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Development of Cutaneo-Motor Coordination in an Autonomous Robotic System

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Abstract. The capability of autonomously discovering relations between perceptual data and motor actions is crucial for the development of robust adaptive robotic systems intended to operate in an unknown environment. In the case of robotic tactile perception, a proper interaction between contact sensing and motor control is the basic step toward the execution of complex motor procedures such as grasping and manipulation.

In this paper the autonomous development of cutaneo-motor coordination is investigated in the case of a robotic finger mounted on a robotic manipulator, for a particular class of micro-movements. A neural network architecture linking changes in the sensed tactile pattern with the motor actions performed is described and experimental results are analyzed. Examples of application of the developed sensory-motor coordination in the generation of motor control procedures for the estimate of surface curvature are considered.

Keywords: autonomous robots, sensory-motor control, tactile perception, artificial neural networks

1 Introduction

Humans are able to perform an enormous variety of motor actions without any particular conscious efforts. They can reach for objects located in critical positions while avoiding collisions with other objects, and they can properly grasp and manipulate objects and tools which differ tremendously in their shape, dimensions and physical as well as functional properties. There is no doubt that such performances are the result of the combined operation of several highly sophisticated subsystems. From a mechanical viewpoint, the human manipulative "tools", such as the arm and the hand, are characterized by a high spatial redundancy provided by a large number of degrees of freedom, which allow them to reach any point in space by many different postures of the system, so as to adapt to different conditions. Furthermore, both the conditions of the environment and those of the body are constantly monitored by an extremely large number of sensing elements, which provide the brain with real-time information of the events occurring in the scene. The combination of perceptual and motor systems results in an accurate sensory-motor coordination which is 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.

Let us consider, as an example of such combination of perception and action, a common operation such as handwriting. At any time, the data provided by the tactile, the visual and the proprioceptive systems are analyzed by the brain so as to adapt the motor behavior to the different conditions determined by pens which can differ in weight, size and smoothness. The perceptual systems monitor, by their different sensory modalities, the same physical events so that a high degree of redundancy is present in the inflowing data. As a result of this inherent redundancy, the system can still partially operate even if one of the sensory modalities involved is eliminated or degraded, such as when we attempt to write with our eyes closed or by wearing a thick glove.

Understanding how different perceptual data are associated into a unitary perception of the environment, and how sensory frames are coordinated with the motor ones, are among the most difficult problems that neurosciences have encountered, and they are still open questions.

Nevertheless, evidence accounts for the development of these coordinations by means of learning (Piaget 1976). For example, experiments with the kittens have shown that visually guided behavior emerges only if sensorial changes in the environment are systematically related to the motor actions performed (Hein 1974).

In recent years, the problem of sensory–motor coordination has received some attention in robotics, after the observation that interaction with the scene can provide useful information for overcoming perceptual difficulties. As research in the field of visual (Bertero et al. 1988) and tactile (Pati et al. 1992) perception has shown, some low-level problems are ill-posed in the sense of Hadamard, that is they are underconstrained and do not have a unique solution, unless *a priori* assumptions are formulated (Tikhonov and Arsenin 1977). It has been shown that by means of an active approach most of these problems can be transformed into well-posed and stable ones (Aloimonos et al. 1988, Bajcsy 1988).

In order to be effective in unknown environments, autonomous robotic systems have to produce adaptive sensory-motor coordinations similar to those of living beings. That is, they should be able to adapt their behavior to unpredictable modifications of their own functional structure due to aging and failures.

The difficulties which are often encountered in the mathematical modelling of physical systems, as well as the need for real-time learning, account for the use of neural network paradigms for the development of adaptive control. In particular, several neural network paradigms allow real-time learning without the need for separating operative and training phases (Maren et al. 1990, Simpson 1990).

Different neural network approaches to adaptive sensory-motor coordination have been attempted in recent years (Albus 1981, Grossberg 1988, Sánchez and Hirzinger 1992). Particular attention has been paid to the problem of visuo-motor coordination, especially for the eye-head and arm-eye systems, and several system architectures have been proposed (Kuperstein 1991, Gaudiano and Grossberg 1991, Mel 1990, Grossberg et al. 1993). In general, in visuo-motor coordination visual images of the mechanical parts of the systems can be directly related to posture signals. This eventually allows the system to reach for the object that it sees (arm-eye coordination), or to properly shift gaze direction for looking at desired parts of the visual field (eye-head coordination).

Much less work has been carried out on the development of similar kinds of cutaneo-motor coordinations between the tactile and motor modalities, mainly due to the fact that tactile perception is often considered as a less important sensory modality than vision, and that tactile sensors are still characterized by low reliability and by a number of technological problems.

In our laboratory, we have pursued 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 (Rucci and Dario 1993, Dario and Rucci 1993). In this framework we have developed a composite robotic fingerpad including different kinds of tactile sensors, and we have focused on the problem of building adaptive cutaneo-motor coordination for autonomous robotics systems. To the best of our knowledge, the work described in this paper is the first attempt to describe a coherent approach to the development of adaptive cutaneo-motor coordination in robots.

The paper is organized as follows: the next section explains the importance of developing cutaneo-motor coordinations in robotic systems, and how such coordination can then be used for manipulation and exploration. Section 3 focuses on the development of cutaneo-motor coordination and illustrates how Piaget's concept of circular reaction can be properly adapted to this special case. A neural network-based implementation of the architecture is described in section 4 for a system composed of a robotic fingerpad mounted on a manipulator, and the results are analyzed in section 5; finally, conclusions are drawn in section 6.

2 Why Develop Cutaneo-Motor Coordination in Robots?

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 have been applied to the detection of contact information (Dario and De Rossi 1985, Fearing and Hollerbach 1985, Nicholls and Lee 1989, Amato 1992, Howe and Cutkosky 1992, Howe and Cutkosky 1993). Thanks to these efforts a wide range of sensors have been developed, most of them able to catch a specific aspect of available tactile information, such as normal force, shear, or vibrations (Webster 1988, Russell 1990). However, the problem of interpreting tactile signals and of using contact information for properly interacting with the surrounding environment has not been considered until recent years (Allen 1987, Allen and Michelman 1990, Fearing and Binford 1991, Pati et al. 1992, Bicchi et al. 1993), 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, to date, on basic problems of tactile perception, such as the integration into a unitary perceptual frame of tactile information acquired with different sensors (Dario and Buttazzo 1987, Caldwell and Gosney 1993), and, more specifically, on the integration of tactile sensations and motor actions (Bajcsy 1984, Howe et al. 1990, Dario et al. 1992, Tremblay and Cutkosky 1993).

Motor control plays a major role in tactile perception, since touch is an intrinsically active sensorial modality. In general, in order to voluntarily gather tactile information, the sensor must be brought in contact with the explored surface and contact position and forces must be properly adjusted. Furthermore, the use of touch as a source of information for exploring an unknown environment implies that the physical structure and the posture of the system are taken into account. Only by means of such geometrical relationships can the spatial location of a stimulus be determined, and spatial structures be discovered, so as to build representations of the environment. Similarly, tactile explorative operations involving the execution of motor control procedures produce useful information on the explored scene, only if the system proprioceptive data are considered at the same time (Lederman and Klatzky 1987).

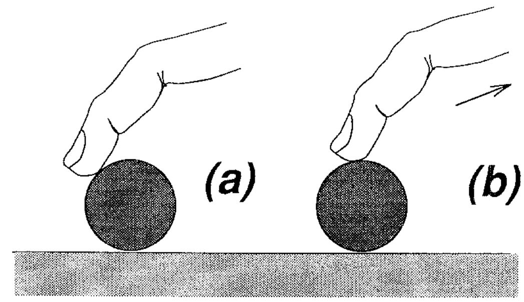


Fig. 1. The intrinsic knowledge of the structural and functional relations of our own manipulative tools, allows us to predict changes in the perceived tactile stimuli resulting from the execution of motor actions.

The development of autonomous systems capable of executing intelligent exploratory movements requires a thorough understanding of the interactions between touch and motor-proprioceptive modalities. Actions such as increasing the grasping force if an object slips away, or finely adjusting finger positions and pressures in a grasp, can be performed only if a strict relationship between tactile and motor modalities has been established first. Such link would allow establishment of an effective physical and functional organization of the system and it is the primary step that an intelligent system should execute toward its perception of the environment.

In order to better elucidate this concept, the example shown in Fig. 1 can be considered. Given the initial contact condition illustrated in Fig. 1(a), our knowledge of the layout of tactile receptors in the skin and of shifts in spatial position resulting from the execution of motor actions, allows us to predict that by moving the finger along the direction indicated by the arrow, tactile stimuli will shift toward the fingertip, as shown in Fig. 1(b). Even if the actual sensed changes in tactile stimuli are dependent on the shape of the contact surface, spatial exploration is made possible by underlying assumptions about the connections among adjacent joints, their relative possible movements, and the organization of tactile receptors. In order for a robotic system to keep its performances unaltered in time, such system-dependent assumptions should adapt to any occurring modification due to aging or damages. It is the autonomous development of this kind of knowledge—which in our view is the basis of tactile perception—that is the focus of this paper.

Once this kind of sensory-motor coordination has been developed, it can be used for generating purposive, "intelligent" motor actions, by asking the system to produce *sensory changes* in the perceived tactile pattern instead of *motor changes* of its posture. That is, the motor action illustrated in Fig. 1 can be produced by requiring a shift of the tactile stimulus toward the fingertip.

The development of this kind of coordination, allows a robot system to formulate of hypothetical predictions on how a sensed tactile contact will be modified by a motor action, which is a basic requirement for producing highly sophisticated motor operations, such as those involved in tactile exploration and in dexterous manipulation. Only if the system has a complete consciousness of its own structure and of its own motor behavior, can it extract useful contact information on the environment.

This approach is very similar to the theory of visual servoing and extends the concepts proposed there (Weiss et al. 1987) to the sense of touch. The real-time motor control of a robot based directly on the results of its tactile perceptual system has not been considered in robotic literature until very recently (Beger and Khosla 1991, Sikka et al. 1993). In particular, the work of Sikka, Zhang and Sutphen explicitly extends the methods of visual servoing to the case of tactile perception and it presents several analogies to the approach proposed in this paper. However, a non-adaptive task-dependent method is followed, whereas in this case, the focus is on the extraction of system-specific sensory-motor invariants.

3 Autonomous Learning of Cutaneo-Motor Coordination

As already pointed out in the introduction, most of the previous work on sensory-motor coordination has focused on the visual sensory modality. However, cutaneo-motor coordination differs significantly from the visuo-motor one, due to its intrinsic dependency on the contacted surface. Tactile information is not passively irradiated by the environment as is visual information, but must be gathered by active contact exploration. As a consequence, the direct association of tactile sensations with the mechanical positioning of robot parts is not feasible, because an environment-dependent tactile pattern is sensed for each system position. That is, a given tactile pattern can be perceived in any position of the space, and in addition the sensed tactile pattern may change with the touched surface for any posture of the system.

A truly effective robotic sensory-motor coordination involving the sense of touch should be able to eliminate the environmental dependencies, in order to emphasize the intrinsic characteristics of the system. That is, the system-dependent invariants of the cutaneo-motor coordination, should be extracted.

In this paper, the case of a robotic finger endowed with a sensitive fingerpad is considered. Fig. 2 shows the possible movements that the finger can perform with respect to the contact surface. A basic qualitative distinction can be carried out between movements along the various degrees of freedom: whereas motor actions along x, y and γ are intrinsically exploratory because they bring new regions of the surface into contact, movements along θ, α and z are mainly adjustment movements, which are allowed by the compliance provided by the rubber cover of the finger. Due to the resemblance of these latter class of motor acts with the finger positioning and pressure adjustment that humans unconsciously perform when they come into contact with the environment, we have called them *feature enhancement micro-movements*. The distinction among the two classes of movements is supported also by the observation that in the first case vision can be used in cooperation with tactile sensing for driving the motor actions of the system, whereas only tactile information is available for feature enhancement micro-movements, because the surface of contact is occluded by the finger itself.

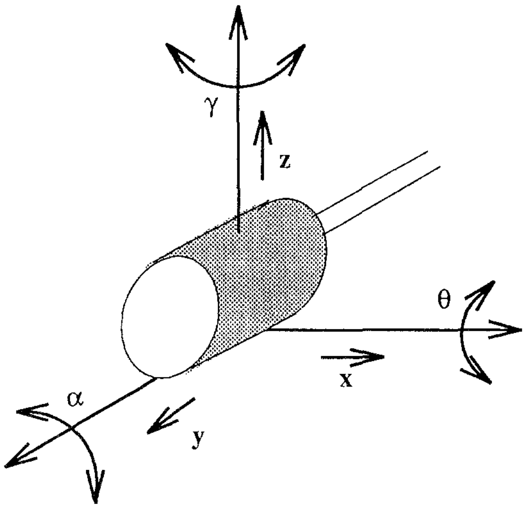


Fig. 2. Possible movements of the robotic finger with respect to an external surface. The reference frame is centered on the centroid of the contact and its cartesian axes are parallel to the principal axes of the finger. Feature enhancement micro-movements involve rotations of the finger along θ and α and shifts along z.

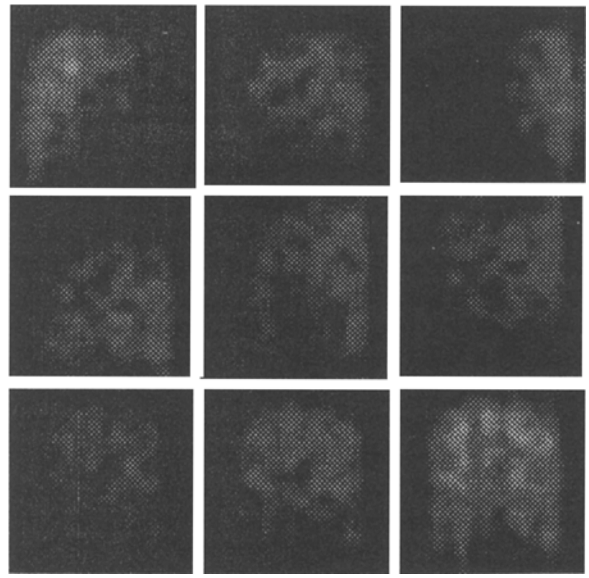


Fig. 3. Typical changes of the tactile patterns sensed while performing feature enhancement micro-movements. (*Top Row*) Rotation along α. (*Center Row*) Rotation along θ. (*Bottom Row*) Shift along z.

Changes in the sensed tactile patterns produced by feature enhancement micro-movements are shown in Fig. 3. As shown in the figure, whereas the two rotations basically produce shifts of the contact area along perpendicular axes of the image, movements along z produce a corresponding variation of the width of the contact area.

In order to begin to address the very general problem of cutaneo-motor coordination in robotics, in this paper we focus on the specific case of feature enhancement micro-movements. The robotic system we have considered consists of an anthropomorphic finger described in section 5 which has been mounted on a robotic manipulator.

The psychological concept of circular reaction has been applied for the learning process. The circular reaction scheme has been proposed by Piaget (1976) to explain how visuo-motor coordination can be achieved in humans. This scheme is based on the association of sensory data and randomly generated movements, so that coordination develops as the eyes keep following the random motion of the arm.

The extension of the circular reaction concept

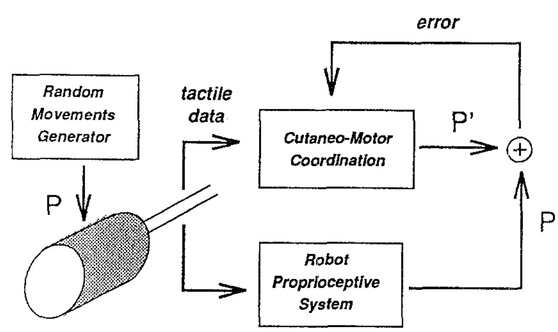


Fig. 4. An extension of Piaget's concept of circular reaction to the case of cutaneo-motor coordination. The variations of robot proprioceptive data sensed during random motor actions are associated with the corresponding changes of the perceived tactile data.

to tactile-motor coordination in a robotic system is shown in Fig. 4. The system can learn its cutaneo-proprioceptive coordination in a totally autonomous fashion (without any external intervention) if changes in the tactile pattern are systematically related to the motor signals produced by the robot proprioceptive system 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.

By means of circular reaction the use of supervised learning techniques becomes feasible, because a measure of the error produced at any time is internally available to the system by comparing the estimates with data belonging to other sensory modalities. In this case, learning proceeds by using as reference signals the outputs of robot encoders. However, it is worth noting that the system develops its coordination autonomously, because no training signals are explicitly provided and the supervision of an external operator is not necessary.

4 A Neural Network-Based Implementation

The system we propose develops a coordination among the tactile and motor perceptual frames, so that the system learns to estimate the direction of a feature enhancement motor action on the basis of the modifications perceived in the tactile contact. That is (see Fig. 2) the directions of movements along z, θ and α are considered. The system architecture has been implemented by means of artificial neural network paradigms and the cutaneo-motor coordination has been learnt according with the circular reaction theory. Applications of this kind of coordination will be illustrated in the following section.

A scheme of the architecture is shown in Fig. 5. As illustrated in Fig. 3 feature enhancement movements along θ, α and z produce modifications of the sensed tactile pattern which consist mainly of translations of the contact centroid and of changes of pattern intensity, respectively. Thus, the architecture includes a separate pathway for each degree of freedom. The system includes three *feature maps* $\mathcal{F}^x$, $\mathcal{F}^y$ and $\mathcal{F}^p$ composed of the units u_k^x, u_k^y, u_k^p and three *motor maps* $\mathcal{M}^\alpha$, $\mathcal{M}^\theta$ and $\mathcal{M}^z$, which are composed of sets of weights $w_k^{\alpha x}$, $w_k^{\theta y}$ and w_k^{zp}. The feature maps include N_x, N_y and N_p units, respectively, and each motor map is composed of the same number of weights as the corresponding feature map, that is $N_\alpha = N_x$, $N_\theta = N_y$ and $N_z = N_p$. As shown in Fig. 5, the activation of

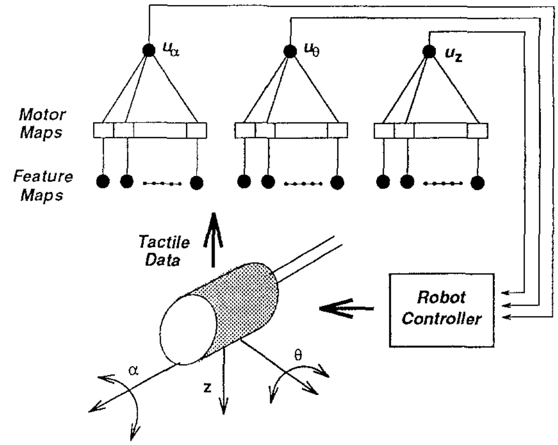


Fig. 5. Scheme of the neural architecture. Changes in intensity and contact centroid of the sensed tactile pattern are processed by separate maps and activate corresponding motor units which represent movements along the 3 d.o.f. (see text for details).

each feature map $\mathcal{F}^x$, $\mathcal{F}^y$ and $\mathcal{F}^p$ is transmitted, through the corresponding motor map, to the motor units u_α, u_θ and u_z, respectively. The activation of these units provides an estimate of the direction of the micro-movement performed along each degree of freedom.

In order to examine how cutaneo-motor coordination is developed, let T_t be the initial tactile pattern, acquired for finger position $P_t = (x_t, y_t, z_t, \theta_t, \alpha_t, \gamma_t)$, and T_{t+1} the final pattern after the motor action has been performed, that is when the finger has position $P_{t+1} = (x_{t+1}, y_{t+1}, z_{t+1}, \theta_{t+1}, \alpha_{t+1}, \gamma_{t+1})$. The feature enhancement constraint implies that x, y, and θ do not change, that is x_{t+1}, y_{t+1}, and γ_{t+1} are equal to x_t, y_t, and γ_t, respectively.

First the two tactile patterns are processed so as to evaluate such basic features as the coordinates of the contact centroid (x_t^c, y_t^c) and the intensity of the pattern p_t:

$$\begin{cases} x_t^c = \frac{1}{p_t} \sum_{i,j} i T_t(i,j) \\ y_t^c = \frac{1}{pt} \sum_{i,j} j T_t(i,j) \\ p_t = \sum_{i,j} T_t(i,j) \end{cases}$$

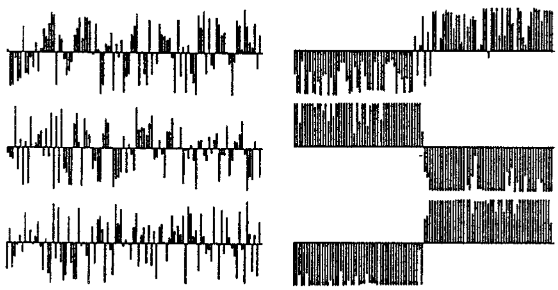


Fig. 6. Weights in the motor maps before training (*Left*) and after several thousands iterations (*Right*). Weights are aligned along the horizontal axis (i.e. the abscissa increases with k), and their values are represented by the length of the corresponding vertical segment. The three motor maps are aligned one above the other, so that the $\mathcal{M}^z$ is on the top, $\mathcal{M}^\alpha$ in the middle and $\mathcal{M}^\theta$ is on the bottom of the figure. Initially weights have random values, but, with training, a structured pattern emerges.

$$\begin{cases} x^c_{t+1} = \frac{1}{p_{t+1}} \sum_{i,j} i T_{t+1}(i,j) \\ y^c_{t+1} = \frac{1}{p_{t+1}} \sum_{i,j} j T_{t+1}(i,j) \\ p_{t+1} = \sum_{i,j} T_t(i,j) \end{cases} \quad (1)$$

The pattern of activation of the units in the feature maps code the variations of the tactile features between times t and $t+1$.

$$\begin{cases} x^c = x^c_{t+1} - x^c_t \\ y^c = y^c_{t+1} - y^c_t \\ p = \log \frac{p_{t+1}}{p_t} \end{cases} \quad (2)$$

Let U^x_k, U^y_k and U^p_k be the activation values of the units u^x_k, u^y_k and u^p_k. Their values are given by the following equations:

$$\begin{cases} U^x_k = A_x \exp - \frac{(x^c - x_k)^2}{2\sigma_x^2} \\ U^y_k = A_y \exp - \frac{(y^c - y_k)^2}{2\sigma_y^2} \\ U^p_k = A_p \exp - \frac{(p - p_k)^2}{2\sigma_p^2} \end{cases} \quad (3)$$

where the constants are:

$$\begin{cases} x_k = \frac{x_{\sup} - x_{\inf}}{N_x} + x_{\inf} \\ y_k = \frac{y_{\sup} - y_{\inf}}{N_y} + y_{\inf} \\ p_k = \frac{p_{\sup} - p_{\inf}}{N_p} + p_{\inf} \end{cases} \quad (4)$$

The constants $x_{\sup}, x_{\inf}, y_{\sup}, y_{\inf}, p_{\sup}, p_{\inf}$ define the range of sensitivity of the feature maps. In this way, each feature map has a Gaussian distribution of activation and is sensitive to one of the extracted tactile parameters. In each feature map, the maximum activation value is registered for the unit whose activation constant is closest to the input feature difference.

The activation value of each output unit is given by

$$\begin{cases} U_\alpha = \frac{1}{A_\alpha} \sum_{k=1}^{N_x} w_k^{\alpha x} U^x_k \\ U_\theta = \frac{1}{A_\theta} \sum_{k=1}^{N_y} w_k^{\theta y} U^y_k \\ U_z = \frac{1}{A_z} \sum_{k=1}^{N_p} w_k^{zp} U^p_k \end{cases} \quad (5)$$

where A_α, A_θ, and A_z are suitable constants, chosen for normalization. The motor directions are then evaluated by comparing the activation of the output units with a prefixed threshold τ: if the magnitude is greater than τ the motor direction is indicated by the activation sign, otherwise it is undetermined.

The weights in the motor maps are modified after each movement of the finger, in order to improve system performance. An error-correction learning rule has been adopted.

$$\begin{cases} w_k^{\alpha x}(t+1) = w_k^{\alpha x}(t) + \epsilon[S(\alpha_{t+1} - \alpha_t) - U_\alpha] U^x_k \\ w_k^{\theta y}(t+1) = w_k^{\theta y}(t) + \epsilon[S(\theta_{t+1} - \theta_t) - U_\theta] U^y_k \\ w_k^{zp}(t+1) = w_k^{zp}(t) + \epsilon[S(z_{t+1} - z_t) - U_z] U^p_k \end{cases} \quad (6)$$

where $S(x)$ is the function sign which gives $+1, 0, -1$ according to the sign of its argument. Even if many different learning rules would have been possible, the one in equations 6 has been chosen mainly on the basis of its simplicity. Due to the gating terms, weights are changed so as to produce the desired output only when the corresponding units in the feature maps have a non-zero value of activation.

The organization of the motor maps before and after several thousands iterations can be appreciated in Fig. 6. In each map, the length of i-th segment is proportional to the weight linking the i-th unit in the corresponding feature map to the corresponding output unit. As it

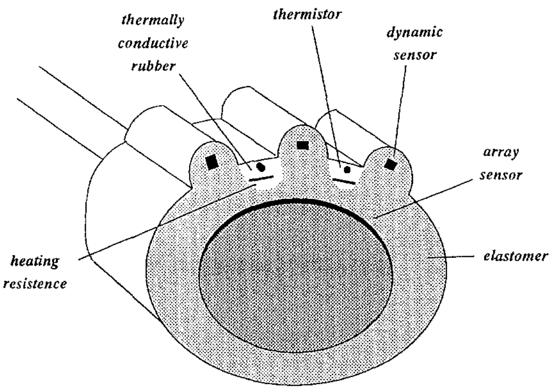


Fig. 7. A section of the multifunctional tactile probe showing the location of the different tactile receptors. Piezoresistive receptors are based on semiconductor polymer technology and are characterized by a high spatial density and by a low frequency range of sensitivity (50–100 Hz) as primate SAI system. Three piezoelectric polyvinylidene fluoride (PVDF) bilayered film strips, embedded into ridges of the compliant layer, emulate the functionality of the RA system (Meissner and Pacinian receptors) with a lower spatial resolution (the strips are only 40 microns thick) and higher frequency range (10–1,000 Hz). Thermal sensors are composed of a miniaturized thermistor and an associated heating resistance embedded in thermically conductive rubber, and are located between the ridges of the elastomer.

should be expected, in the motor maps a spatial organization emerges which is basically sensitive to the sign of the differential tactile feature coded.

5 Experimental Results

The experiments have been carried out by means of a multi-functional robotic tactile probe (a robotic fingerpad), which has been developed in our laboratory as a basic tool for investigating artificial tactile perception in robotic systems.

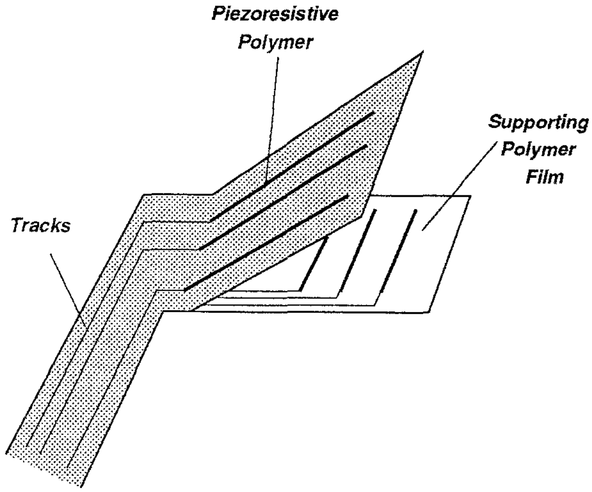
The fingerpad emulates the organization of the human tactile system (Dario et al., 1992, Rucci and Dario, 1993, Dario and Rucci, 1993) and it includes piezoresistive, piezoelectric and thermal tactile sensors, which, due to their intrinsic properties, mimic primate *Slowly Adapting I* (SAI), *Rapidly Adapting* (RA) and thermal systems of afferent fibers, respectively (Johnson and Hsiao 1992).

A section of the robotic finger illustrating the layout of various sensors is shown in Fig. 7. Only the signals produced by piezoresistive sensors were considered for the experiments. Piezoresistive sensing elements are organized in a space-variant array configuration (the *ARTS Tactile Sensor*) designed in our laboratory and manufactured by Interlink Europe[1]. The sensor, shown in Fig. 8, includes 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 and in the human fingerpad, implements a trade-off between the width of the sensed field and the number of sensing elements, allowing one to obtain a larger tactile field with a fixed number of receptors.

For the experiments the robotic finger was mounted on a PUMA manipulator. As illustrated in Fig. 9, tactile data scanned by a dedicated multiplexing unit, are communicated through a serial port to an 80486-based computer. The communication between the computer and the PUMA controller is also handled by a serial link. In order to avoid virtually dangerous conditions, contact forces are monitored in real-time by means of a Lord 30-100 Force-Torque sensor located at the robot wrist before the tactile probe.

In order to build cutaneo-motor coordination which does not depend on the tactile pattern perceived, contact conditions relative to different curvature radii were obtained by means of a set of aluminum cones (see Fig. 10). In this way, by producing a contact with the major axes of the finger and of the explored cone kept perpendicular, the sensed pattern varies at least along one direction of the image, depending on where—at which height of the longitudinal axis of the cone—the finger was located. A low angle (3 degrees) was used for the cones generatrix so as to assume a constant curvature along all the contact area.

The system was implemented with 100 units in each feature map ($N_x = N_y = N_p = 100$). Constant values were $\sigma_x = \sigma_y = \sigma_p = 1$ and $A_x = A_y = A_p = 1$ in eq. 3. Training was carried out with ϵ equal to 0.05, and tactile patterns were pre-processed by filtering them with a gaussian filter in order to reduce sensor noise.



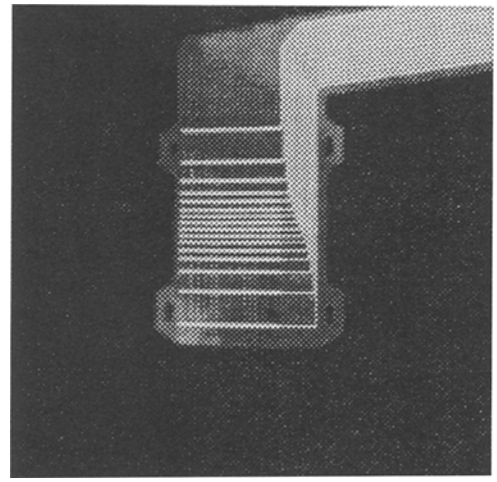


Fig. 8. The ARTS Tactile Sensor. *(Left)* Two piezoresistive polymerlayers with perpendicular conductive strips are placed one upon the other. An analog multiplexing scanning unit senses the polymer resistance at the strips intersection points with an image rate equal to 50 Hz. *(Right)* The spatio-variant layout of the sensing sites mimicks the nonuniform distribution of Merkel receptors in the human fingerpad. The sensor includes 16×16 sensing sites (corresponding to the intersection points of the conductive bars) which are located in an area of 2.92×3.07 cm^2. The spatial resolution varies from 1.8 mm in the fovea to 4.4 mm in the periphery, and can be used in a force range approximately equal to 0.1–20 N.

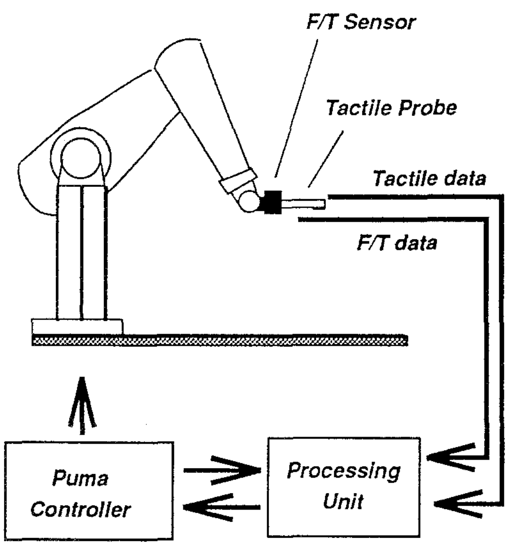


Fig. 9. The system experimental setup. All the communications are performed by serial links, except the acquisition of force-torque data, which are transmitted through a parallel connection.

The accuracy of the developed cutaneo-motor coordination was tested by presenting to the system variations in the sensed tactile pattern, and by comparing the estimated micro-movement direction with the one actually performed. Fig. 11 shows that the learning error (which is the average number of errors on a fixed number of randomly generated test cases) decreased as training proceeded, so that after 4000 iterations the results illustrated in Table I (Fig. 12) were obtained. The data refer to the estimate of the direction of the feature enhancement micro-movement performed. For the three degrees of freedom, the rates of correct, wrong and uncertain (output unit activation lower than τ) determination are illustrated. These results show that a robust sensory-motor coordination has been developed which is characterized by low error rates. Also, it can be noticed that in critical cases, instead of selecting a wrong direction, the system tends to produce an undetermined response.

Furthermore, the spatial distributions of errors and uncertainties with respect to the magnitude of each feature change, which are shown in Fig. 13, account for the fact that wrong motor actions are typically performed only when the desired position has almost been reached.

Two examples of how the developed sensory-motor coordination can be used for tactile explo-

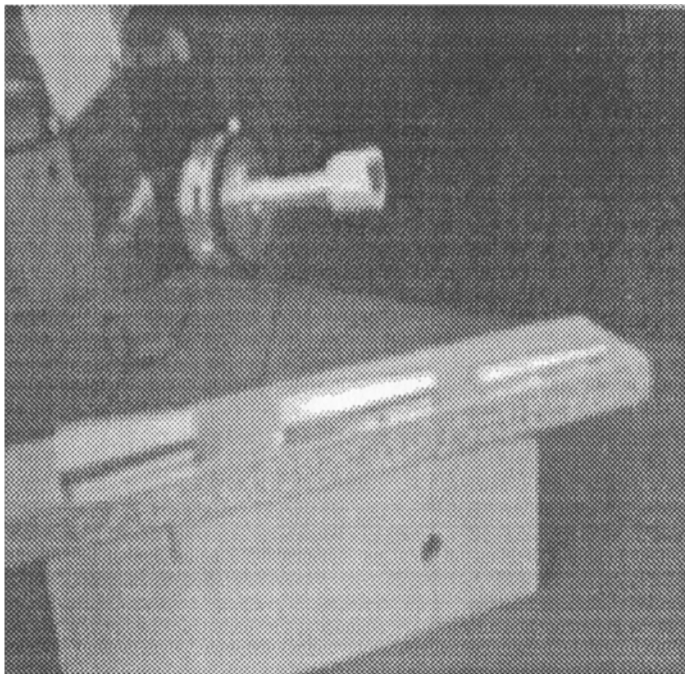


Fig. 10. The robotic finger mounted on a PUMA manipulator and the cones used for the experiments.

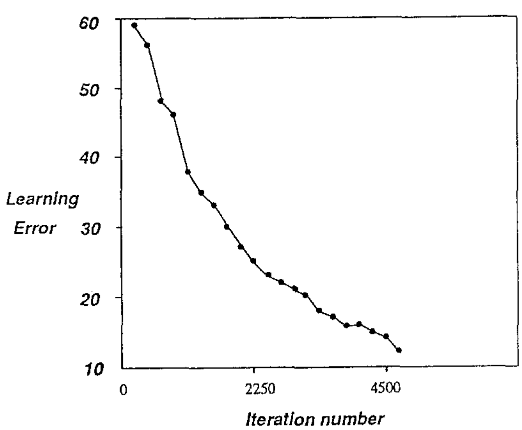


Fig. 11. Development of sensory motor-coordination. The average number of errors performed by the system decreases with training.

	z	θ	α
Correct	82	94	96
Uncertain	10	5.6	3.6
Wrong	8	0.4	0.4

Fig. 12. System performances.

ration of the environment are provided herein. Both refer to the active estimate of the curvature radius of the contact surface. Tactile patterns were provided by the same cones used for acquiring the coordination.

In the first set of experiments cutaneo-motor coordination was applied to the problem of transforming the currently sensed pattern into a target one acquired with different finger posture and pressure. As emphasized in section 2, such a capability plays a major role for fine manipulation and spatial exploration. By purposively changing the sensed contact condition, forces and postures of the fingers can be optimized according to the current task, which can be, for example, a particular kind of grasping operation or an explorative control procedure.

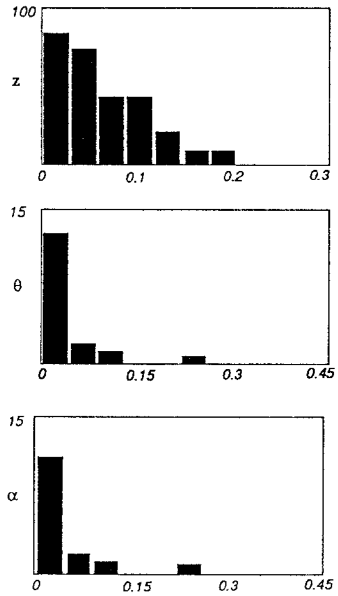


Fig. 13. Distribution of errors and indetermination with respect to feature changes magnitude (data are expressed in cm).

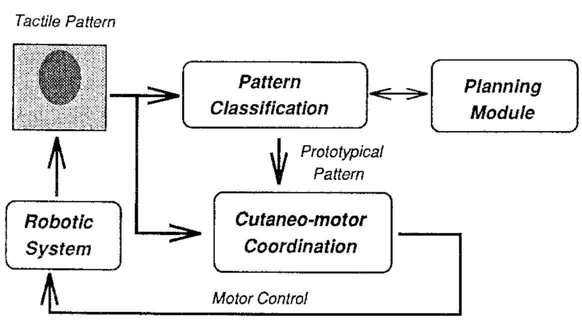


Fig. 14. Application of cutaneo-motor coordination to the classification of tactile patterns. System posture is iteratively refined, so as to increase the similitude between the input pattern and a prototypical tactile pattern selected by the planning module.

Such a skill can also be used for improving the classification of the perceived tactile features, as illustrated in Fig. 14, by moving the finger so as to better exploit the range of sensitivity of the sensors. This approach was applied to the problem of curvature estimation. A set of tactile patterns were acquired at different heights of the cones, and surface curvature was classified as belonging to one of 10 classes in the range 10–30 mm. Patterns were acquired with fixed standard conditions: the finger was positioned with its major axis perpendicular to the longitudinal axis of the cone, and with an inclination of 3 degrees, so as to follow the slope of the surface (this allows a contact with the center of the piezoresistive array). A pressure of 13 N, which was experimentally found to produce a good discrimination among different curvatures, was applied for gathering the signals. The patterns were then classified by means of a neural network composed of four, full-connected layers with 256, 8, 5 and 10 units, respectively. The network was trained with the back-propagation algorithm (Rumelhart et al., 1986). Thanks to the standard conditions of data acquisition, percentages of correct classification observed on patterns not included in the training set were above 90%.

The approach illustrated in Fig. 14 was applied, as an illustrative example, by using a reference database composed of a set of patterns representative of each class. For each curvature class, one of the training patterns of the classifying network was chosen as a prototypical pattern. Then, feature enhancement motor actions were performed, so as to increase the similarity between the currently sensed tactile pattern, acquired with random position and pressure of the finger, and a prototypical one. The basic control problem of the selection of the target pattern at any time was not addressed here, instead a simple control procedure based on the initial selection of the most similar pattern was applied. The sequence of motor actions was interrupted when an euclidean distance between the patterns equal to or lower than 2 was reached, or after a maximum prefixed number of movements. Even with such a trivial control rule (the target pattern selected in this way is not always acquired with the same curvature radius) a success rate of 74% was achieved. In general, given two tactile patterns corresponding to the same surface curvature, but acquired with different finger positions, it was possible to find a sequence of motor actions linking the two configurations in more than 96% of the cases.

Once the cutaneo-motor coordination has been developed, surface curvature can also be estimated by evaluating the relations between

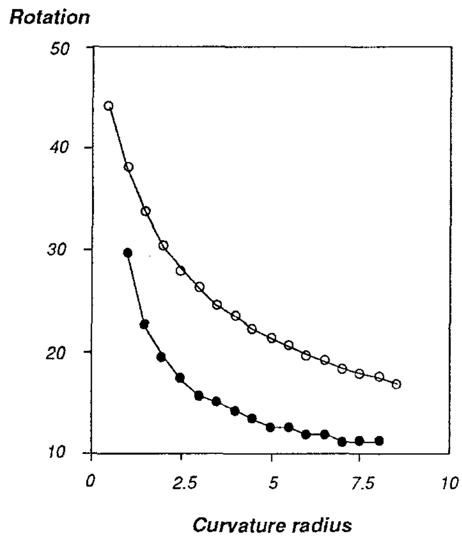


Fig. 15. Rotation along θ (degrees) with different surface curvature (cm). (*Filled dots*) The target shift of the contact centroid is reached. (*Empty dots*) Rotation stops for having reached the force threshold.

the performed motor actions and changes in the sensed tactile patterns. It can be observed that the link between shifts of the contact centroid along the y direction and the amplitude of rotations performed along θ depends on the curvature radius of the explored surface. Fig. 15 shows such a relation for two different cases: in the first case, the finger is rotated until a prefixed shift along the y coordinate is achieved. In the second one, the motor action is interrupted for having reached a safety force threshold of 20 N. The curves show that in both the situations the average rotation performed is dependent on the surface curvature. This fact can be used for the active estimate of surface curvature, by requiring the system to produce a desired shift in the y coordinate of the contact centroid. This translates into a corresponding activation of the units of the $\mathcal{F}^y$ feature map, which determine the direction of rotation through the activation value of unit u_θ. The average extent of rotation for both the cases of completed and interrupted movement can then be used as a measurement of surface curvature as illustrated by the values of the curves in Fig. 15.

6 Conclusions

Tactile information is crucial for developing robotics systems which are able to operate in uncertain environments. General-purpose effective 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 produced sensors specific to different contact information. Such sensors, even if far from producing highly accurate quantitative measurements, provide qualitative information which needs to be interpreted to give meaningful results. This is similar to the behavior of human receptors, whose responses seem to be far from systematic.

We believe that using already available tools, intelligent autonomous systems can gather useful tactile information from the environment, and can build representations of the explored world, if they know first the physical and functional organizations of their own systems. The discovery of such organizations implies the understanding of how sensory 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, and for a particular class of motor actions. However the approach is general and could in principle be applied to much more sophisticated systems, such as robotic dexterous hands.

Even if the focus of the paper is on the development of a particular kind of cutaneo-motor coordination, it has been also shown that, after that the sensory-motor association has been established, "intelligent" purposive motor actions (such as those for estimating surface curvature) can be produced by searching sensory—and not proprioceptive—changes. That is, a movement can be carried out by the system so as to produce an expected desired change in the tactile stimulation. This capability has a fundamental importance for achieving skilled manipulation and it is very strictly related to the concepts proposed by the paradigms of visual servoing and active perception.

The experiments that we have shown are part of a general approach to robotic tactile perception that we are currently following, which relies on the integration of tactile data acquired with 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 adaptive robots, but it could also guide experimental analysis toward the understanding of human sensory-motor control.

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Notes

1. Force Sensing Resistor, Interlink Electronics Europe, Echternach, Luxembourg

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