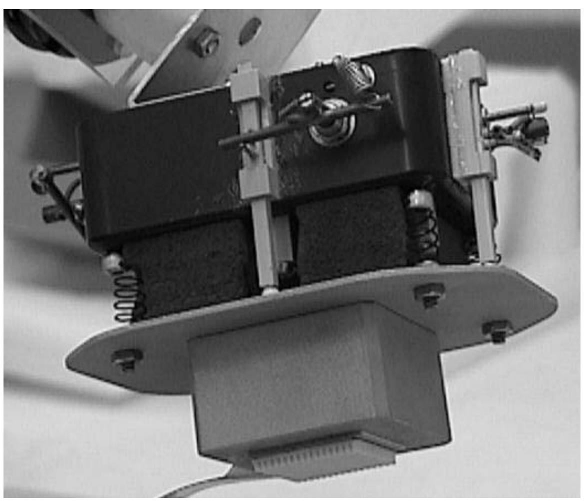

Fig. 2. The instrumented passive-compliant wrist with the tactile sensor probe.

III. TACTILE SENSOR

Most of the known tactile sensors: (conductive elastomer, piezoelectric or piezoresistive) measure the contact force profile rather than the contact displacement profile. Under the pressure from an external bias force the local object geometric profile indents an elastic pad [1]**.** The induced contact forces are transmitted through an elastic overlay to a force sensitive array of transducers. There is a complex and difficult to control relation between the displacement and the effectively measured strain in the elastic pad [17, 18], as shown in Figure 3. Despite these problems the force sensitive tactile sensors are very robust and very good candidates for industrial applications.

The piezoresistive tactile sensor consists of a 16x16 matrix of Force Sensing Resistor (FSR) elements spaced by 1.5875 mm (1/16 inch) on a 645.16 mm^2 (1 square inch) area [19]. The FSR elements exhibit exponentially decreasing electrical resistance with applied normal force: the resistance changes by two orders of magnitude over a pressure range of 1 N/cm^2 to 100 N/cm^2. These elements sense compression forces and thus should be placed on a rigid backing.

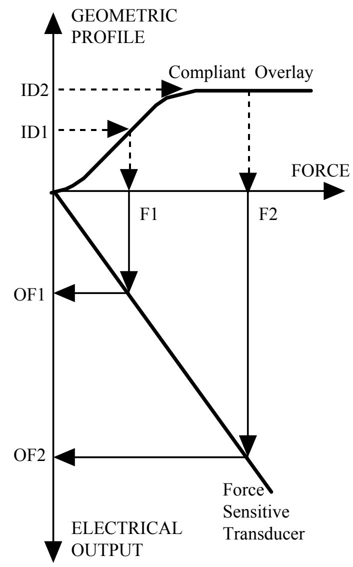

Fig. 3. I/O characteristics of a force sensitive transducer and its elastic/compliant overlay.

The elastic overlay has a protective damping effect against impulsive contact forces [20, 21], and its elasticity resets the measuring system when the sensor ceases to touch the object. Moreover, in order to avoid the inherent blurring effect of the one-piece elastic pads we are using a proprietary elastic overlay with protruding round tabs sitting on top of each node of the FSR matrix providing a *de facto* spatial sampling as shown in Figure 4.

Based on recommendations made in [22, 23], we are using circular tabs, which occupy 50% of each 2D sampling area. This allows each tab to expand laterally without any stress allowing for a proportional relationship between the

displacement in the normal direction and the resulting stress component in each tab. As a result, the tactile probe output is a 16x16 array of data that represent normal displacement components of the 3D geometric profile of the investigated object surface [$z(i,j)$ | i=1,…,16; j=1,...,16], where i and j are the row and column coordinates of the tactile sensor matrix.

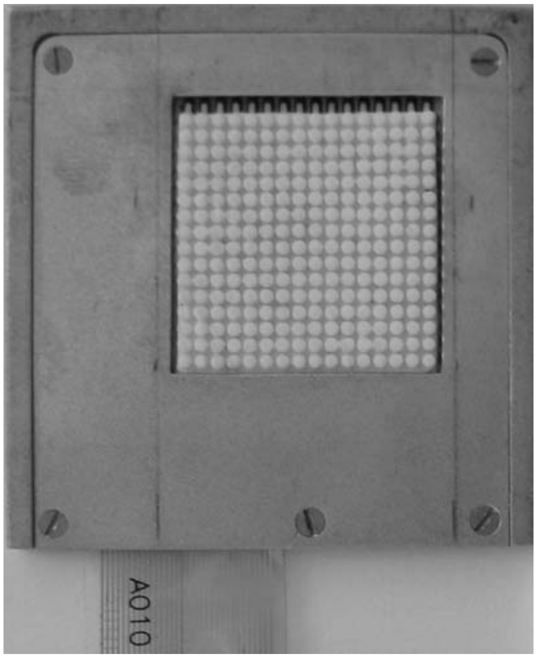

Fig. 4. The FSR sensor array with the tab-shaped elastic overlay on top.

IV. TACTILE SENSOR INTERFACE

An onboard PIC microcontroller gathers the data from the four linear displacement sensors on the compliant wrist and calculates the 4x4 homogeneous transformation matrix representing the *kinesthetic* sensor data that define the tactile sensor position and orientation. The microcontroller also provides a serial data communication interface to transfer these parameters to the user interface.

Figure 5 illustrates the block diagram of the tactile sensor interface. Two analog multiplexer circuits, one for the selection of the selected row address and another for the selection of the column address, allow random access to any individual force sensitive resistor within the 16x16 FSR array. The resistance of each selected FSR element is measured by an A/D convertor onboard a 16-bits PIC microcontroller. The microcontroller also provides the following sensor control functions: FSR address selection, and serial data communication interface.

Auto-calibration and basic image filtering functions are implemented in software, running on the PC. The auto-calibration function allows systematic correction of measurement errors due to changes in the analog electronics. A *graphical user interface* (GUI), provides convenient access to all these functions.

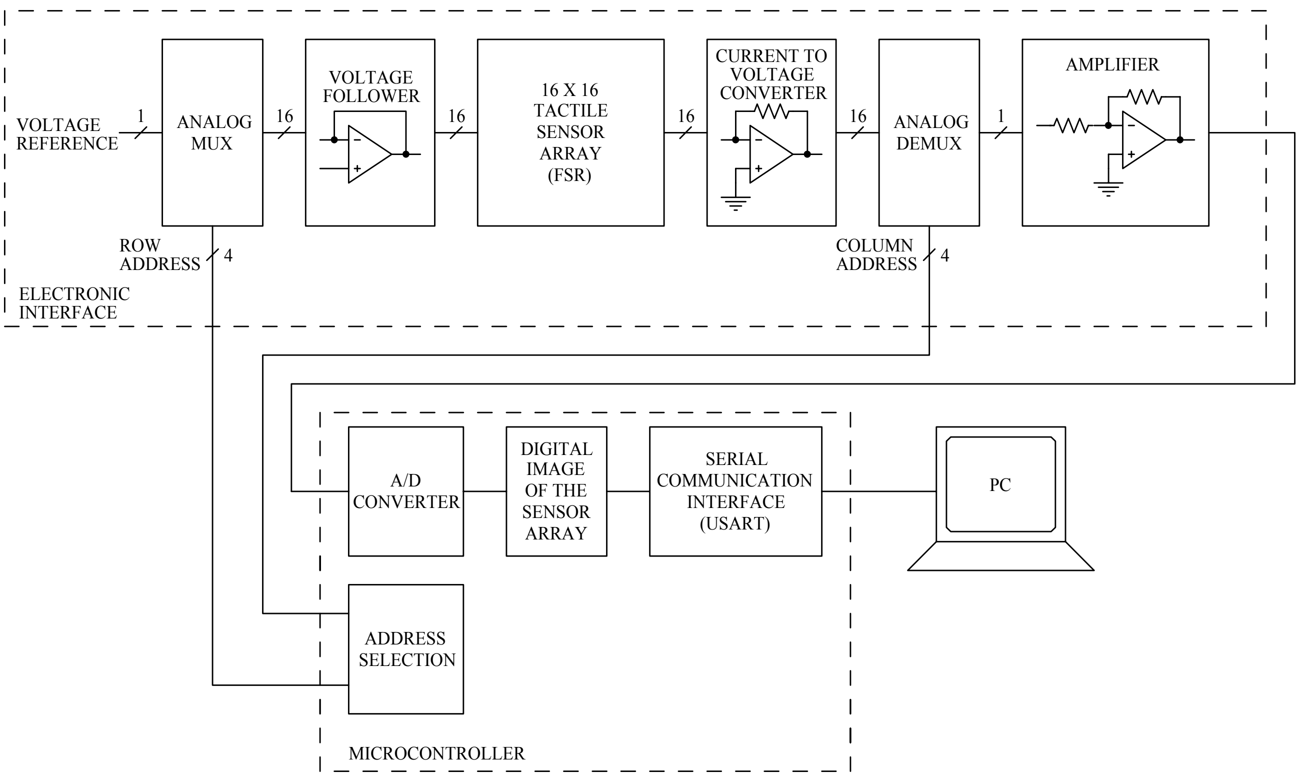

Fig. 5. Block-diagram of the tactile sensor interface.

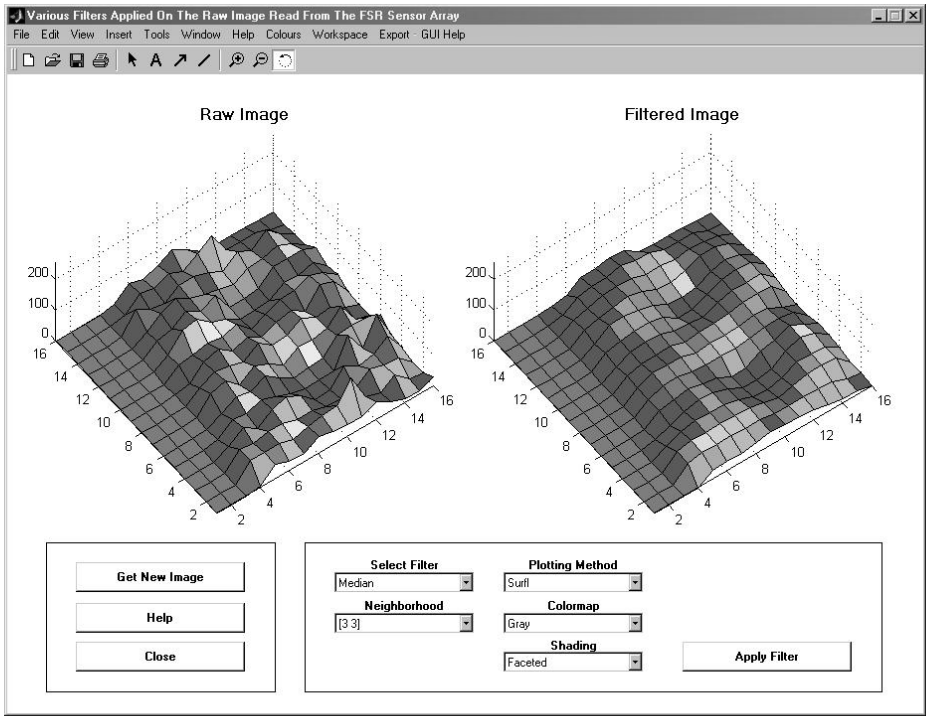

Fig. 6. Example of PC implemented GUI window.

V. OBJECT RECOGNITION WITH TACTILE DATA

The intelligent haptic sensor system has been tested for model-based blind tactile recognition of 3D objects [24]. Conveniently shaped geometric symbols representing quaternary terms of a *pseudo-random array* (PRA) defined over the Galois field GF(4) $=\{0, 1, A, A^2\}$ are embossed on object surfaces.

Symbols recovered by tactile probing are recognized using a *neural network* (NN) and then clustered in a 2x2 PRA window that contains enough information to fully identify the absolute coordinates of the recovered window within the encoding PRA. By knowing how different object models were mapped to the PRA, it is possible to unambiguously identify the object face and the exact position of the recovered symbols on the face [24].

A two-layer feedforward architecture, with 8 neurons in the first hidden layer and 4 in the second one as shown in Figure 7 is employed to classify tactile data representing the four encoding symbols. The network receives as inputs four 8x12-element vectors and the corresponding target will be indicated by a *one* in the position of the recognized character and *zero* elsewhere. The network is trained with 8x12 binary maps of the tactile images of the centered four characters as illustrated in Figure 8. A gradient descent backpropagation with momentum and adaptive learning rate is used as a training algorithm. A value of 0.95 for the momentum constant and a sum-squared-error goal of 0 are applied over 5000 epochs.

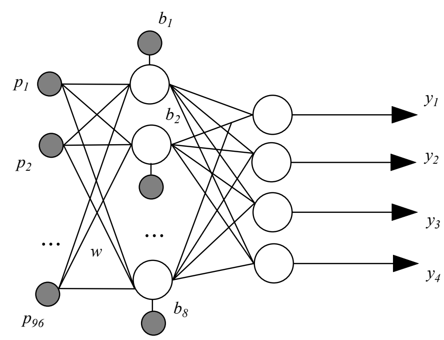

Fig. 7. Two-layer feedforward NN architecture for four characters classification.

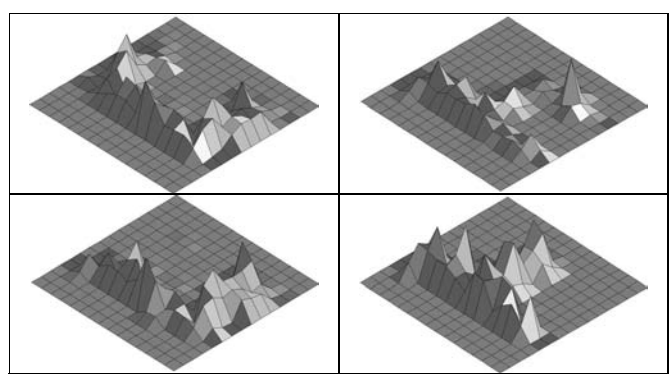

Fig. 8. Tactile images of the four symbols used to emboss PRA terms on the encoded object surfaces.

The NN was trained using two noise free images of the characters then with a series of images corrupted with noise levels of 0.1, 0.15 and 0.2 respectively and then finally trained one more time with noise free images in order to make sure that noise free images are always identified correctly.

To evaluate the generalization capability, the network was tested for different levels of noise with a mean of 0 and a standard deviation varying from 0 to 0.5. The average recognition rate and the error rate are presented in Figure 9 and Figure 10 respectively.

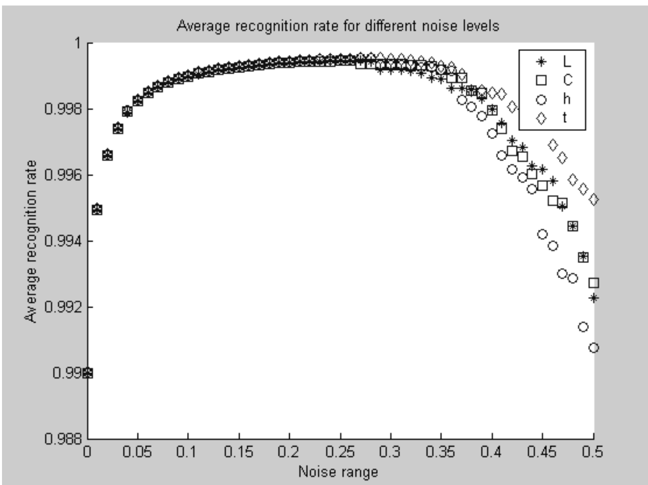

Fig. 9. Average recognition rate for noise ranging between 0 and 0.5.

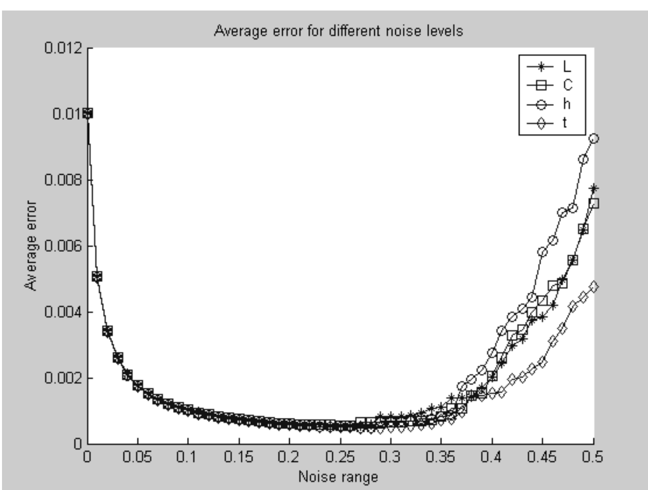

Fig. 10. Average error rate for noise ranging between 0 and 0.5.

Another set of tests is run to test the behavior of the network in case the characters are not in vertical position. The network as presented previously is only able to detect characters rotated by 90 degrees. To solve this problem, the initial character recognition module is cascaded with a transformation module. The purpose of the latter is to recuperate the displacement information between a raw character and the characters stored in a database of centered and aligned objects.

The transformation network has no hidden layer and receives as inputs a map of the raw character and as outputs a map of the character in the database. It has a linear activation function and is trained using gradient descent backpropagation with momentum and adaptive learning rate, with a value of 0.95 for the momentum constant and a sum-squared-error goal of 0, for 530 epochs in 5 steps. The training procedure lasts for about 5 sec. The neural network learns and stores in its weights the displacement information between the vertical character and the rotated one. This information is then used to align the rotated character to the vertical position in order to be subsequently recognized.

A sample of rotated tactile data and the corresponding aligned data are shown in Figure 12 and Figure 13 respectively. As expected, once the training is completed, the raw object is aligned with the character in the database and this aligned object becomes the input of the tactile recognition module.

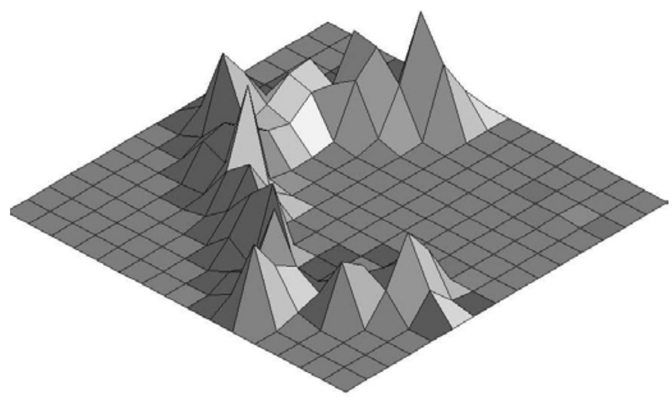

Fig. 12. Raw rotated data

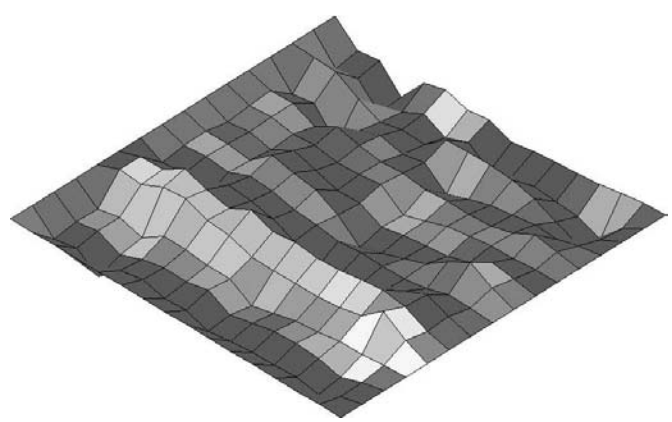

Fig. 13. Raw aligned data

VI. CONCLUSION

Experimental results have shown that the intelligent haptic sensing system presented in this paper increases considerably the performance of the tactile sensor initially developed in our laboratory [5].

The incorporation of a microcontroller has resulted in a more compact electronic interface for the FSR tactile sensor. It also makes possible the straightforward migration of the calibration and basic image filtering functions, which are still running on the PC.

Simulation and experimental results have shown that the NN recognition of the tactile images of the specially designed symbols embossed on object surfaces has error rates better than 0.6% even in the case of images having up to a 50% noise ratio.

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