Touch-based Admittance Control of a Robotic Arm using Neural Learning of an Artificial Skin

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Abstract— **Touch perception is an important sense to model in humanoid robots to interact physically and socially with humans. We present a neural controller that can adapt the compliance of the robot arm in four directions using as input the tactile information from an artificial skin and as output the estimated torque for admittance control-loop reference. This adaption is done in a self-organized fashion with a neural system that learns first the topology of the tactile map when we touch it and associates a torque vector to move the arm in the corresponding direction. The artificial skin is based on a large area piezoresistive tactile device (ungridded) that changes its electrical properties in the presence of the contact. Our results show the self-calibration of a robotic arm (2 degrees of freedom) controlled in the four directions and derived combination vectors, by the soft touch on all the tactile surface, even when the torque is not detectable (force applied near the joint). The neural system associates each tactile receptive field with one direction and the correct force. We show that the tactile-motor learning gives better interactive experiments than the admittance control of the robotic arm only. Our method can be used in the future for humanoid adaptive interaction with a human partner.**

I. INTRODUCTION

The sense of touch is a powerful feature to endow humanoid robots in order to interact closely with humans and to collaborate with them. According to Albu-Schffer [1], robots without the sense of touch will remain far from the performance of human beings. For instance, it can be interesting to have robots capable of using their tactile information to self-calibrate the physical limits of their body [2], [3], [4], to prevent the risks of causing of its physical damage by an obstacle [5], [6] or of causing bodily harm to human using the safety-rated information on contact [7]. It is also advantageous to have robots that comply to an imposed direction that a person wants the robot to follow. Moreover, tactile modality can contribute not only for general robotic services [8] but also for careful interactions during robot-assisted plays in the context of autism therapy [9]. Tactile modality also helps robots to improve motor coordination behaviors during interaction with humans as well as the person own's perception of the robot presence and action [10]. However, it can be difficult for robot designers to model correctly the interactive control since the robot geometry has to be known in advance as well as the type of physical interactions the robot will have with a person.

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The measures of the joint torques are important to build the control loops for robot interaction with a human. The joint torque is usually measured by pervasive joint built sensor contains the information about applied torque by the electrical drive and the torque caused by the physical interaction with a human or robot environment. Thus, adding the humans interaction complicates the organization of the interaction control loop. It is advantageous to have information about the applied force and its direction, which can be successfully implemented by introducing admittance loop, that will handle the measured force on the entire surface of skin equipped robot link. To our knowledge, only Calandra *et al.* [11] proposed the demonstration of how joint torques can be learned on a humanoid robot *iCub*, equipped with tactile and force/torque sensors in the presence of contacts.

Machine learning techniques, instead, can help to have an adaptive control of the robot limbs by estimating the spatial location and the amplitude of the applied force. To this purpose, we propose to use a neural architecture that learns the admittance control of a robotic arm covered with a tactile skin to orient it safely. We use two artificial neural networks that learn in an unsupervised manner *(1)* the topological configuration of the tactile device not known in advance and *(2)* the force compliance to apply when a tactile signal has been detected. The first neural network corresponds to the Kohonen self-organizing map (SOM) with neurons that learn the topology of the un-gridded tactile device; each tactile neuron will learn a specific receptive field [12]. The second neural network, based on the neuron model of the Perceptron, will learn to estimate from the position on the tactile surface and from the pressure applied to it the actual compliant forces to apply to control our two degrees of freedom robotic arm in the four directions. Our main goal is to achieve the development of multimodal body representations, tactile and proprioceptive, in humanoid robots for physical interactions with persons and environment. It is the first step to integrating other modalities like vision and more degrees of freedom.

The paper is organized as follows. Section II presents our experimental setup with our robotic arm and the tactile device used in our experiments. The Methods section presents the equations of the admittance control used to control the arm and the definition of the neural networks implemented to locate the tactile force on the arm and to estimate the counter-force to apply on it. Section III consists of three experiments. The first step in our experimental study is to identify the joint torques during physical contact with robot link. The second experiment serves to learn the tactile map on the arm in a self-organized manner by touching the robot with a SOM. The third experiment serves to learn the complete sensorimotor loop with a second neural network that associates tactile information with its corresponding proprioception. The results are the dynamical control of the robotic arm by a person in the four directions and their combinatory vectors, on all its surface, even with light touches.

II. MATERIALS

A. Robotic arm

We use robotic arm Jaco from Kinova company with seven degrees of freedom (DoF). Each axis is controlled independently and driven by a brushless DC motor and a gear system. The firmware of the robot arm Jaco provides Cartesian or angular trajectory control measuring the angular positions and calculating the errors every $10ms$. In our work, we use only the angular position control mode. The speed of each motor is controlled by a high-level controller in the arm and, therefore, cannot be controlled directly.

B. 'Artificial skin' tactile sensor

In order to design the artificial skin for a robot, we introduced a low-cost system based on the Electrical Impedance Tomography (EIT) method for data acquisition from the conductive fabric [12]. In our experiments, we use the conductive material (Velostat film (3M)) with the volume resistivity around $500\,\Omega \cdot cm^3$. It is made of opaque, volume-conductive, carbon impregnated polyolefin whose resistance decreases when pressured. Sixteen electrodes are attached uniformly along the perimeter of the rectangular conductive layer of dimension $250 \times 320\,mm$. The EIT is a non-invasive technique particularly used in medical imaging to measure iteratively the voltages resulting from rotating injection of small electrical currents through electrodes placed on the circumference of the investigated object. In order to estimate the conductivity and permittivity distribution in an electrically conductive material, we applied the neighboring method which is one of the popular EIT technique [13]. A simple multiplexer/demultiplexer circuit is used to retrieve the resistance field from the pairwise electrodes injecting the direct current (200μA) and the electrodes measuring the output voltage from the conductive fabric, see Fig. 1 a. A microcontroller governs the injection of the current and measurement of the voltage output patterns and performs its 12-bit analog-digital conversion. The spatial patterns of the tactile contact can be acquired and localized in real-time (40Hz). We show in Fig. 1 b the Jaco Arm with one section covered by an artificial skin. This section (forearm-like) was chosen for its convenience and usability in physical human-robot ineraction. On the long term, we plan to cover all the arm with the skin.

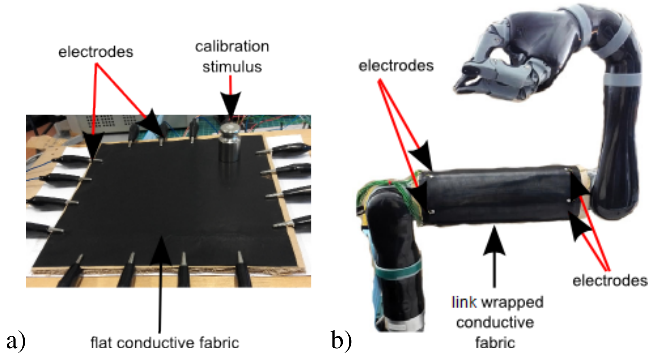


Fig. 1. Jaco Arm whose only one link is covered with skin: a - flat conductive fabric with the electrodes and calibration stimulus on it; b- robot link wrapped in the conductive fabric

III. METHODS

In control theory, interaction control is the general approach used to regulate the robot's dynamic behavior with the environment [14], for which the most common forms are to regulate the manipulators impedance or admittance. The admittance controller accepts a force as input and reacts with a displacement that is a unique solution for position guided robot control system. Admittance control can be combined with other techniques to improve the control under real-world conditions of uncertainty and noise [15].

In this paper, we present two admittance controllers: *(1)* a classical controller using measured joint torques and *(2)* a neural controller using perceptron predicted joint torques associated with tactile patterns from the artificial skin.

A. Admittance control using measured joint torque

As we mentioned before the firmware of the robot arm Jaco provides angular trajectory control i.e. position control loop, see Fig. 2 and the robot behaves like a mechanical impedance [16]. For this reason, the interaction controller is designed to be a mechanical admittance.

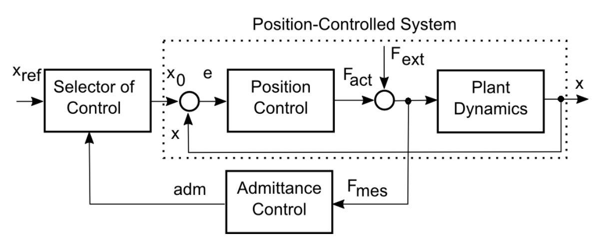


Fig. 2. Block scheme of a structure to control a robot joint with admittance control (inspired by [16])

Let's consider a single degree-of-freedom system in which a mass interacts with an environment. Let m and x be the generalized inertia and displacement of the mass, respectively, and let F and F_{ext} be the control force and external force of the environment acting on the mass. The equation of motion of the mass can be written as follows:

$$m\ddot{x} = F + F_{ext} \tag{1}$$

The control objective for Impedance and Admittance Control consists in of designing the control force F_{act} that provides a given relationship between the external force F_{ext} and the deviation $e = (x - x_0)$ based on a desired equilibrium trajectory x_0. Generally, a linear second-order relationship is considered:

$$M_d \ddot{e} + D_d \dot{e} + K_d e = F_{ext} \tag{2}$$

where the positive constants M_d, K_d and D_d are the desired or virtual inertia, the stiffness and the damping, respectively.

While the interaction control allows producing a general behavior, in many robot applications the restriction of the desired behavior to the linear is sufficient [16].

B. Admittance control using neural learning and an artificial skin

In this section, we propose a neural architecture for admittance control of the Kinova arm (2 DoF) using a self-organizing map (SOM) and the perceptron neurons, see Fig. 3. We use the SOM to reconstruct the spatial location of a contact point on an artificial skin from the distribution of the resistance density. The voltage signals from the tactile device (208 values) are used for the learning of the self-organizing map (unsupervised learning, see section III-B.1).

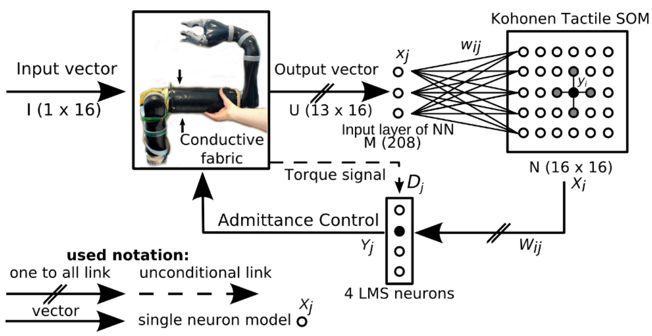


Fig. 3. Neural architecture for admittance control of a robotic arm using an artificial skin based on a Kohonen map to categorize the tactile patterns into a spatial topology. This tactile SOM is then used to feed a LMS neuron to predict the torque signal of the robot arm based on the tactile location of an applied force when we touch the tactile surface.

In addition to the SOM that encodes tactile information inputs, we use a Least Mean Square (LMS) neural algorithm, which is a Perceptron without softmax output filtering. The LMS predicts the two joint torques depending on the spatial location of a contact point provided by the tactile map. During learning stage, the measured torques (4 values) are used as an unconditional stimulus and the SOM output as conditional stimulus (supervised learning, see section III-B.2). The predicted torque values (LMS output) serve for the admittance control. The SOM and perceptron neural networks have respectively 16×16 neurons and only 4 neurons for the four directions.

1) Tactile neural network: SOMs consist of elements called 'nodes' or neurons connected topologically, see Fig. 3. Each node $i \in N$, with N the dimension of the neural network, is connected to the input vector $j \in M$, with M the dimension of the input vector, via synapses, a vector of weights w_{ij} with $i, j \in N \times M$ and each node has a local influence on its direct neighbours. Learning takes place iteratively as follows. At each cycle, the distance d_i between all weights and the input vector is computed; see Eq. (3). The neuron with the smallest distance is called the winning neuron. Its weights and those of its direct neighbors are modified to reduce the distance to the input vector; see Eq. (4), also, their output is computed as the inverse of the distance; see Eq. (5). The position of the neurons on a 2-dimensional grid determines the Kohonen map topology.

During the training stage, a distance d (usually an Euclidian or L1 distance) between the input vector x and the neurons' weights w is associated with each output neuron y as in Eq. (3):

$$d_i = \sqrt{\sum_{j=1}^{M} (x_j - w_{ij})^2} \tag{3}$$

where x_j is the j-th component of the input vector x and M is the dimension of the input vector x; d_i is the distance associated with i-th neuron within a population of N neurons. The smaller d is, the closer is the receptive field of the neuron to that input vector. The output neuron with the smallest distance $d_i^* = \ argmin(d_i)$ is written i^* and is then considered as the winner neuron. Its weights are updated following Eq. (4) as well as the neurons within a certain neighborhood radius h_{ci^*} [17]:

$$w_{ij}(t+1) = w_{ij}(t) + \varepsilon h_{ci}(x_j(t) - w_{ij}(t)) \tag{4}$$

where ε is the learning rate, for iteration time t.

The Kohonen learning rule Eq. (4) changes the weights of the winner neuron and its neighbors [18], [19], [20], which get closer to the input vector and cause the decreasing of the distance to it. As a result, the Kohonen network learns to classify topologically similar vectors. The output value y_i of the neuron i is the inverse of the distance d_i measured in Eq. (5):

$$y_i = \frac{1}{1 + d_i} \tag{5}$$

2) Tactile-motor neural architecture: The Least Mean Square (LMS) neural network is used in conditional learning paradigms. It learns to predict a desired output derived from an unconditionnal stimulus and associate this output with a conditionnel stimulus. The group of the neurons uses a modified Widrow-Hoff learning rule [21] described in Eq. (6). The output of each neuron is computed as described in Eq. (7).

$$\frac{dW_{i,j}}{dt} = \mu(t) \cdot (D_j - Y_j) \tag{6}$$

where D_j is the desired activity of the neuron j (i.e., the torque), $\mu(t)$ is the learning rate, $W_{i,j}$ the weights and Y_j the predicted output. The equation to compute the neural activity is:

$$Y_j(t) = f(\sum W_{i,j} \cdot X_i) \tag{7}$$

where X_i is the vector input (i.e., the tactile neurons of the SOM) and f the unitary function. This architecture is equivalent to a Pavlovian conditioning or reinforcement learning, which associates the prediction of one articular couple with the activity of the tactile map.

IV. EXPERIMENTS

A. Experiment 1 – Interaction control for Jaco manipulator

The goal of this experiment is to realize a classical admittance control using measured joint torque, that presented in III-A. This experiment consists of two parts.

First part aims to estimate the response of the position-driven robot arm to a series of unknown external force perturbations exerted by a human (in the horizontal plane) and to verify the usability of the algorithm [22] that allows robot control without knowledge of any measures of force or torque. The results are shown in Fig. 4. The force F_{ext} applied at the extremity of the robot link ($l = 0.41m$) by a human, and its value reaches $40N$. There is a delay $\Delta t = 1s$ between the occurrence of the disturbance and the response of the system to this disturbance until external force; its value reaches $13,8N$ (in both directions) before joint torque starts to change. Position-controlled joint keeps the reference Θ_{ref} and the interactional perturbation is rejected. The joint remains stiff, and there is a negligible displacement $\Theta_{mes} = 1deg$. Proposed in [22] adaptive algorithm cannot be implemented for Jaco robotic arm due to the high joint stiffness. This is the reason why we implement the admittance control loop in this work.

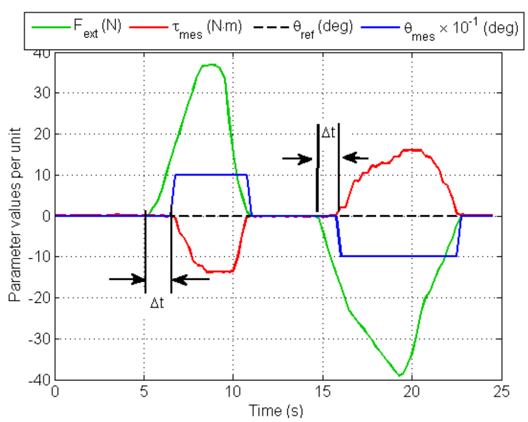


Fig. 4. Dependences of position controlled joint angle variation $\theta_{mes}(t)$ (blue line), the reference $\theta_d(t)$ (black line) and joint torque $\tau_i(t)$ (red line) in case of the external force perturbation F_{ext} (green line).

The second part of this experiment aims to implement an admittance control in order to adjust the behavior of the manipulator's joint to an external force caused by a physical interaction with a human. Fig. 5 shows the joint parameters of the admittance controller during two phases of interaction. The actual joint position is the desired position, and there is no joint torque caused by physical interaction on the time range 0 to $4.1s$. Here, the system is in equilibrium state until a physical contact occurs and that an induced torque acts on the robot's joint. During first period 4.1 to $11.4s$, the human pushes the robot link with increasing force F_{ext} that the mean is $30N$. The admittance controller provides the new reference for the position controller, after a time lag of $\Delta t = 1s$ external force $13.8N$ and the robot starts to move in the same direction with the applied force. After $t = 11.1s$,

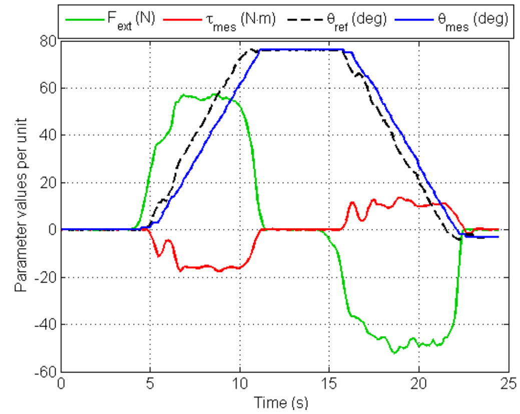


Fig. 5. Dependences of admittance controlled joint angle variation $\theta_{mes}(t)$ (blue line), the reference $\theta_d(t)$ (black line) and joint torque $\tau_i(t)$ (red line) in case of the external force perturbation F_{ext} (green line).

there is no joint motion because the physical interaction is over. During second period 14.3 to $22.4s$, the human pushes again the robot link in another direction with increasing force F_{ext} that the mean is $34N$. Joint reacts after a time lag of $\Delta t = 1s$ on the external force $13.8N$, and the robot starts to move in the same direction with the applied force.

B. Experiment 2 – Learning stage on tactile neural network self-organization

In previous work [23], we conducted experiments with a self-organizing neural network which is adapted to the structure of a flat round-shaped tactile sheet. In this paper, we use a Kohonen map to learn the topology of the square-shaped artificial skin curved on the Kinova arm (2 DoF). One of the advantages of the Kohonen map is that it can adapt dynamically to the topology of the incoming structure of a tactile sheet and spatial resolution of the input tactile device. Moreover, the spatial location of a contact point cannot be determined using the parametric methods if the shape of the tactile surface is unknown or modified.

The learning stage is done as follows. We touch the tactile sheet on all its surface and we retrieve the voltage signals from the tactile device (208 values) for the learning of the self-organizing map and the reconstruction of the spatial localisation of a contact point. At the same time, we collect the torque which will be used as the conditional stimulus for LMS learning, see Fig. 3.

To illustrate the results of a reconstruction of the spatial localisation of a contact point, we display in Fig. 6 the activity of the SOM after learning (right column) and for five different locations around the arm (left column). As observed in a previous work [23], the Kohonen map learns the topological configuration of the tactile sheet without giving its XY coordinates. The resolution here is just 16×16 although, it is possible to go higher. When we go from one side of the tactile map to the other, the winner neuron and its neighbors in red follows the motion displacement of the human partner. Once the tactile neurons have learned their receptive fields, the second neural network can use this

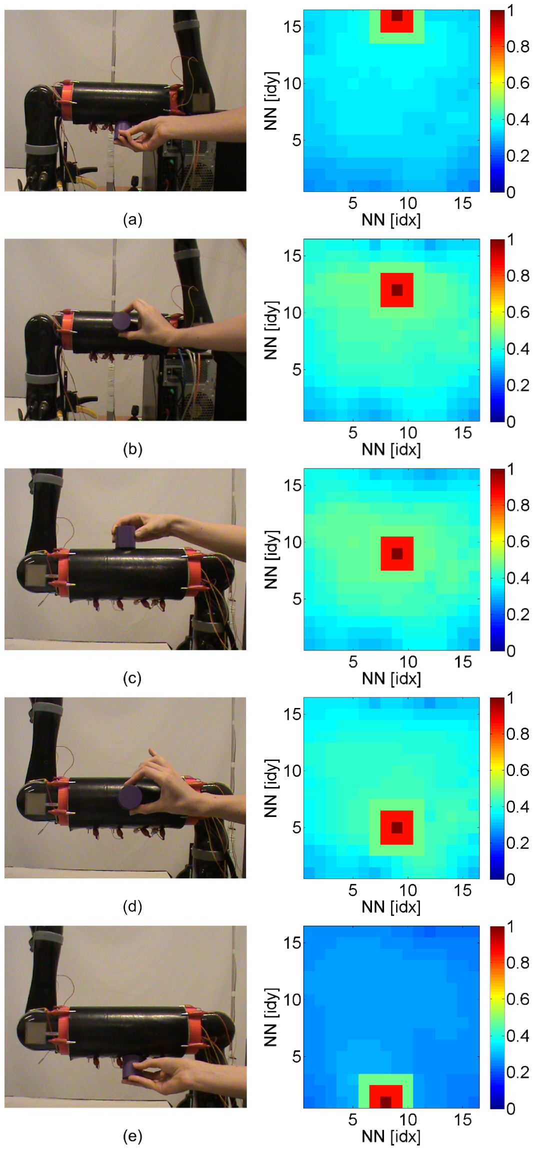


Fig. 6. Five receptive fields of the SOM during contact touch on five different locations; resp. lower part, lower-middle, middle, middle-upper and upper part. The winning neuron of the SOM follows well each receptive field on the tactile surface; the integration is done by categorizing the electrical field for the various locations.

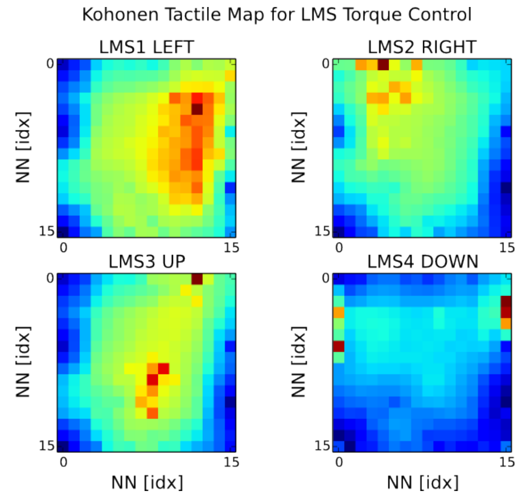


Fig. 7. Tactile receptive fields of the LMS Torque neurons. Projection of the averaged tactile map activity when the LMS Torque neurons fire. The LMS neurons have learned the spatial distribution of their force direction depending on the tactile information on the SOM.

information for the admittance control.

C. Experiment 3 – Experiment of learning admittance control for a skin-covered articulation

We present in this experiment the control of the robotic arm using the tactile SOM. Four LMS perceptron-like neurons learn the association between the tactile information from the Kohonen map and the measured joints torque. Depending on the position of the physical contact with the tactile sensor, each LMS neuron estimates the corresponding value and direction of the torque on the two axes. We plot in Fig. 7 the average activity of the tactile map for each LMS neuron, which also corresponds to their respective receptive fields.

The tactile receptive fields of LMS 1, corresponding to the torque control in the left direction, has a large pattern anisotropic on the Y axis on a right-side column. The receptive field of LMS 2, corresponding to the torque control on the right direction, has a pattern centered more on the left-side. Those of LMS 3 and LMS 4, respectively up and down directions, are more sensitive to tactile activity in the middle region and on the external sides where the tactile sheet is wrapped. From this figure, each LMS neuron has learned a distinct spatial distribution of the torque and direction depending on the tactile information on the SOM. The four LMS neurons have learned a body map that links orientation with tactile signals.

After convergence, the LMS neurons are capable of estimating the torque value from the tactile input to implement the admittance control loop for the robotic arm without real torques measures. The direction of motion of robot arm defines by the maximal value of LMS neurons activations. We plot in Fig. 8 the estimated torque value (solid blue line) by the four LMS neurons with the corresponding measured torque value (dotted red line) – the output and input of LMS, respectively. The subplots correspond to four possible motion directions (right, left, up and down) that linked with the activity of specific LMS neuron respectively to a number of the subplot.

The first time range from 0 to $2s$ has a significant variance estimated and real values of the joints torques that indicate physical contact on the robot link. The applied force is not perpendicular to any robot axis and is decomposed into two torques (left and down) due coupling effects among rotational joints. We can observe that only the fourth neuron is active (red dotted line) it means that the contact is detected on the bottom of the tactile sensor, thus, the arm moves up. The second time range from 2 to $8s$ the robot arm moves to the right (contact is detected on the left side of the tactile sensor). From $6s$ has a small activity of the third neuron, it

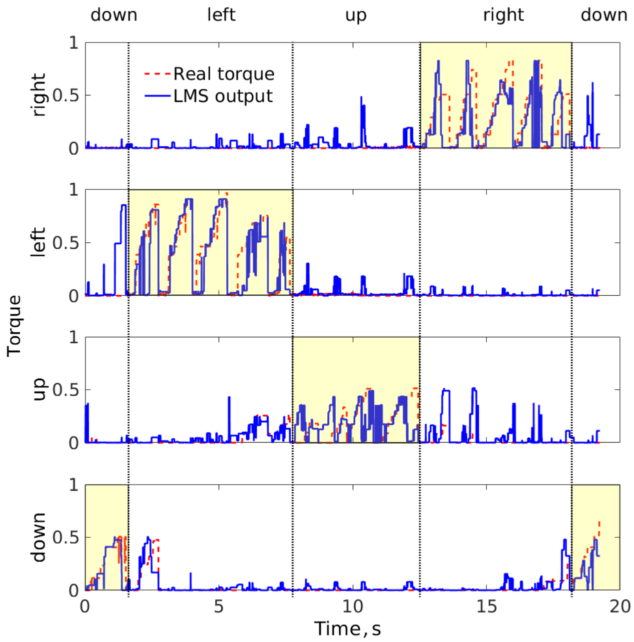
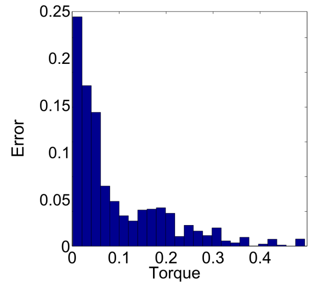
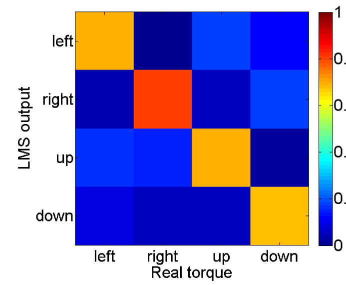


Fig. 8. Estimation of the torque of 2-DoF robot arm by the LMS neurons based on tactile activity in the Kohonen map. The obtained results are shown for all possible contact points if we move along a link arm and then, gradually move across the full surface of the artificial skin. The positive values of first and second joint torque are represented by the activity in the first and the third LMS neurons. The negative values of the joints torques presented as positives in the second and fourth neurons. Furthermore, the torque values are normalized between 0 and 1 with the scaling factor of $15\,N \cdot m$.



(a) LMS Torque error



(b) LMS Torque direction error

Fig. 9. Error histograms of the torque estimated by LMS neurons (a) and for the four torque directions (b).

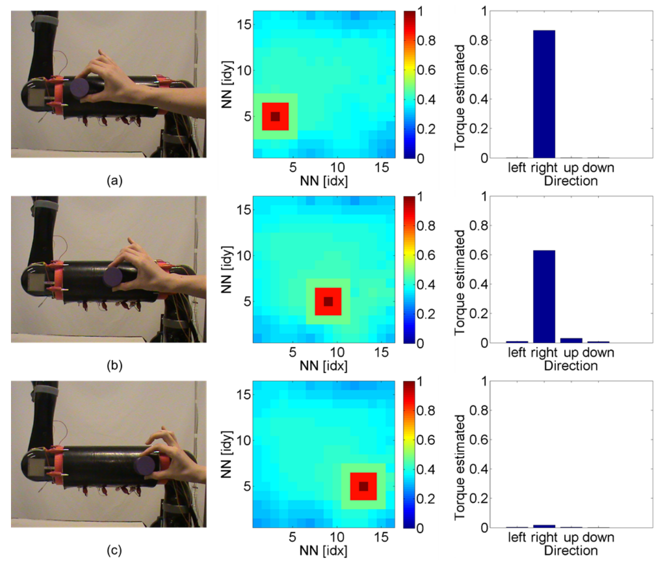


Fig. 10. Torque estimated by the LMS neurons based on the three spatial locations of the contact point along the robot link: away, in the middle and near the axis of joint. The value of applied forces is approximate equals during all tests. We can observe that the torque value decreases as we approach the joint axis.

means that the interactional force is no longer perpendicular to any robot axis. However, the robot continues to move the same direction because the value of torque predicted by the second neuron exceeds the value of the third neuron. The neural controller exhibits the same behavior of robot arm for other cases depicted in the Fig. 8.

Further, we plot in Fig. 9 the histogram of the torque estimation error for the four LMS neurons, and the histogram of the torque direction error; resp. a) and b). It is the difference between the measured torque which is the input of LMS and the estimated torque at the output of LMS. The graph in Fig. 9 a) shows that the LMS makes most of the error for small torque under $1\,N \cdot m$ whereas ' makes less error to estimate the higher torque value. This small error is explained partly by the resolution and the size of the SOM, as the SOM gets bigger, the categorization error will be reduced on the tactile surface.

We consider now the diagram of the torque direction error estimated by the LMS neurons on the robot arm, see Fig. 9 b). The diagram displays a strong correlation between the estimated direction of the torque by the four neurons and the real ground truth direction. The neurons are robust in 70 percent of the time.These results show that the LMS neurons re-transcribe better the directionality of the torque than the amplitude of the torque, and this for significant torque values rather than for small torques. Let us note that this error is much less than the minimum torque required ($1\,N \cdot m$) for the implementation of admittance control, see Fig. 5. Therefore, the neural architecture is capable of controlling the robot behavior using the tactile input with more sensitivity than the admittance control.

To proof the designed neural controller concept we created the experimental scenario. This scenario aimed the interaction along the joint axis at all surface of the skin sensor to verify the relationship between tactile information and estimated value of the torque and its direction. The analysis of experimental data (Fig. 10) shows that the LMS interpret correctly the tactile information from the Kohonen map. The amplitude of the joint torque changes according to the spatial the position of the contact point on the tactile sensor surface, i.e., decreases as it approaches the axis of the articulation. The observed behavior corresponds to physical phenomena.

V. DISCUSSION & CONCLUSIONS

We have presented an adaptive neural architecture that learns the admittance control of a robotic arm using tactile sensors for compliant interactions with human partners. We took the advantage of an artificial skin to localize the contact points where force is applied – when a person is interacting with the robot arm, and we made to learn a neural network to associate then the spatial location on the tactile surface with the corresponding torque received from the joints. After learning stage, the proposed neural controller is capable of estimating the torque value from the tactile input to implement the admittance control loop for the robotic arm without real torques measures. To the best of our knowledge, this is the first time demonstration of self-calibrating and controlling a robotic arm in a self-organized way using neural networks learning the torque model *and* its tactile body image. In that sense, it differs from the research done by [24].

The model is applied to a two degrees-of-freedom manipulator but can be easily extended to a humanoid's full body. At first, the voltage signals are learned through a Kohonen SOM that recreates the topology of the tactile sheet [23]. In second, this information is then used by four LMS neurons that simulate a torque vector in the four directions at the contact point. The advantages of using an artificial skin are to learn to control the robotic arm without using of joint axis mounted torque sensors, even with the soft touch or near the joint and to filter smoothly the admittance control of the small jerks and slits during the motion of the robot joint. The advantages of using neural networks are also to self-calibrate the robot arm in an unsupervised way and to generalize from it: for instance, a SOM can be used for multitouch and the Perceptrons can combine different torque vectors with respect to the contact points. By doing so, the neural networks can learn a multimodal body image useful for physical and social interactions [25]. In future works, we are planning to extend our results by adding vision and by adding more degrees of freedom to control the robot by touch and visually [26], [27], [28].

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