An Artificial Neural Network approach for Haptic Discrimination in Minimally Invasive Surgery

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Abstract—In this paper we investigate the possibility of processing the tactile perception by using a novel biomimetic approach for the pattern recognition module. The goal is to enhance the perception in complex virtual environments deriving from haptic displays mimicking human tactile discrimination. To do this we explored a Minimally Invasive Surgery application where the tactile information are strictly limited. In fact, this promising technique suffers from some evident limitations due to the surgeon loss of tactile perception during palpation of internal organs. This is basically due to the mechanical transmission of the elongated tools used during operation. We propose to integrate an Artificial Neural Network in an electronic board capable of processing data provided by a sensorized laparoscopic tool.

The capabilities of several pattern recognition techniques present in literature, the Principal Component Analysis (PCA), a Multilayer Perceptron (MLP) and a Kohonen Self-Organising Map (KSOM) are investigated. The results are compared with that obtained psychophysically on five viscoelastic materials.

Index Terms—Minimally Invasive Surgery, tactile perception, haptic display, artificial neural networks.

I. INTRODUCTION

THE ability of humans to detect softness of different objects by tactual exploration is intimately related to both kinesthetic and cutaneous perception, and haptic displays should be designed so as to address such multimodal perceptual channel.

Kinesthetic information can be referred to geometric, kinetic and force data of the limbs, such as position, velocity and acceleration of joints, actuation forces, etc., which is mainly mediated by sensory receptors in the muscles, articular capsulae, and tendons. Cutaneous information is provided by pressure and indentation distributions, both in space (on the skin) and in time, and is mediated by mechanoreceptors innervating the derma and epidermis of the fingerpads.

Information synergistically conveyed by the kinesthetic and tactile channels, and elicited by the central nervous systems, forms the object of 'haptic', or touch-related, sciences and technologies [18].

On the other terms, the high degree of dexterity which characterizes grasping and manipulative functions in humans, and the sophisticated capability of recognizing the features of an object are the result of a powerful sensory-motor integration which fully exploits the wealth of information provided by the cutaneous and kinaesthetic neural afferent systems.

Moreover an unconstrained hand during manipulation allows for better softness discrimination and removes perceptual artifacts generated by wearing heavy and/or cumbersome exoskeletons or by dealing with rigid constraints.

New generation of haptic interfaces are playing an important role in improving performance and extend functionalities of Tele-surgery, virtual surgery, Minimally Invasive Surgery (MIS).

In MIS the role of advanced technology for providing tactile feedback is perhaps more important than in other field.

In a laparoscopic operation, the surgeon operates through small openings in the abdominal wall of the patient. One of the openings is used to introduce a miniature camera, including a light source. Camera images are shown on a monitor while the camera is guided by an expert operator. The haptic transmission from the handle to the tip is actuated by means of levers. Nevertheless this promising technique still suffers from some important limitations. The most important one is the surgeon loosing of both tactile and kinesthetic sensibility due to friction and backlash present in the transmission mechanism of the elongated tools. The surgeon may manipulate patient viscera only using long tools, observing actions and movements on a monitor visualizing abdominal environment [2]. He can not either touch or see viscera directly and that restricts the application of this technique only to some specific fields, such as resection and removal of organs. Diminished tactile sensibility causes a loss of surgeon palpation evaluation capability, in particular with regard to tissue compliance and viscosity. These effects are so important that it becomes very difficult to discriminate the anatomical nature of the manipulated tissue. In particular this is constrincting if the camera images are not sufficient or absent. In such cases, losses on perception may cause important lesions.

A better sensibility may diminish the incidence of these events and optimize grasping force during manipulation.

Moreover, at the present state of the art and technology most remote haptic systems implement only visual feedback [21] and stimulate kinesthetic channel. Indeed, the parts of a haptic system that refer to cutaneous tactile information are the most difficult to realize.

On the other hand, in the psychophysical literature, it has been firmly established by the fundamental work of [14], [17] that loss of the tactile channel reduces human capability of

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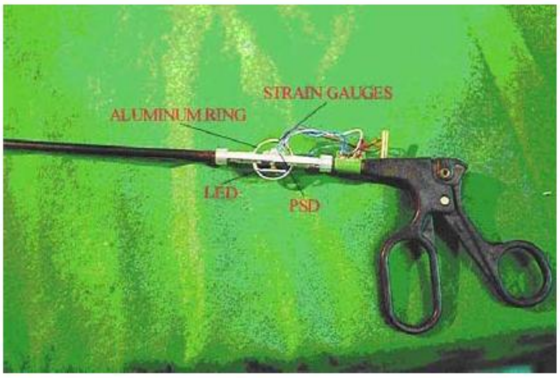

Fig. 1. Sensorized laparoscopic tool

haptic discrimination dramatically.

In a previous work authors designed and implemented miniaturized force and position sensing devices in a laparoscopic surgery tool, whose measurements are used to elicit information about the rheological properties of manipulated tissues [1], [9].

The system allows a deterministic recognition of different materials having different stress-strain characteristics.

Unfortunately the system cannot identify materials having similar compliance. Moreover the operator, during tactile tasks, imposes an uncertain deformation on the specimen.

The approach have been improved by equipping the laparoscopic system with a new embedded electronic system capable to process and to acquire the tactile signals (force and/or displacement) in real time. The signals acquired can be suitably conditioned and processed from a proper Neural Network.

This application is one of the most promising for the new technologies [4].

The raw signals obtained from the tool are pre-processed in order to extract relevant features, such as force applied on the specimens.

Features vectors constitute the dataset for the pattern recognition processes. The pattern recognition was performed by an Artificial Neural Network. The results were processed with the performances of the Principal Component Analysis (PCA), a Multilayer Perceptron (MLP) and a Kohonen Self-Organising Map (KSOM) [3], [14], [15], [17], [5]. Each network was tested with the same datasets coming from laparoscopic sensors. Data were acquired during the analysis of five different samples.

II. HARDWARE AND SOFTWARE

A. *Hardware display*

In order to overcome the limitation of loss of tactile perception in Minimally Invasive Surgery and provide surgeons with the flexibility of traditional open surgery while operating through tiny apertures, the elongated tool can be suitably sensorized and actuated. The sensorization was implemented by using the approach previously proposed [22].

The commercial tool, laparoscopic pliers, has a very simple mechanical structure: a rigid beam is actuated by the handle fig.1. Its forward-backward movement closes and opens the jaws. Module sensor was positioned near the handle, to respect the simplicity of the original mechanism. The sensors were able to measure the applied force and the jaws position. The force sensor was realized applying two strain gauges to an aluminium ring: the ring deformation causes gauge resistance variation. The position sensor is realized using an optical position sensing device (PSD). It is a semiconductor optical device on which a light emitting diode (LED) is placed. Light injection causes the generation of two currents: the difference of these currents is a linear function of the LED position above the PSD. The LED is integral with the rigid beam which actuates the opening and closure of the jaws, hence its position is an indirect measure of the jaws angles (fig.1). These signals can be used to identify the rheology of the biological tissues manipulated by the sensorized laparoscopic tool and convey them to a suitable display which has to be controlled to replicate the rheology.

1) Embedded electronic system: In order to implement such system we equipped the laparoscopic sensorized tool with a customized electronic system based on microcontroller (μP) architecture. The prototypal electronic board is shown in fig.2. The data were gathered concerning the contact force measured by a strain gauges shown in fig.1 and the displacement measured by an optoelectronic sensor.

Specifically, the μP provided is a PSoC processor, $CY27443$ produced by Cypress MicroSystems. It is a controller programmed at 24 MHz. It is endowed with $16\,kb$ Rom and 256 bytes Ram for code and data storage. This microcontroller architecture guarantees limited computational power being part of a portable and compact system.

The flexibility of the $PSoC$, programmable arrays mixed analog and digital components, allows to realize a simple embedded system capable to acquire and to process, "in real time", the low-level signals derived from transducers and sensors of the sensorized laparoscopic system.

It provides a series of analog signals conditioning for the strain gauges and the resistive PSD sensors in our system.

These signals typically have wide dynamic range and low frequency. The proposed implementation provides two analog input channels of a low-level differential amplifier and a single-ended high-level programmable gain amplifier. Its analog output, externally provided, is also processed by an on-chip low-pass filter, which can be programmed and customized to allow adjustment of the filter cutoff and output update rate.

At the same time an ADC converter process all the available data to plot and to transmit through a standard serial RS-232 protocol. The low-level differential inputs ranges approximately from 0 to $100\,mV$ depending on the selected gain, can process signals designed to interface single-supply $5\,V$ or more. This solution allows to reduce a large part of supplementary hardware necessary for the signal conditioning.

In fig.3 is shown the sensorized laparoscopic equipped with the electronic board.

B. *Software architecture*

The software architecture has been designed as a hierarchical structure whose root is a manager module. Several

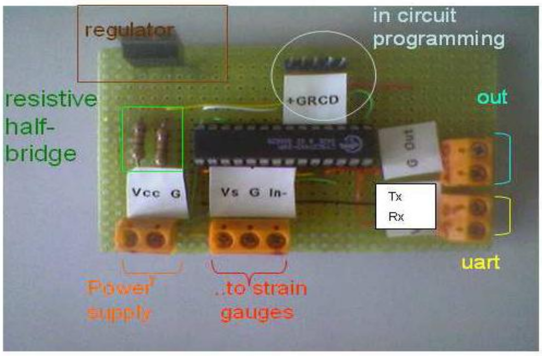

Fig. 2. Embedded electronic board

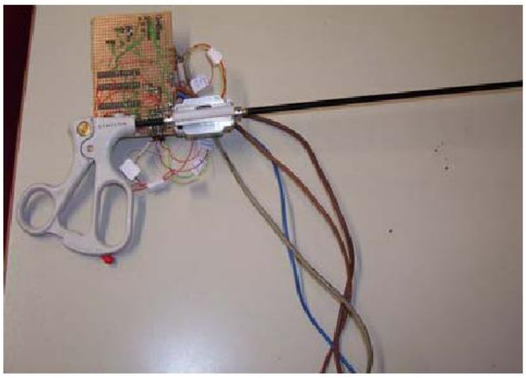

Fig. 3. Sensorized laparoscopic tool equipped with electronic board

application processes runs inside the core acting on dataset available into the framework I/O buffer. The framework is able to control all the modules of the elaboration chain, including analysis protocol management and interfaces. During a signal preprocessing stage various purposes are served, including baseline manipulation, compression, normalization and drift compensation. After, data are sent to a dimensionality reduction module in order to perform a feature extraction. Selected features are ready for analysis, classification and clustering tasks. A process devoted to data normalisation gets sensory data from the framework I/O interface. Normalised data are sent to a process devoted to feature extraction in order to build the dataset. Different pattern recognition processes described in the following sections performs the dataset classification task. A process devoted to the evaluation of the pattern recognition by means of cross-validation shows the classification results.

1) Features extraction: As regards the signals coming from laparoscopic system, in general let $x_n^k(t)$ the voltage versus time t of the *n-th* of N sensors as the response to the *k-th* of K samples. $x_n^k(t)$ signals were windowed and normalised over the time, i.e. the samplings were selected within the time interval $L = (t_1, t_2)$, resulting in the function $\overline{x_n^k}(t) = x_n^k(t)/(x_{min}^k - 1)$, where x_{min}^k represents the minimum value of $x_n^k(t)$ in the time interval L. A set of F features from the normalized signals was extracted; let $f_{n_1}^k, ..., f_{n_F}^k$ be the features. The features were: the energy, i.e. $E_n^k = \sum_{i \in L} \overline{x_n^k}(t)^2$; the absolute maximum value; the angular coefficient of the line connecting $\overline{x_n^k}(t_1)$ and $\overline{x_n^k}(t_{max})$; the angular coefficient of the line connecting $\overline{x_n^k}(t_{max})$ and $\overline{x_n^k}(t_2)$. Thus a dataset, where each response can be represented as a point in $\Re^{K \times F}$, were obtained. Features were normalized in the 0-1 interval.

III. PATTERN RECOGNITION PROCESSES

The concept of Artificial Neural Networks (ANNs) is to imitate the structure and workings of the human brain by means of mathematical models. ANNs possess an adaptable knowledge that is distributed over many neurons which can communicate (locally) with one another. The structure of the single neuron model, the network topology and the adaptation (learning rule) defines the ANN architecture. The neurons (processing units) are single elements and consist principally of a connection function, an input function, an activation (transfer) function, and an output function. A neuron receives signals via several input connections. These are weighted at the input to a neuron by the connection function. The weights define the coupling strength (synapses) of the respective connections and are established via a learning process, in the course of which they are modified according to given patterns and a learning rule. In the case of supervised learning, in addition to the input patterns, the desired corresponding output patterns are also presented to the network in the training phase. In the case of unsupervised learning, the network is required to find classification criteria for the input patterns independently. Stochastic learning methods employ random processes and probability distributions to minimize a suitably defined energy function of the network. A large number of neural models now exist, and each of these models is available in various forms. The Integrand-and-Fire (IF) neuron model [14] is often used in to create ANNs suitable for classification and forecast tasks. However when dealing with ANNs, as shown by Goodner et al. [8], the risk of data over-fitting can lead to counterfeit classifications. According to these authors the ratio between samples and variables should be greater than six in order to obtain reliable results.

A. *Principal Component Analysis (PCA)*

The principal component analysis (PCA) [3] is a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables, which are ordered by reducing variability, called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. The uncorrelated variables are linear combinations of the original variables, and the last of these variables can be removed with minimum loss of real data. Objectives of principal component analysis were to discover or to reduce the dimensionality of the data set and to identify new meaningful underlying variables. This mathematical method is based on the linear transformation of the different variables in principal components which are assembled in clusters.

B. Multi-Layer Perceptron (MLP)

The Multi-Layer Perceptron (MLP) [14] is a type of neural network, where the IF neuron model is adopted, allowing representation of the relations between input and output values. This type of network is trained with the help of a supervised learning method, i.e. input and output values are specified and the relations between them learnt. The neural network approximates every non-linear mapping of the form $y = f(x)$. Every data record consists of input data and the corresponding output data. The multilayer perceptron learns the input/output behavior of the system examined via a training data set.

In the training phase, for each data record, each activation function of the artificial neurons is calculated. The weight w_{ij} of a generic neuron i at the time T, for the input vector $\overline{f_n^k} = f_{n_1}^k, ..., f_{n_F}^k$ is modified on the basis of a well-established technique, the propagation of the resulting error between the input and the output values. The response of the MLP is a boolean vector; each element represents the activation function of an output neuron. After the training process, the performance of the classification task is commonly evaluated using the confusion matrix [15]. The generic element r_{ij} of the confusion matrix indicates how many times in percentage a pattern belonging to the class i was classified as belonging to the class j. A more diagonal confusion matrix corresponds to a higher degree of classification. Since each pattern may be confused with more than one pattern, the sum on each row and column may differ from the value of 100%. In order to check the generalization capability of the neural network, a cross-validation process is carried out.

C. Kohonen Self-Organizing Maps (KSOM)

A Kohonen Self-Organizing Map (KSOM) [17] maps the original space into a two-dimensional net of neurons in such a way that close neurons respond to similar signals, in order to solve classification tasks and to find structures in data. KSOMs are unsupervised neural networks, i.e. they exploit similarities of samples apart from the class which they belong to. In the unsupervised training process, the synaptic weight vectors of the artificial neurons of the KSOM are adapted by means of the training data set examples in such a way that the KSOM supplies as good a representation as possible of the training data set. The synaptic weight vector of an artificial neuron of a KSOM corresponds to the feature vector of an object in the feature space under study. In a KSOM, a *winner-takes-it-all* training algorithm is performed. In this work the IF neuron model was adopted. It is worth mentioning that the KSOM learns to discriminate in such environmental conditions; therefore, in the case of uncontrolled environmental parameters, a new data set for each measurement campaign is needed. For each input vector, the neuron that has the minimum distance $d = min_i \left\|\overline{f} - w_i\right\|$ from the input vector is the winning unit z. The weight w_{ij} of a generic neuron i at the time T, for the input vector $\overline{f_n^k} = f_{n_1}^k, ..., f_{n_F}^k$, is modified as follows [16]:

$$w_{ij}(T) = w_{ij}(T-1) + \alpha(T) r_{iz}(T) \left[\overline{f}_j(T) - w_{ij}(T-1)\right]$$

where:

Fig. 4. Blinded specimens used for the psychophysical test

- $\alpha(T) = f_\alpha \alpha(T-1)$, learning rate with a learning rate factor .
- $r_{iz}(T) = e^{-\frac{d^2}{\sigma^2}}$, feedback function of neuron i to the winning neuron z.
- $\sigma(T) = f_\sigma \sigma(T-1)$, learning radius with learning radius factor f_σ.

The response of the KSOM is a boolean vector; each element represents the activation function of a neuron. After the training process, a supervised labeling step is performed. Cluster labels are assigned to the individual artificial neurons. This is done via the interpretation of the content of the synaptic weight vectors (feature vectors) of the artificial neurons. Here the same label can be assigned to several artificial neurons so that cluster can be represented by several artificial neurons. After validation of the KSOM by examples of a test data set, performance of the classification task is commonly evaluated using the above mentioned confusion matrix. In order to check the generalization capability of the neural network, a cross-validation process is carried out.

IV. EXPERIMENTAL RESULTS

A. Physchophysical Analysis

We qualitatively performed a psychophysical experiment with the help of volunteers using the equipment previously described in our laboratory. The experiment consisted in measuring the capability of 15 volunteers to tactually recognize 5 different items. Recognition rates using direct exploration, and the laparoscopic tool have been compared.

We selected and collected 5 specimens with different softness corresponding to the contact of a rigid surface with surfaces of decreasing compliance (fig.4).

In particular two materials have similar compliance. Volunteers were asked to explore the materials directly by manual exploration with their index finger and with the laparoscopic tool. Indeed they were asked and to report on their associations with different items. In order to keep experimental conditions as constant as possible in experiments with different items and to focus the recognition task on tactile perception, we performed a blinded test.

Indeed, volunteers were asked to perform recognition of different items by exploration of the original items themselves, presented in random order. The results of the sets of data concern correct recognition of different levels of softness.

Results concerning correct recognition of different levels of softness during direct exploration through finger are reported in fig.5.

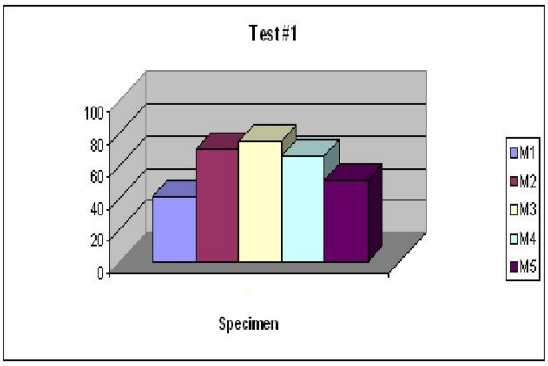

Fig. 5. Direct exploration: Percentage of successfull recognition of 5 different levels of softness

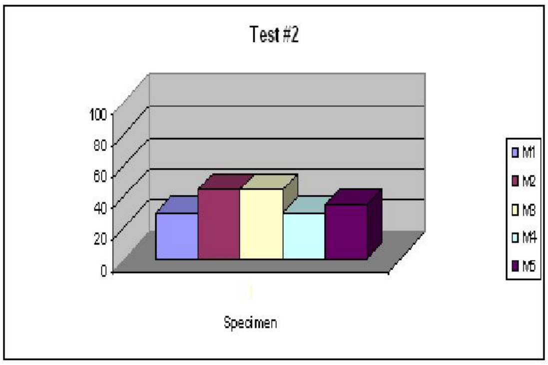

Fig. 6. Laparoscopic forceps: Percentage of successfull recognition of 5 different levels of softness
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The ability to recognize different object through palpation by a laparoscopic forceps is more scarce than direct exploration.

Results concerning correct recognition of different levels of softness through laparoscopic forceps are reported in fig.6.

To experimentally validate the psychophysical results we performed indentation tests on five specimens by means of a compressional indentor driven by an electromagnetic mini-shaker. The experiment consisted in applying on each specimen stepwise strains with increasing amplitude and acquiring relative stress relaxation curves. The strain imposed was 10%, while the application time (about 3 sec) is similar to the manual tactile interaction (fig.7).

TABLE I

CONFUSION MATRIX OBTAINED BY THE MULTI LAYER PERCPETRON USING THE TEST DATASET

	M1	M2	M3	M4	M5
M1	**100.0**	0.0	0.0	0.0	0.0
M2	0.0	**100.0**	0.0	0.0	0.0
M3	0.0	0.0	**100.0**	0.0	0.0
M4	0.0	0.0	33.3	**66.6**	0.0
M5	0.0	0.0	0.0	0.0	**100.0**

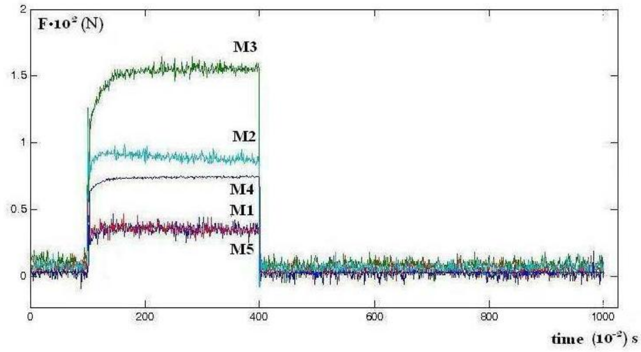

Fig. 7. Response of each specimen to stepwise strain of 10%

TABLE II

CONFUSION MATRIX OBTAINED BY THE KOHONEN MAP (7X7 NEURONS) OVER THE TEST DATASET

	M1	M2	M3	M4	M5
M1	**100.0**	0.0	0.0	0.0	0.0
M2	0.0	**100.0**	0.0	0.0	0.0
M3	0.0	0.0	**80.0**	20.0	0.0
M4	0.0	0.0	0.0	**100.0**	0.0
M5	0.0	0.0	0.0	0.0	**100.0**

B. Neural Network analysis

The signals provided by the laparoscopic sensorized system have been processed according to the block schema showed in fig.8. During the first stage, a Discrete Fourier Transformation (DFT) was applied to the input raw data acquired from the embedded electronic system. The magnitude of the power spectrum components in the range 1-5 Hz of the frequency domain were filtered and dispatched to a PCA-based pre-processing block. The first two principal components are shown in fig.9 as well as the clustering results.

The PCA analysis shows a high degree of classification with minor overlapping regions. A dataset containing the first two principal components was built and dispatched to the artificial neural network modules realised by means of a MLP and a KSOM. The dataset was splitted into a Training Set (TS) and a Validation Set (VS) following a two-folds cross validation approach. for the MLP, the dimension of the input layer is fixed to 2 neurons according to the size of the input data; the output layer is composed by 5 neurons according to the number of the classes to be recognised; the size of the hidden layer was fixed to 4 neurons; one bias neuron was connected to each neuron of the hidden and to the output layer. for the KSOM we fixed the parameters $\alpha(T) = 0.8$, $f_\alpha = 0.85$, $\sigma(0) = 5$, $f_\sigma = 0.9$. Both the modules were trained for 1500 epochs, which allows to obtain the best performance of the networks.

Results were summarized by means of the confusion ma-

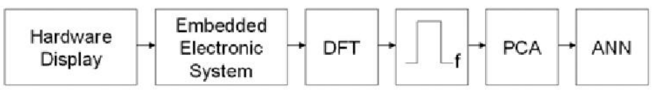

Fig. 8. Block schema of the processing architecture

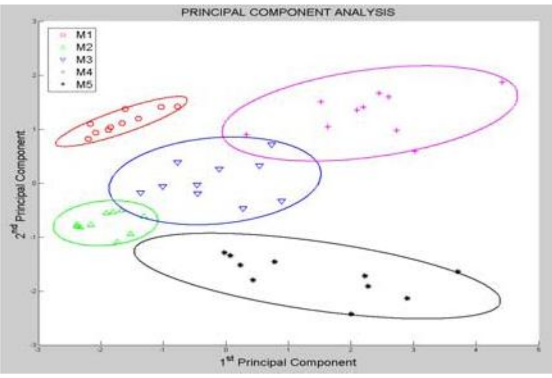

Fig. 9. Results obtained with PCA analysis

trix which shows the degree of the achieved classification. The confusion matrix possesses a number of both rows and columns equal to the number of classes to be recognized. The generic element $r(i,j)$ represents the degree of recognition of class i as belonging to class j. A more diagonal confusion matrix corresponds to a higher degree of classification.

The results reported in TABLE I and TABLE II are in agreement with the stress-strain data and the psychophysical test. The $M1$ and $M5$ materials appear really comparable in softness but both Networks approaches discriminate $M2$, $M3$ and $M4$ materials.

Indeed the artificial neural network approach allows to discriminate differences in compliance more finely than the laparoscopic forceps display in agreement with psychophysical predictions when the operator manipulates directly the objets hand.

The analysis of the variance of these data considered two treatments, manual and kinesthetic displays exploration,shows that the Neural Network approach increases the haptic perception in comparison with a simple kinaesthetic display.

V. CONCLUSIONS

In this paper we proposed a new approach of neural networks for tactile applications. As described in addition to kinaesthetic channels cutaneous information should be conveyed to the operator and we proposed a solution where force-position feedback is enriched by additional cutaneous sensing cues to augment haptic perception. Indeed, it has been described in the psychophysical literature that the ability to discriminate softness by touch is intimately related to both kinesthetic and cutaneous tactile information in humans. In replicating touch with remote haptic devices, there are serious technological difficulties in building devices for sensing and displaying fine tactile information.

The experiments aimed at assessing the capability of subjects to discriminate between different virtual objects in terms of softness using a laparoscopic sensorized tool in comparison with direct exploration.

We selected five specimens having similar softness in order to thoroughly test the ability of subjects of recognizing different materials through palpation with the laparoscopic tool without sensors information and the results were scarse.

To enhance recognition we proposed an innovative solution where an Artificial Neural Network is implemented in an electronic device that, integrated on the sensorized tool, process automatically the data provided from the sensors.

The results, supported by psychophysical test and experimental data, are very encouraging and confirm that the tactile perception is significantly augmented.

In future work, due the flexibility of the device, a real time Artificial Network could been implemented in hardware increasing the number of trials and the numerical resolution.

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