Autonomous Learning of Tactile-Motor Coordination in Robotics

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Abstract

The development of autonomous systems capable of executing intelligent exploratory procedures requires the understanding of the interactions between touch and motor control modalities. In robotic tactile perception this is the basic step toward the execution of highly sophisticated motor procedures such as grasping and manipulation.

In this paper the problem of autonomous learning of tactile-motor coordination is investigated in the case of a robotic system composed of a multi-functional tactile probe mounted on a robotic manipulator. A neural network architecture linking changes in the sensed tactile pattern with the motor action performed is described, and experimental results are analyzed. The generation of motor control procedures for actively estimating surface curvature is considered as an example of application of the proposed approach.

1. Introduction

During the last two decades research on artificial tactile perception has mainly focused on the design and the development of new sensors, and a large number of technologies has been applied to the detection of contact information [1] [2] [3]. Thanks to these efforts a wide range of sensors have been developed, most of them able to catch a specific aspect of the available tactile information, such as normal force, shear, vibrations, etc. [4] [5]. However, the problem of interpreting tactile signals and of using contact information for properly interacting with the surrounding environment has not been seriously considered until recent years [6] [7], mainly due to the fact that most of the developed sensors were, and still are, far from producing accurate and reliable measurements. Thus, not much work has been carried out so far on basic problems of tactile perception, that is the integration into a unitary perceptual frame of the tactile information acquired with different sensors [8] [9], and, in particular, on the integration of tactile sensations and motor actions [10] [11] [12] [13] [14].

Motor control plays a major role in tactile perception, since touch is an intrinsicly active sensorial modality. In general, in order to volountarily gather tactile information the sensor must be brought in contact with the explored surface and contact position and forces must be properly adjusted. The use of touch as a source of information for exploring unknown environment cannot be carried out without taking into account the physical structure and the posture of the system. Only by means of such geometrical relationships the spatial location of a stimulus can be determined and the spatial structures necessary for building representations of the environment can be identified. The use of active interaction with the scene has recently received further attention after the observation [7] that some tactile low-level problems are ill-posed in the sense of Hadamard [15] [16]. In fact, as research in the field of visual perception has shown, underconstrained problems can be transformed in well-posed and stable ones if additional information is gathered by means of an active interaction with the environment [17].

The development of autonomous systems capable of executing intelligent exploratory movements requires the understanding of the interactions between touch and motor control modalities. Actions such as increasing the grasping strength if an object slips away, or finely adjusting finger positions and pressures during a grip, cannot be performed if a strict relationship between tactile and motor modalities has not been estabilished first . Such link would allow to estabilish an effective physical and functional organization of the system and it is the basic skill that an intelligent system should posses in order to be able to perceive the environment. It is our every-day experience that humans develop accurate sensory-motor coordination adaptable to functional and physical changes of the body such as variations in the power of the muscles and in the dimensions of the limbs and organs. Neurophysiological and psychological evidences account for the development of this coordination by means of learning [18]. For example, experiments with the kitten have shown that visually-guided behavior emerges only if sensorial changes in the environment are systematically related to the motor actions performed [19].

Autonomous robots have to produce similar adaptive coordinations if they are to be effective in unknown environments. They should be able to adapt their behaviour to unpredictable modifications of their own structure due to aging and damages. Difficulties in modelling mathematically physical systems, as well as the learning requirements, account for the use of neural networks paradigms for adaptive control.

In our laboratory, we are pursuing an approach to tactile perception in robotics which is strongly inspired by the biological world both in terms of sensor configuration and of tactile signal processing. According to such a guiding philosophy we developed a composite robotic fingerpad including different kinds of tactile sensors, and we focused on the problem of building adaptive tactile-motor coordination for autonomous robotics systems. To the best of our knowledge, the work described in this paper is the first attempt to develop adaptive tactile-motor coordination in robots.

The paper is organized as follows: next section describes the robotic fingerpad enphasizing the analogies with human finger; section 3 focuses on the development of tactile-motor coordination in the case of the robotic finger; in section 4 an example of how the developed coordination can be applied to the execution of intelligent exploratory procedures, such as the active estimation of surface curvature, is described and experimental results are analyzed; finally, in section 5, conclusions are drawn.

2. An anthropomorphic finger for investigating robotic tactile perception

The human skin includes a large number of tactile receptors which differ substantially one from the other both from an anatomical and a functional point of view. During tactile stimulation, corpuscles with different receptive fields width and frequency sensitivity range are activated by different features of the tactile stimuli, so that the contact information is intrinsically coded into a distributed representation. Research in neurophysiology and psychophysics has elucidated that such a parallel organization of the tactile perceptual system is crucial for the powerful human capabilities, and a functional modular organization reflecting the anatomical one has been found. In particular, it has been proposed [20] that the sub-system composed of slowly adapting receptors with narrow receptive field (*SAI system*), such as the Merkel corpuscles, is the primary spatial system and is responsible for tactual form and roughness perception when the fingers contact a surface directly, and also for the perception of external events through the distribution of forces across the skin surface. Also, evidence exists that Pacinian corpuscles (*RAII system*) are involved in the perception of external events that are manifested through transmitted high frequency vibrations, and that Merkel receptors (*RAI system*) are responsible for the detection and representation of localized movements between skin and surface, as well as for surface form and texture detection, when surface variations are too small to engage the SAI system.

A robotic tactile probe (a robotic fingerpad) which emulates the organization of the human tactile system has been developed in our laboratory as a basic tool for investigating artificial tactile perception [21] [22] [23]. The present configuration of the fingerpad includes three kinds of tactile sensors: piezoresistive, piezoelectric and thermal sensors. Thanks to their intrinsic properties, piezoresistive and piezoelectric sensors are well suited for mimicking the functionality of SAI and RA systems, respectively. It should be considered that these two systems account for more than 70% of the whole number of afferent fibers in humans [23]. A section of the robotic finger illustrating the layout of various sensors is shown in Figure 1.

Piezorestive receptors are based on semiconductor polymer technology and they are arranged into an array structure located under a compliant layer made of silicon rubber. As in the SAI system, sensing elements are characterized by a high spatial density and by a low frequency range of sensitivity. In order to replicate the distribution of the Merkel corpuscles in the human fingerpad, a space-variant array (the ARTS *Tactile Sensor*) has been designed in our laboratory and erestom manufactured by Interlink Europe [25]. The sensor, shown in Figure 2, has a high spatial density central area - a sort of *tactile fovea* - where spatial acuity is maximized, and a peripheral area where the density of the sensing elements decreases gradually from the fovea. This distribution, which is similar to the layout of the receptors in the eye, implements a trade-off between the width of the sensed field and number of sensing elements, thus allowing to obtain a larger tactile field with a fixed number of receptors. The sensor includes 16x16 sensing sites (corresponding to the intersection points of the conductive bars) which are located in an area of 2.92x3.07 cm^2. The spatial resolution varies from 1.8 mm in the fovea to 4.4 mm in the periphery. The sensor is scanned by an analog multiplexing unit with an image rate equal to 50 Hz, and it can be used in a force range approximately equal to 0.1-20 N.

The functionality of the RA system (Meissner and Pacinian receptors) is emulated by piezoelectric sensors. As shown in Figure 2, three polyvinylidene fluoride (PVDF) film strips are embedded into ridges of the compliant layer [26][21]. These strips are only 40 microns thick, and are sensitive to high frequency (10-1,000 Hz) stimuli related to the strains induced in each strip by vibrations and contact [27]. Such dynamic sensors are associated with an appropriate charge amplifying unit which acquires data at a sampling frequency of 1 Khz.

In addition to the piezoresitive and piezoelectric sensors, also thermal sensors have been included in the finger in order to acquire the thermal properties of the examined object material [8][28]. Thermal sensors are located between the ridges of the elastomer and they are composed of a miniaturized thermistor and an associated heating resistance embedded in thermally conductive rubber .

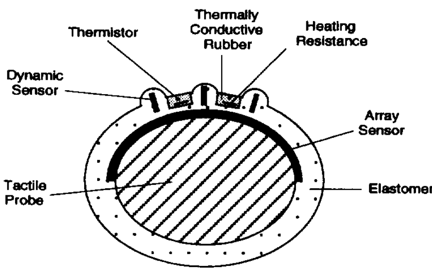

Figure 1. A section of the multifunctional tactile probe showing the location of the different tactile receptors.

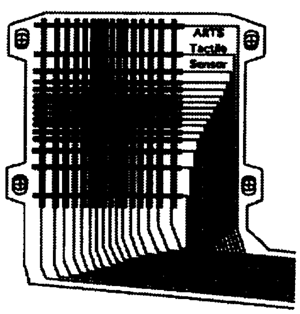

Figure 2. The ARTS Tactile Sensor.

3. Development of tactile-motor coordination

Different neural networks approaches to adaptive sensory motor coordination have been attempted [29] [30]. Particular attention has been paid to the problem of visuo-motor coordination, in particular for the eye-head and arm-eye systems, and several system architectures have been proposed [31] [32] [33] [34]. In general, in visuo-motor coordination, visual images of the mechanical parts of the systems can be directly related to posture signals. This will eventually allow the system to reach for the object that it sees (arm-eye coordination), or to properly shift gaze direction for looking to desired parts of the visual field (eye-head coordination).

However, the tactile-motor case differs significantly from the visuo-motor one, due to the intrinsic dependency on the contacted surface. Tactile information is not passively irradiated by the environment as in vision, but it should be gathered by actively producing contact conditions. As a consequence, the direct association of tactile sensations with mechanical positioning of the parts is not feasible because an environment-dependent tactile pattern is sensed for each system position.

In tactile perception a very important aspect is to understand how a given contact condition will be modified by motor acts, that is after having achieved a first contact, analyze where and how contact will be sensed after a system movement.

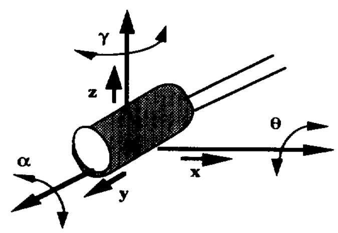

Figure 3. Finger movements with respect to an external reference frame. Feature enhancement movements involve rotations of finger along θ and α, and shifts along z.

In this way, environmental dependency can be eliminated and the invariants of the tactile-motor correlation which are only dependent on the physical and functional relationships of the system can be extracted. The develoment of such a coordination is crucial for sophisticated operations such as tactile exploration and manipulation. Only on the basis of this link finger position can be adjusted so as to properly adapt the contact (for example by shifting the contact area from the periphery to the fingerpad, if necessary) with a grasped object for a more reliable grip. Also, with this kind of tactile-motor coordination the highest resolution tactile parts can be brought into contact with an object which has been involuntarily bumped in order to explore it.

Figure 3 shows the possible movements that a robotic finger can make with respect to an external reference frame fixed with the contact surface. A basic qualitative distinction can be carried out among movements along the various degrees of freedom: whereas motor actions along x, y and γ are intrinsically explorative because they bring new regions of the surface into contact, θ, α and z are involved mainly in adjustement movements which are allowed by the compliance provided by the rubber sheet of the finger. Owing to the resemblance of this latter class of motor acts with the finger positioning and pressure adjustement that humans unconsciously perform when they come into contact with the environment, we have called them *feature enhancement micromovements*.

As regards learning, the psychological concept of *circular reaction*, which has been proposed by Piaget [18] to explain how visuo-motor coordination can be achieved in humans, has been applied [35]. The circular reaction scheme is based on the association of sensorial data and randomly generated movements, so that coordination develops by following with the eyes the random motion of the arm. An extension of the circular reaction concept to tactile-motor coordination is shown in Figure 4. The system can learn its tactile-proprioceptive coordination in a totally autonomous fashion, without any external intervention, if changes in the tactile pattern are systematically related to motor signals produced by the proprioceptive system of the robot when random motor actions are performed. The error between the motor action estimated on the basis of the developing correlation and the actual movement performed can at any time refine the coordination, so as to adapt to changed conditions.

In this paper we focus on the development of sensory-motor coordination in the case of feature enhancement micromovements. The system we have considered consists of the robotic finger described in section 2 mounted on a robotic manipulator. Only signals provided by the piezoresistive sensor array have been considered in the experiments described in the following paragraphs.

4. A neural network-based implementation

The system architecture which has been used for learning tactile-motor coordination is shown in Figure 5. The goal of the system is to estimate the direction of a feature enhancement motor action on the basis of modifications in the sensed tactile pattern. Let T_1 be the initial tactile pattern, acquired at the finger position $P_1=(z_1,\theta_1,\alpha_1)$, and T_2 the final pattern after that the motor action has been performed when the finger has the position $P_2=(z_2,\theta_2,\alpha_2)$. At first the two tactile patterns are processed and the coordinates (x_1,y_1) and (x_2,y_2) of the centroid of the contact areas are estimated, along with the global intensities (I_1,I_2) of the patterns:

$$x_1=\frac{1}{I_1}\sum_{ij} i\cdot T_1(i,j) \quad y_1=\frac{1}{I_1}\sum_{ij} j\cdot T_1(i,j) \quad I_1=\sum_{ij} T_1(i,j) \qquad (1)$$

$$x_2=\frac{1}{I_2}\sum_{ij} i\cdot T_2(i,j) \quad y_2=\frac{1}{I_2}\sum_{ij} j\cdot T_2(i,j) \quad I_2=\sum_{ij} T_2(i,j)$$

As illustrated in the figure, each feature difference activates the units of a corresponding feature map composed of N_x, N_y and N_I units, respectively. The unit ith in each map has, the following gaussian activation function

$$\begin{aligned} u_i^x &= \exp\left(\frac{\delta_x-\lambda_i^x}{2\sigma_x}\right)\\ u_i^y &= \exp\left(\frac{\delta_y-\lambda_i^y}{2\sigma_y}\right)\\ u_i^I &= \exp\left(\frac{\delta_I-\lambda_i^I}{2\sigma_I}\right)\end{aligned} \qquad (2)$$

where the constants are:

$$\begin{aligned}\lambda_i^x &= \frac{\delta x_{sup}-\delta x_{inf}}{N_x}\, i + \delta x_{inf}\\ \lambda_i^y &= \frac{\delta y_{sup}-\delta y_{inf}}{N_y}\, i + \delta y_{inf}\\ \lambda_i^I &= \frac{\delta I_{sup}-\delta I_{inf}}{N_I}\, i + \delta I_{inf}\end{aligned} \qquad (3)$$

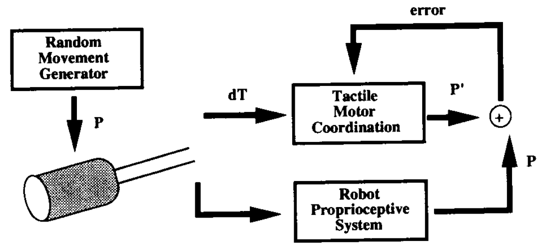

Figure 4. The circular reaction scheme for learning tactile-motor coordination.

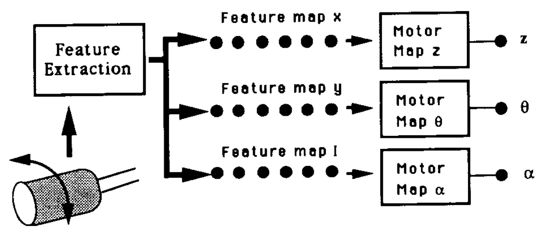

Figure 5. Scheme of the neural architecture (see text for details).

As a result, the activation of each unit is maximum if the registered input feature difference is equal to a specific value which the unit represents. The units of each feature map are linked through a corresponding motor map (a layer of weights) with a single output unit whose activation indicates the motor action direction to be performed along one of the degrees of freedom. The activation value of each output unit is given by:

$$\begin{aligned} u_\alpha &= \sum_i w_{xi} u_i^x\\ u_\vartheta &= \sum_i w_{yi} u_i^y\\ u_z &= \sum_i w_{Ii} u_i^I\end{aligned} \qquad (4)$$

The actual direction of movement is evaluated by comparing the magnitude of the output with a threshold: if the magnitude is larger than the threshold, the motor direction is indicated by the activation sign; otherwise it is undetermined. By means of learning, the weights in the motor maps are slightly modified after each movement of the finger, in order to improve system performance:

$$\begin{aligned} w_{xi}(t+1) &= w_{xi}(t)+\varepsilon(\mathrm{Sgn}(\alpha_2-\alpha_1)-u_\alpha)u_i^x\\ w_{yi}(t+1) &= w_{yi}(t)+\varepsilon(\mathrm{Sgn}(\vartheta_2-\vartheta_1)-u_\vartheta)u_i^\vartheta\\ w_{Ii}(t+1) &= w_{Ii}(t)+\varepsilon(\mathrm{Sgn}(I_2-I_1)-u_I)u_i^I\end{aligned} \qquad (5)$$

Figure 6 shows the organization of the motor maps before and after several thousands iterations. In each map, the length of the i-th segment is proportional to the weight that links the unit ith in the corresponding feature map to theoutput unit.

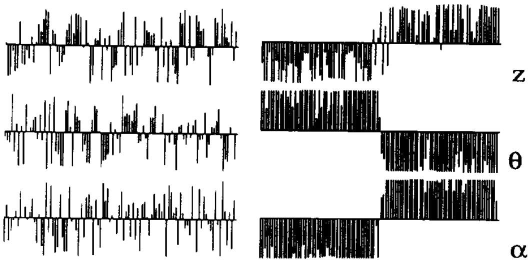

Figure 6. Weights in the motor maps (Nx= Ny =N_I=100) before training (*left*) and after several thousands iterations (*right*), for each degree-of-freedom (z, θ, α).

5. Experimental Results

For the experiments the robotic fingerpad has been incorporated into a robotic finger and on a PUMA manipulator (see Figure 7). Resultant contact forces are monitored in real-time by means of a Force-Torque sensor located at the robot wrist. Tactile patterns relative to different curvature radii were obtained by means of set of aluminum cones. A low angle (3°) was used for the cones generatrix so as to assume a constant curvature along all of the contact area. Motor actions were performed by the PUMA manipulator while the forces and torques values were carefully controlled so as to avoid critical conditions. The system was implemented with N_X=100, N_y=100 and N_I= 100 units in the feature maps, and with σ_x=1 σ_y=1 and σ_I=0.3 in eq.(2).
Tactile patterns were preprocessed by filtering them with a gaussian filter (σ=2) in order to reduce sensor noise. The learning error (the avarage number of errors on a fixed number of tests) decreased with the iteration number as shown in Figure 8 so that after 4000 iterations the right direction was estimated in the 82, 94 and 96 percent of the cases along the degrees of freedom z,θ and α, respectively. In the remaining cases uncertainties were 10, 5.6 and 3.6 percent so that error rates were very low. Furthermore, the spatial distribution of errors and uncertainties with respect to the magnitude of each feature change, (shown in Figure 9), account for the fact that wrong motor actions are performed only when the desired position has almost been reached. The transition from the learning to the operative phase is one of the most crucial problems of neural network-based architectures. An autonomous system should be able to determine when a sufficient performance level has been achieved, and to inhibit learning-dependent modules. In the case of the system described in this paper, the Random Movement Generator could be inhibited when a priori set error rate threshold is reached. Empirically, we stopped the learning phase after 4600 iterations.
It is worth noting that, even if random motor actions are no larger generated, weights are changed also during the execution phase, so as to adapt to possible changing conditions.

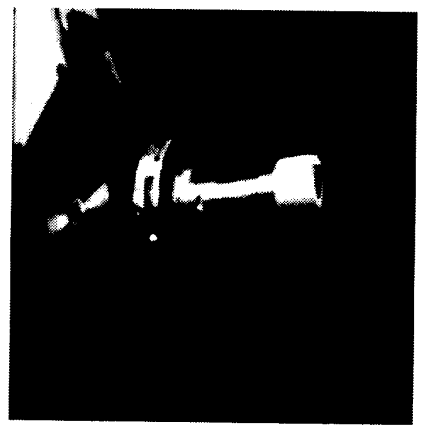

Figure 7. The robotic finger mounted on a PUMA manipulator.

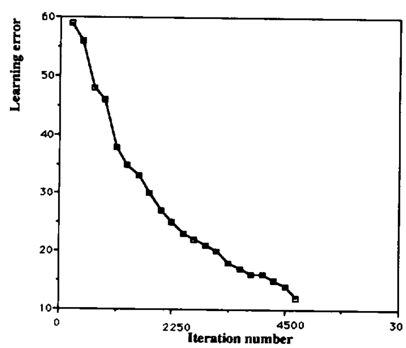

Figure 8. The number of errors decreases with learning (ε=0.05).

An example of how this type of sensory-motor coordination can be applied to the production of intelligent motor actions in the active estimate of surface cuvature follows. Due to the fact that the explored surfaces (the aluminium cones) have different curvature along a single direction, only rotations along the θ degree of freedom were considered. In order to execute the rotations, the system was required to reach an arbitrary target change in the y coordinate of the contact centroid. As a result of this constraint the finger rotated until either the target change was sensed in the corresponding feature map, or the monitored force reached a threshold of 20 N. As shown in Figure 10, in both the cases the average rotation performed depends on surface curvature. This result is consistent with human every-day experience that smaller curvature radii (which correspond to a "steeper" slope of the plot in Figure 10) can be differentiated more easily by active probing.

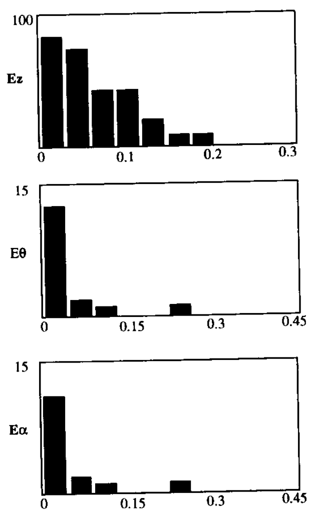

Figure 9. Distribution of errors and undetermination with respect to feature changes magnitude.

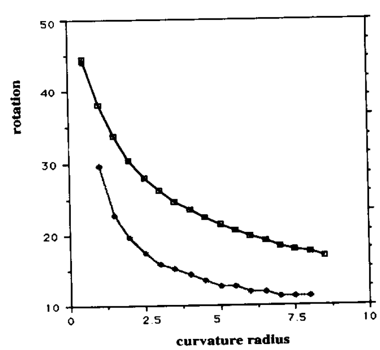

Figure10. Rotation (deg.) along θ for different surface curvatures (mm). (*Filled dots*): the target shift of the contact centroid is reached. (*Empty dots*): rotation stops for having reached the force threshold.

6. Conclusions

Tactile information is crucial for developing robotic systems which operate in uncertain environments. General-purpose robots should be able to properly perceive if a contact with the surrounding world has been achieved, and to grasp, manipulate and analyze objects of interest, all operations that require tactile capabilities. In the last 20 years, research on robotic tactile perception has achieved significant improvements in the accuracy and reliability of tactile sensors and has generated sensors specific to different contact information. Such sensors, even if far from producing highly accurate quantitative measurements, provide qualitative information which needs to be interpretated to give meaningful results. This is similar to the behavior of human receptors whose response has proved to be far from systematic.

We believe that using already available tools, intelligent autonomous systems can start to gather tactile information from the environment and to build representations of the explored world, if they know the physical and functional organizations of their own system. The discovering of such organizations implies the understanding of how sensorial data and motor actions are related, that is the development of sensory-motor coordination.

In this paper, the problem of developing adaptive sensory-motor coordination has been applied to a simple robotic system composed of a single finger mounted on a robotic arm. However the proposed approach is general and could be applied to much more sophisticated systems, such as robotic dexterous hands. Also, it has been shown how intelligent purposive motor actions, such as those for curvature estimation, can be easily produced after that the sensory-motor connection has been estabilished.

The experiments that we have shown in this paper are a part of a general approach to robotic tactile perception that we are currently following, which relies on the integration of tactile data acquired by different receptors, and on the active interaction with the scene based on the cooperation of different modalities. Progress with this approach could not only become the basis for developing more adptive robots, but could also guide experimental analysis toward the understanding of human sensory-motor control.

Acknowledgements

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