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CHAPTER 9

Understanding haptics by evolving mechatronic systems

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Abstract: Haptics can be defined as the characterization and identification of objects by voluntary exploration and somatosensory feedback. It requires multimodal sensing, motor dexterity, and high levels of cognitive integration with prior experience and fundamental concepts of self versus external world. Humans have unique haptic capabilities that enable tool use. Experimental animals have much poorer capabilities that are difficult to train and even more difficult to study because they involve rapid, subtle, and variable movements. Robots can now be constructed with biomimetic sensing and dexterity, so they may provide a suitable platform on which to test theories of haptics. Robots will need to embody such theories if they are ever going to realize the long-standing dream of working alongside humans using the same tools and objects.

Keywords: tactile sensing; haptics; robots; perception; cognition; learning; sensorimotor control; dexterity.

Introduction

The term "haptics" has been used variously by psychologists to mean the science of the sense of touch, by computer technologists for tactile feedback from an electronic device, and by aesthetic philosophers to denote affective responses to manual exploration. We shall use it here to denote the intersection of these usages as "the identification of properties of objects via voluntary exploration and somatosensory feedback." The entity doing the identification can be human or machine, the properties of the object can be physical or aesthetic, somatosensory includes both tactile and proprioceptive modalities from any body part (or their machine equivalents), and the interaction must involve active movement.

Natural scientists usually seek to understand a phenomenon by reducing it to its component parts. Psychologists have catalogued the

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exploratory behaviors made by human adults and infants when confronted by a novel object and neuroscientists have identified and characterized the receptors activated by such behaviors (Jones and Lederman, 2006). Nevertheless, we are lacking what David Marr called a "theory of computation" (Marr, 1982). In recent years, fairly strong theories of computation have been developed for many aspects of perceptual and even cognitive behavior. These usually derive from systematic recordings of neural activity from various brain regions of highly trained animals performing tasks and correlations of such activity with various parameters of the performance. This strategy is difficult to apply to haptics because few animals have anything like the manual dexterity of humans. For haptic behaviors that are feasible for animals, the movements and forces between the digits and objects are difficult to capture and the steps in the complex sequences tend to be variable and uncontrollable by the experimentalist. The difficulties of a reductionist approach to haptics can be appreciated by comparison with locomotion, another class of sensorimotor behaviors. The mechanics and control of walking in animals are now fairly well understood because reproducible behavior is easily generated and measured in both intact and reduced preparations (McCrea and Rybak, 2008). Some of the principles have been successfully incorporated into robots that perform reasonably well (Buchli and Ijspeert, 2004).

The process of building machines that incorporate principles of operation of living organisms is called biomimetic design. We propose that a theory of haptics can be developed and tested by starting with biomimetic robots and attempting to emulate the behaviors and capabilities of human subjects. Recent advances in mechatronics (engineered systems combining mechanical components with electronic control) have made it possible to emulate the mechanical behavior of biological hands and limbs (Delcomyn, 2007). Sensors built into the actuators and mechanical linkages provide the equivalent of proprioceptive information. Impedance control of the actuators can be used to emulate the natural compliance of biological limbs (Hogan, 1984; Pratt et al., 1996). Multimodal tactile information can be provided by a new sensor array that mimics the mechanical properties and robustness of a human fingertip (Wettels et al., 2008). It may be possible and perhaps even necessary to emulate the hierarchical structure of the biological nervous system, in which the brain formulates high-level strategies and tactics and the spinal cord coordinates the action of muscles and regulates the interactions with external objects (Raphael et al., 2010). If the controller of a mechatronic equivalent of a biological system could use a theory of computation to achieve humanlike haptic performance, this would be suggestive that the brain may be using a similar theory of computation. It should also be possible to apply such knowledge to the design of neural prosthetic systems to restore dexterity to patients with paralysis or amputation of their arms (Fig. 1).

Components of haptic behavior

The motor strategies that humans use to explore, characterize, and identify objects have been catalogued by psychologists (Jones and Lederman, 2006; Lederman and Klatzky, 1987). These strategies seem reasonable in view of the various somatosensory modalities that have been identified neurophysiologically, but they fall far short of a theory of computation for haptic behavior and they provide no insight into how they developed in the first place.

Development of internal representations of objects

We shall start with the assumption that the developing nervous system has little or no preconceived information about itself or the other entities that comprise its world and must instead

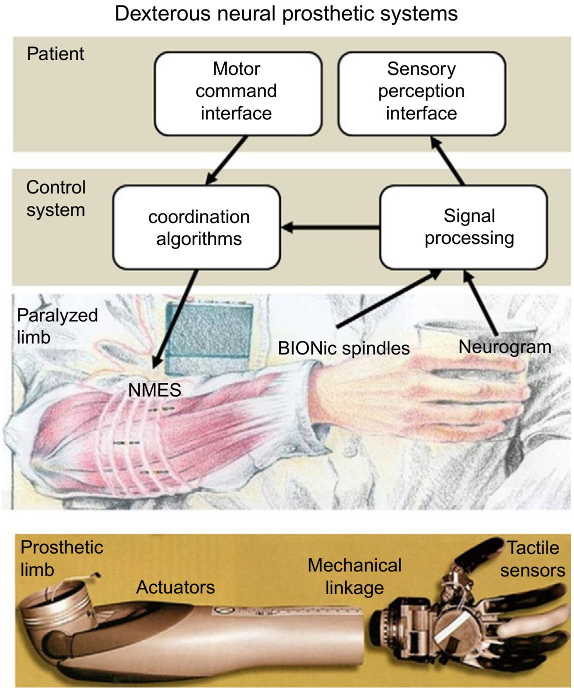

Fig. 1. Restoration of haptic function in patients with paralysis or amputation of the upper extremity requires both bidirectional interfaces with sensory and motor signals and a control system that can integrate those signals with command signals from the patient to provide coordination and rapid adjustments. Neuromuscular electrical stimulation (NMES) interfaces in the paralyzed limbs could utilize injectable, wireless microdevices called BIONs (Loeb et al., 2001; Sachs and Loeb, 2007).

self-organize its internal representations by detecting patterns of coherence in the incoming sensory information and its own outputs. This is the starting assumption for the unsupervised neural networks that were modeled in the early days of artificial intelligence (Haykin, 1999; Hebb, 1949). It is now clear that a certain amount of signal processing is genetically hardwired into the physical structure of primary sensory receptors and their associated local circuitry, which presumably predisposes the perceptual nervous system to start with specific salient features. Nevertheless, the development of internal representations is known to depend on actual experience, often associated with "critical periods" of neonatal development and plasticity (Crair et al., 1998; Hubel and Wiesel, 1970). We shall here assume that the objects to be represented centrally have an identity that is static, but this identity must be built up from highly dynamic interactions and it includes information required to predict dynamic behavior of the object.

Identification of self

The first thing that a self-organizing brain is likely to recognize is that some, but not all, of the sensory information coming back is contingent on motor signals that the brain sends out, initially randomly and eventually purposefully. The contingent sensory data are associated with the existence of a self; sensory data that are constant or inconsistently modified by efferent signals constitutes evidence of external entities, which are defined later. The representation of self is essentially a mapping between efferent signals and proprioceptive and visual afferent signals that represents the set of movements that the organism can make.

Efferent and afferent feedback In order to recognize the correlations between efferent and afferent signals, both must be available as inputs to a perceptual center. This explains why efferent projections are accompanied by recurrent projections that are organized similarly to afferent sources.

Internal reference frames Much has been written about the coordinate frames used by various parts of the brain to represent the relationships of the self to the external world. Some of them appear to be inherent in the structure of sense organs (e.g., retinotopic and cutaneous maps), others are likely to arise as the CNS detects robust correlations among the senses (e.g., extrapersonal space as fusion of visual information with gaze direction and proprioceptive feedback of posture), and some are purely mathematical creations designed to account for psychophysical data (e.g., shoulder-centered kinesthesia; Soechting and Flanders, 1989).

One likely outcome of adaptive neural networks is that they can extract more-or-less orthogonal representations of whatever principal components are present in their input data, but this begs the question of what the extracted coordinates might represent. If a given dataset can be adequately represented by a particular orthogonal coordinate frame (an eigenvector), it can also be equally well represented by other coordinate frames that are rotations of the first in eigenspace. At the early stages of sensory information processing, the coordinate frames of the neural representations may bear a strong resemblance to the physical structure of the sense organs from which the input signals are derived, but they will become increasingly abstract at higher levels where inputs are multimodal. The motor cortex integrates highly abstracted representations from many areas of association cortex plus relatively low-level direct input from proprioceptors. Thus, it is not surprising that simple attempts to correlate its output signals or its topography to simple physical coordinates based on either sensory input (extrapersonal space) or motor output (muscles) have been frustrating (Churchland and Shenoy, 2007).

The notion of first identifying "self" suggests that the internal coordinates of many, if not most, cortical areas will be different from each other but will reflect a combination of both afferent and efferent information. Such hybrid coordinate frames do not have simple physical or mathematical analogs and may vary from subject to subject (see below), so we have no guesses to correlate with neural activity. If they exist, we must first identify the neural processes and hierarchies that lead to their emergence.

Definition of surfaces

Once the organism has a repertoire of movements in extrapersonal space, it is in a position to recognize visual signals that do not change as a result of such movement (except occlusions by self) but that give rise to somatosensory and perhaps auditory signals when the movement reaches the place of those visual signals. Thus, the first externality to be represented in the brain seems likely to be the notion of surfaces that obstruct otherwise free limb movements.

Definition of rigid objects

Once the organism knows how to make contact with surfaces in extrapersonal space, it is in a position to recognize that contact between itself and a subset of those surfaces can result in changes in subsequent visual appearance and somatosensory feedback from those surfaces. This is the definition of a movable object as opposed to a fixed surface. By systematically reorienting its view of a rigid object, the brain can associate all the different patterns of sensory feedback that can be produced by that object, forming a fused percept. By systematically grasping and exploring the object, the brain can include in this percept information about weight, inertia, friction, thermal properties, etc.

Definition of deformable objects

Once the organism can recognize and manipulate rigid objects, it can appreciate that certain types of object have an even richer set of visual and somatosensory feedback depending on which of a limited set of states they occupy. Those states, in turn, may depend on the history of interactions with the object (e.g., hingelike motion) or the forces being applied (e.g., elastic deformation).

Definition of tools

Once the organism can recognize and manipulate any object, it is in a position to cause interactions between objects and surfaces, for example, using one object to hit and cause noise and/or movement of another object or surface. This is the definition of rudimentary tool use.

Definition of materials

An organism that can recognize objects that have a closed set of possible appearances can then recognize interactions that cause an object to change its appearance permanently. This is the definition of breaking or otherwise permanently changing an object, which renders it a material that can be used to create other objects (e.g., flaking stone tools, molding clay pots). Infants commonly handle known objects aggressively, as if they are fascinated by whether or not they fall into the category of things that can be broken.

Integrating exteroceptive senses

In the developmental sequence hypothesized above, visual information is only one of many types of sensory and efference copy information from which the structure of the self and the external world must be defined. By contrast, most roboticists start with sophisticated machine vision and use that as the basis for motor planning and sensory fusion. Infants are relatively slow to develop visual acuity, relying instead on tactile information from both fingers and mouth (Gibson, 1988). Adults who are blind from birth develop sophisticated representations of objects and dexterity in manipulating and characterizing them (Marks, 1983; Smitsman and Schellingerhout, 2000). What they do lack is a sense of how the visual appearance of objects changes with point of view (Heller et al., 1996). This is actually a problem rather than an attribute of vision, and much of machine vision and presumably human vision is concerned with overcoming this problem so as to maintain a veridically fused representation of individual objects. Thus, it seems both easier and more appropriate for these high-level visual capabilities to emerge spontaneously based on the perceived utility of visual information rather than as a preordained organizing principle for the brain.

The sounds made by objects and their interactions are rarely considered in robotics but they appear to be of great interest to infants. Sound contains valuable information that may be difficult to extract from other sensory modalities and it tends to be integrated centrally with other sensory modalities including touch (Bresciani and Ernst, 2007). Most obviously, sound provides precise temporal information, which can be useful for understanding kinetic interactions during touch. It also provides a valuable hint about the mutability of objects—articulated objects often change shape silently or with repeatable sounds whereas breaking an object is often accompanied by a nonrecurring sound. Attributes such as hollowness may be impossible to perceive in any other way. The vibrotactile spectrum (up to ~800 Hz) substantially overlaps the acoustic spectrum (20–20,000 Hz). Both may use temporospatial cross-correlation to extract useful information (Johansson and Flanagan, 2009; Loeb et al., 1983), but neither biological mechanism is well understood. Nevertheless, acoustic information is easy to acquire electronically and to preprocess in a way that conveys at least some of its biological saliency.

Testing new entities against internal representations

Once the organism has defined all major classes of entities in its world and has a reasonable library of sensorimotor patterns associated with previously encountered entities in each class, then its daily existence and continued development depend on two complementary capabilities:

- Recognizing when a newly encountered entity is sufficiently similar to a previously known entity to treat them as identical.
- Recognizing when a newly encountered entity is sufficiently dissimilar to all previously known entities to warrant creation of a new item in the library.

These decisions can be seen as forced-choice outcomes of Bayesian decision making, in which the probability of picking one or the other usually depends on fragmentary data and a complex set of prior information about the probability of a known entity being present, the importance of not making a mistake, and the cost of obtaining additional information. This cost has at least two dimensions, reflecting the energetic cost of the exploratory movement and its execution time. For many of the haptic discrimination tasks facing a hunter-gatherer, execution time will be critical—foraging time is limited and prey whose own motor behaviors cannot be identified and countered tends to escape. Bayes' theorem is useful for decision making once the new data are in hand (Kording, 2007), but it must be extended to account for the decision about *which data* to pursue based on the relative costs and the expected discriminative value of the new data. This depends on having an accurate and immediately accessible representation of all the possible associations between exploratory movements and the sensory data that they are likely to yield (Fig. 2). This suggests that the internal representation of the properties of objects in the brain is not in the usual canonical coordinates that we define in physics (e.g., mass, rotational inertia, hardness, friction, etc.), but rather in the associational coordinates of learned exploratory movements and the critical raw sensory signals associated with them. For example, the representation of mass of a given object is the association between the parameters of a hefting exploratory movement and the proprioceptive and tactile data resulting from hefting that object. In fact, it is possible that the goal of hefting

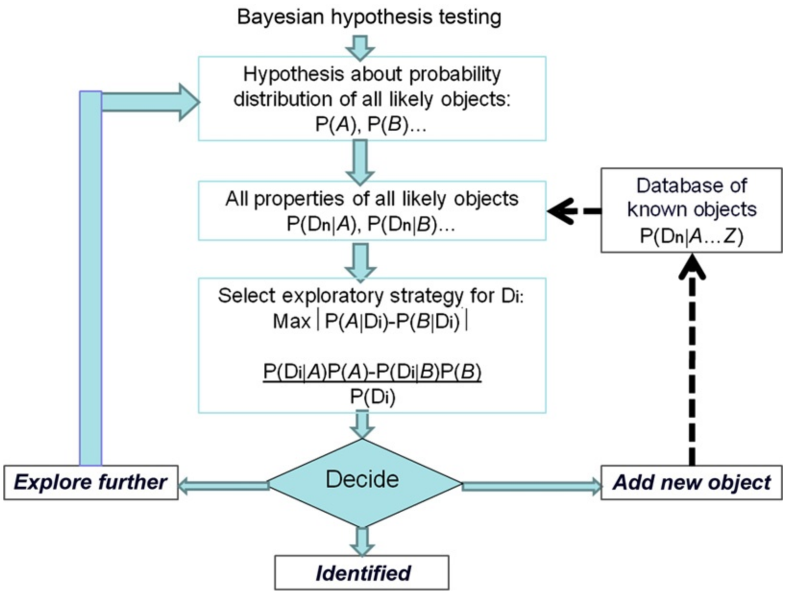

Fig. 2. Haptic exploration to identify an object can be conceptualized as an interactive sequence of hypothesis testing designed to collect specifically those data Di that are most likely to shift the prior probabilities P(A), P(B) sufficiently to conclude that the object matches an object that produces similar data when subjected to those exploratory strategies.

is to obtain similar sensory feedback from all objects, in which case the discriminative information is actually in the parameters of the hefting movement itself (e.g., amount of motor effort required to produce a given acceleration of the object). Similarly, the shape of an object obtained from contour following may be reflected in the sequence of exploratory movements required to keep the fingertip following a feature and thereby generating constant tactile feedback.

The choice of exploratory movement also involves the decision to stop exploration and settle on whatever is the currently most likely identification. There are many circumstances when erroneous “lumping” with previous experience is “good enough,” which accounts for a wide range of illusions, beloved of psychophysicists, magicians, and trial lawyers. When the brain insists that all is not familiar even after exhaustive exploration, the problem becomes one of creating a new percept that is associated with and based upon the closest known match. This leads to both a parsimonious extension of the coordinates of the existing internal representations and associations that facilitate access to previously developed strategies for handling similar but different entities. It is important to recognize that this incremental learning about the world is likely to give rise to internal representations of the same entity that are quite different among individuals, because they depend on the sequence of all other entities to which each individual was exposed during its prior experience.

Hierarchical system of sensorimotor control

The nervous system may start out “tabula rasa” but it is not free from genetically determined structures that evolved because they promote and accelerate the functionality that must develop ontogenetically. Each part of the nervous system tends to start with certain types of computational elements (neurons) whose various properties are specified. The initial interconnections among them appear to follow certain general rules and the rules for modifying that connectivity as a result of experience appear to be quite specific. In sensory systems, the sequence of embryological development gives rise to topographic gradients that are related to physical coherence in the signals that will later be experienced (e.g., retinotopic, cochleotopic, and somatotopic maps), so it has been natural (but not necessarily useful; see below) to interpret the higher levels of perceptual processing in those same coordinate frames. Organizing the motor system from periphery upward is appealing because the peripheral elements effectively define the computational problem that must be solved at higher levels of motor planning, but the major information flow is necessarily in the opposite direction from sensory systems. This discussion considers what is known about the structure and relationships from the bottom up but from the perspective of motor function, which is top-down.

Design of the spinal regulator

Industrial robots use hierarchical control that is usually divided into a movement planning level and a servocontrol level. For the last 50 years, sensorimotor neurophysiologists have tried to interpret the brain and spinal cord as analogous to those respective engineering subsystems, with little success. As details of the anatomical circuitry and physiological signals have been elucidated, it has become clear that they are not consistent with such an interpretation. The circuitry in the spinal cord is much more complex and integrative than an engineering servocontrol and the signals in the brain correlate only loosely with many different aspects of the output behavior. The spinal cord may function more like another, more sophisticated engineered system—a programmable regulator (He et al., 1991; Loeb et al., 1990). Recently, models of neuromusculoskeletal systems based on the known circuitry of the spinal cord have been shown to have highly useful emergent properties that were completely unexpected (Raphael et al., 2010). The biological regulator consists of component circuits with specific combinations of input and output signals that have evolved and remained stable over many millions of years of vertebrate evolution. The brain can "program" the gains of these elements via relatively simple descending command signals so that the highly phasic and coordinated sequences of muscle activations required to perform each task are generated by the nonlinear combinations of these commands and ongoing sensory feedback. Despite the large number of gains that must be set, simple gradient descent algorithms converge rapidly and inevitably to stable solutions that perform similarly to human subjects doing the same tasks. The set of interneurons defines a high dimensional space that is rich in "good enough" local minima. When started from random gains, the controller quickly "discovers" a nearby local minimum defined by the cost function used for training. Because the output is generated by circuits that include rich combinations of sensory feedback, the solutions automatically handle whatever types of noise, perturbations, or complex loads were included in the training set.

Since the pioneering work of Nicolas Bernstein in the 1930s, both motor psychologists and roboticists have been concerned with resolving the problem of "redundancy," in which there are more articulations or actuators than necessary to perform a given task (Bernstein, 1967). The programmable regulator turns this problem around, greatly expanding the redundancy at the interneuronal level to ensure that a single system can generate a virtually unlimited repertoire of desirable behaviors depending on the goals at hand. Evolutionary success is defined by rapidly finding good enough solutions rather than meticulously computing globally optimal solutions. We intend to demonstrate that robots controlled by similar programmable regulators can achieve similarly robust functionality. We can compare their strengths and weaknesses with state-of-the-art compliant controllers based on more traditional trajectory planning and servocontrol.

The problem with applying a regulator to a robot is that we do not have any blueprints. The properties of most mechatronic systems are so different from biological musculoskeletal systems that the patterns of interneurons known in the spinal cord cannot be applied to the robot. So we will have to recapitulate the evolution of the spinal regulator by using a genetic algorithm (Ijspeert, 2001). Genetic algorithms create and evolve structures incrementally, keeping components that improve performance and rejecting those that do not. In this case, the performance criterion is the speed and security with which a simple gradient descent controller can learn to perform a repertoire of diverse tasks using each new generation of regulator. Because the mechanical dynamics and sensors of the robot are actually substantially simpler to model than their biological counterparts, it should be feasible to evolve a fairly sophisticated regulator using a fast PC.

Learning to perform tasks

The redundancy problem is not really a problem for the nervous system because, unlike most robotic controllers, it does not try to compute analytical solutions to new problems. Rather the brain starts with one of the motor programs that it already knows (or a random output if an infant) and gradually refines that program until it gets what it wants. Given a reasonable repertoire of motor skills, most of the problem posed by a new task is the perceptual one of recognizing similarities to something already in the repertoire. The process of refinement by trial-and-error is made efficient and reliable by the many, good enough local minima of the regulator. This is distinctly different from servocontrollers, whose gains and input commands are more critical and are better set by analytical solutions for optimal control (Todorov and Jordan, 2002). Given a suitable regulator and a suitable cost function defining a task, it should be straightforward to train a model of cortical motor control. To achieve performance similar to a human, the cost function should probably include both kinematic terms related to accuracy and energetic terms related to effort. Interestingly, the spinal-like regulator seems predisposed to identifying motor strategies that result in minimal coactivation of actuators (Raphael et al., 2010), similar to the patterns seen in well-learned tasks performed by biological subjects.

Cortical consolidation

Surprisingly, after adequate performance has been achieved in a motor task, the controller in the brain continues to introduce large, apparently random fluctuations in its behavior (Churchland et al., 2010). We can surmise that the next level of controller upward in the hierarchy (e.g., premotor cortex) is performing its own trial-and-error learning to minimize some cost function. What might that cost be? From the well-described plasticity of cortical representations, we can surmise that the computational resources of the cortex are finite and perhaps a limiting factor in the repertoire and resolution of motor tasks that can be learned. When good enough performance is first achieved, the number of cortical motoneurons contributing to the net gains in the spinal regulator is likely to be much larger than necessary. This is because those net gains are the result of diverse excitatory and inhibitory functions controlled directly by each corticospinal motoneuron as well as indirectly via extrapyramidal subsystems that are also ultimately under the control of the cerebral cortex. By gradually adjusting the commands to the motor cortex, the premotor cortex should be able to reduce overlapping and conflicting activity. Shrinking the cortical neural representation of a given task frees up computational machinery to learn another task. The robustness of the spinal regulator, with its many good enough local minima, makes it relatively easy and safe to employ trial-and-error learning in all stages.

Cortical representations

Because there are many good enough solutions to common motor tasks, the repertoire of solutions that a given brain has at its disposal is likely to be rather different from another brain that has learned to achieve similar nominal performance. If a previously learned task is complicated by new loads, perturbations, or accuracy requirements, those different starting strategies may have different utilities and consequences. Psychophysicists studying motor learning usually create learning curves by averaging the data from many different subjects with similar starting skills, but these smooth, averaged curves do not reflect the apparently random, stepwise processes that actually occur in the individual subjects (Gallistel et al., 2004). They also fail to account for sport coaching practices that are required to force athletes out of idiosyncratic, well learned but ultimately suboptimal habits.

By utilizing trial-and-error learning of good enough behaviors instead of analytical optimal control, biological systems have accepted a Faustian bargain that roboticists have traditionally rejected: biological systems can rapidly achieve acceptable and stable performance with noisy components but are unlikely ever to achieve globally optimal performance. One consequence of that bargain is that the signals that can be recorded from behaving biological systems can never be fully understood by correlating them with the predictions of analytical engineering tools (e.g., Churchland and Shenoy, 2007). The deeper one dives from the unavoidable requirements of physics into the more arbitrary details of neural representations, the more the data become colored by the unique and essentially random experiences of the individual subject. This fundamental limit to experimental reductionism provides the rationale for our alternative approach based on simulation and synthesis. We choose haptics over other motor behaviors that have already been studied reductionistically because haptics requires rich sensorimotor integration and it has little reductionist baggage to discard.

Development and testing of Haptic robots

Mechatronic platform

A great variety of robotic arms and hands for both research and industrial applications have been developed over many years (Table 1). The more anthropomorphic systems of late tend to be more expensive and more fragile, both because of their complexity and their limited production for research. It is not clear what level of verisimilitude is necessary to generalize lessons learned from a haptic robot to a haptic human or vice versa.

Biomimetic tactile sensing

A variety of technologies have been used in tactile sensors (Table 2), but commercially available tactile sensors tend to be limited to relatively coarse arrays of normal-force sensors based on compression of elastic materials. In fact, most of the commercially available hands listed in Table 1 are not supplied with any tactile sensing. Many technologies are difficult to apply to the curved, deformable "skin" that facilitates grip and few are able to resist damage in the electromechanically hostile environments in which hands are often used (moisture, grit, sharp edges, etc.). One promising new candidate is the BioTac®, a biomimetically designed, multimodal array that provides most of the dynamic range of human tactile sensing for location, magnitude, and vector direction of contact forces, microvibrations associated with slip and textures, and thermal flux resulting from contact with objects that differ in thermal effusivity (Lin et al., 2009; Raphael et al., 2010; Wettels et al., 2008, 2009) (Fig. 3).

Compliant control algorithms

Many of the exploratory movements that underlie human haptics involve force or impedance control rather than position control, meaning that the trajectory of the limb results from a dynamic interaction between the robot and objects that it encounters. Most robots use highly geared DC and stepping motors that generate whatever torque is required to produce precise movements. When external forces are applied to them, they behave in a stiff rather than a compliant manner. In order to behave compliantly, these motors must be fitted with torque or force sensors that actively modify the position commands to which they are responding. If these control loops and motors are sufficiently fast, the system can achieve a reasonable approximation of the compliant control that arises naturally from biological muscles, which generate forces that depend on position and velocity of movement. Recently, such control principles have been organized into Dynamic Movement Primitives (DMP; Schaal, 2006), a system of nonlinear differential equations whose parameters correspond to the speed and accuracy criteria that are typically applied to biological affordances (Pastor et al., 2009; Schaal, 2007).

Visual targeting

Much haptic behavior in humans tends to start with visual information about an object of interest and its location in extrapersonal space. If the object is familiar, this information alone may be sufficient to identify the object and its expected handling properties. If not, it may provide convenient, albeit occasionally misleading, starting assumptions (e.g., large objects tend to be heavy, shiny surfaces tend to be slippery, etc.). Location,

Table 1. Summary of mechatronic hands

Research group	Tactile sensing technology	DOF	Comments
Utah/MIT hand	Capacitive normal force	16	
USC/Belgrade hand	Normal-force-sensitive resistors	20	
Honda hand	Normal-force-sensitive resistors	2	+ part of ASIMO robot
Hirzinger hand	Normal-force-sensitive resistors	12	+
NASA robonaut 2	6-DOF load cells in fingertip	24	+
GiFu III hand	Pressure-sensitive conductive ink	16	+
Southampton hand	Piezoelectric polymer film	4	Prosthetic prototype
Stanford/JPL hand	6-axis strain gauge	9	
UB III hand	6-axis IT sensors	16	+
Smart hand	Triaxial MEMS array	16	Follow-on from cyber hand
Dist hand	Triaxial force, slip sensors	16	+
DLR II hand	Conductive polymer grid	13	+
Shadowhand	Quantum tunneling composite	24	*
Yokoi III	Force sensitive resistors	13	+ Tsukasa Kiko engineering
iLIMB pulse	None		* for prosthetic use
LMS hand	Unknown	16	+
BUAA hand	Unknown	16	+
Zurich/Tokyo hand	Force sensitive resistors	13	+
Torino hand	Unknown	Unknown	
RCH-I hand	Unknown	Unknown	
MA-I hand	None	16	
SARAH hand	None	10	*
RTR II hand	None	9	+ Prosthetic prototype
Vanderbilt hand	None	9	+ Pneumatic (peroxide)
ACT hand	None	24	+
Barrett hand	None	4	*
Vecna HG2	None	6	* Hydraulic, hand camera
Heidelberg fluid hand	None	Unknown	+
LMS hand	None	16	
Anybots Monty hand	None	18	+
Tuat/Karlsruhe hand	None	20	Prosthetic prototype
Ultralight	None	13	+
Elumotion–Sheffield hand	None	20	+
Orebro University Sweden	None	12	
Manus Colobi	None	3	
TBM hand	None	Unknown	+ Prosthetic hand
Otto Bock Michelangelo 2	None	2	* for prosthetic use

* denotes currently available commercially; + denotes currently under development by research teams.
http://www.davidbuckley.net/RS/HandResearch.htm
http://asimo.honda.com/asimo-specs/
http://robonaut.jsc.nasa.gov/default.asp
http://www-arts.sssup.it/newCyberhand/smarthand/index.htm
http://www.dlr.de/rm/en/desktopdefault.aspx/tabid-3802/6102_read-8923/
http://www-lar.deis.unibo.it/activities/dexterousmanipulation/UBHandIII/index.html
http://robot.gmc.ulaval.ca/en/research/theme304.html
http://www.touchbionics.com/Pulse
http://www.vanderbilt.edu/exploration/stories/bionicarm.html
http://www.vecnarobotics.com/solutions/end_effectors/hg2.shtml
http://haptic.buaa.edu.cn/English_dexteroushand.htm
http://neurobotics.cs.washington.edu/projects.html
http://www.barrett.com/robot/products-hand.htm
http://www.elumotion.com/shefarm.html
http://www.ottobock.com/cps/rde/xchg/ob_com_en/hs.xsl/32149.html?openteaser=1

Table 2. Summary of tactile sensors

Transduction method	No. of axis	Multimodal	Advantages	Disadvantages	Example
Capacitive	1	No	Small, very high resolution taxels, can be flexible, wide dynamic range, sensitive	Hysteresis, noise	Pressure profile systems robotouch: http://www.pressureprofile.com/technology-capacitive.php
Inductive	1	No	High sensitivity, repeatability	Complex, vulnerable construction, low spatial resolution	Futai et al. (2003)
Resistive: deformable contact area	1	No	Flexible, thin	Hysteresis	Inaba: Inastomer http://www.inaba-rubber.co.jp/en/b_products/inastomer/index.html
Resistive: conductive fabric	1	No	Flexible, robust, simple	Unable to resolve more than one contact point	Pan and Zhu (2005)
Resistive: quantum tunneling composite	1	No	Sensitive, wide dynamic range	Hysteresis, gas absorption	QTC: http://www.peratech.com/
Resistive: strain gauge	6	No	Same as above	Bulky, expensive	ATI: Nano 17 load cell: http://www.ati-ia.com/products/ft/sensors.aspx
Resistive: Piezoresistive conductive polymer	1	No	Thin, low cost, simple	Hysteresis, stiff	Tekscan Flexiforce: http://www.tekscan.com/flexiforce.html
Resistive: Piezo-MEMS	6	Yes	Small, multielement	Large number of wires in workspace	Oddo et al. (2009), Beccai et al. (2005)
Polymer-MEMs (multimodal)	6	Yes	6-DOF force, temperature and heat flow, roughness	Large number of wires in workspace, wiring complexity	Engel et al. (2006)
Piezoelectric	1	Yes	Detects dynamics for slip and texture	Only detects dynamic events, thermal sensitivity	Dario et al. (1984), Howe and Cutkosky (1993)
Optical: video processing	3	No	Very high resolution, sensitive	Computationally intensive, sensitive to ambient light	Hristu et al. (2000), Ohka et al. (2004)
Optical: resistive	1	No	Flexible, low hysteresis	Complex fabrication	http://www.skilsens.com/index.html
Magneto-elastic	1	No	Very sensitive, low hysteresis	Sensitive to external magnetic fields	Mitchell et al. (1986)
Magneto-resistive	6	No	Robust, sensitive, low hysteresis	Noisy	Hackwood et al. (1983)
Ultrasound	1	Yes	Static and dynamic	High voltage, complex electronics	Brashford and Hutchins (1996), Grahn and Astle (1986)

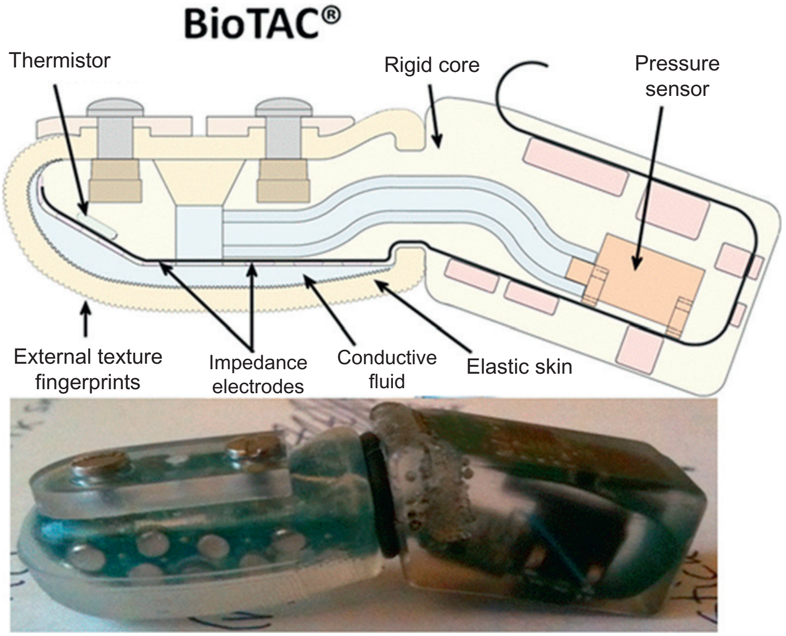

Fig. 3. A biomimetic, multimodal tactile sensor with the physical form and mechanical properties of a fused middle and distal phalanx consisting of a deformable skin inflated over a rigid core by a conductive fluid. Location, magnitude, and direction of contact forces can be extracted from changes in the pattern of electrical impedances measured through the conductive fluid by electrodes distributed over the surface of the core (visible through transparent skin in photo below). A pressure sensor connected to the fluid functions like a hydrophone to detect acoustic vibrations associated with slip or sliding over textured surfaces, which are enhanced by fingerprint-like ridges molded into the skin. The thermal material properties of objects contacting the finger can be assessed by a thermistor that measures heat flow from the heated core (Lin et al., 2009; Wettels et al., 2009). Sources: Upasani et al. (1999), Biagiotti et al. (2002), Puig et al. (2008).

size, and regions of interest for grasp or contour following can be extracted readily from stereovision. Machine vision has developed fairly sophisticated algorithms for all of these functions.

Exploratory algorithms

As discussed above, the decision about which exploratory movement to employ at any given time depends on whatever prior information is currently available about the probable identity of an object and the property of the object that is most likely to distinguish it from other possible objects. After selecting and initiating a specific exploratory strategy, the details of the movement may need to be driven by received sensory data (e.g., contour following) or adjusted iteratively to fine-tune discrimination (e.g., repeated hefting to assess weight or stroking to assess texture).

Internal representations

In order to extract a typical canonical physical property of an object (e.g., weight, texture, etc.), any sensory data received during an exploratory movement would have to be deconvolved with the parameters of the exploratory movement in order to yield information specific to the object. In order to use canonical physical properties to inform the dexterous manipulation of that object, the anticipated dynamic effects of those properties on the proposed manipulation would have to be computed, something that has been attributed to "internal dynamic models" (Imamizu et al., 2000; Kawato, 2008). Alternatively, the brain could represent objects as a set of learned associations in which each association includes both the output parameters of the exploratory movement (available from the many copies of efferent signals that project recurrently in the central nervous system) and the sensory data associated with the object being manipulated in that way (e.g., tactile, proprioceptive, visual, auditory; Pastor et al., 2009). This would facilitate the Bayesian strategy selection described above as well as the recall of appropriate motor strategies for dexterous manipulation of the object.

Conclusions

Haptic behaviors do not lend themselves to the types of reductionist studies in animals that have been effective in revealing the neural computational algorithms that underlie other perceptual capabilities such as vision and hearing. Instead, it may be possible to develop and test theories of haptic computation by applying them to robotic platforms whose sensory and motor capabilities are increasingly biomimetic. For this to be effective, however, it may be necessary to recapitulate at least some of the early cognitive stages during which intelligent organisms develop representations of themselves and the external world. Those representations and strategies may be somewhat idiosyncratic, further emphasizing the importance of understanding the processes rather than the results.

References

Beccai, L., Roccella, S., Arena, A., Valvo, F., Valdastri, P., Menciassi, A., et al. (2005). Design and fabrication of a hybrid silicon three-axial force sensor for biomechanical applications. *Elsevier, Sensors and Actuators*, *120*, 370–382.

Bernstein, N. (1967). *The coordination and regulation of movement.* New York: Pergamon.

Biagiotti, L., Lotti, F., Melchiorri, C., & Vassura, G. (2008). *How far is the human hand? A review on anthropomorphic robotic end-effectors.* Bologna, Italy: University of Bologna.

Brashford, A. G., & Hutchins, D. A. (1996). Characteristics of ultrasonic micromachined capacitance transducers in water. *IEEE Ultrasonics, Ferroelectrics, and Frequency Control Society*, *2*, 955–958.

Bresciani, J.-P., & Ernst, M. O. (2007). Signal reliability modulates auditory-tactile integration for event counting. *Neuroreport*, *18*, 1157–1161.

Buchli, J., & Ijspeert, A. J. (2004). Distributed central pattern generator model for robotics application based on phase sensitivity analysis. *Biologically Inspired Approaches to Advanced Information Technology*, *3141*, 333–349.

Churchland, M. M., Afshar, A., & Shenoy, K. V. (2010). A central source of movement variability. *Neuron*, *52*(6), 1085–1096.

Churchland, M. M., & Shenoy, K. V. (2007). Temporal complexity and heterogeneity of single-neuron activity in premotor and motor cortex. *Journal of Neurophysiology*, *97*, 4235–4257.

Crair, M. C., Gillespie, D. C., & Stryker, M. P. (1998). The role of visual experience in the development of columns in cat visual cortex. *Science*, *279*, 566–570.

Dario, P., De Rossi, D., Domenici, C., & Francesconi, R. (1984). Ferroelectric polymer tactile sensors with anthropomorphic features. *IEEE International Conference on Robotics and Automation (1984),* pp. 332–340.

Delcomyn, F. (2007). Biologically inspired robots. *Advanced Robotic Systems International and I-Tech*, (in press).

Engel, J., Chen, N., Tucker, C., Liu, C., Kim, S.-H., & Jones, D. (2006). Flexible multimodal tactile sensing system for object identification. *5th IEEE conference on sensors,* pp. 563–566.

Futai, N., Matsumoto, K., & Shimoyama, I. (2003). Simulation, fabrication and evaluation of microinductor-based artificial tactile mechanoreceptor embedded in PDMS. In *IEEE MEMS,* pp. 206–209.

Gallistel, C. R., Fairhurst, S., & Balsam, P. (2004). The learning curve: Implications of a quantitative analysis. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(39), 13124–13131.

Gibson, E. J. (1988). Exploratory behavior in the development of perceiving, acting, and the acquiring of knowledge. *Annual Review of Psychology*, *39*, 1–41.

Grahn, A. R., & Astle, L. (1986). Robotic ultrasonic force sensor arrays. *Robot Sensors*, *2*, 297–315.

Hackwood, G. B., Hornal, L. A., Wolfe, R., & Nelson, T. J. (1983). A torque sensitive tactile array for robotics. *International Journal of Robotics Research*, *2*, 46–50.

Haykin, S. (1999). Neural networks: A comprehensive foundation. In (2nd ed.). Upper Saddle River, NJ: Prentice Hall.

He, J., Levine, W. S., & Loeb, G. E. (1991). Feedback gains for correcting small perturbations to standing posture. *IEEE Transactions on Automatic Control*, *36*(3), 322–332.

Hebb, D. O. (1949). *The organization of behavior.* New York: Wiley.

Heller, M. A., Calcaterra, J. A., Tyler, L. A., & Burson, L. L. (1996). Production and interpretation of perspective drawings by blind and sighted people. *Perception*, *25*(3), 321–334.

Hogan, N. (1984). An organising principle for a class of voluntary movements. *Journal of Neuroscience*, *4*(11), 2745–2754.

Howe, R. D., & Cutkosky, M. R. (1993). Dynamic tactile sensing: Perception of fine surface features with stress rate sensing. *IEEE Transactions on Robotics and Animation*, *9*, 2.

Hristu, D., Ferrier, N., & Brockett, R. W. (2000). The performance of a deformable-membrane tactile sensor: Basic results on geometrically-defined tasks. *IEEE International Conf. on Robotics and Automation 1*, pp. 508–513.

Hubel, D. H., & Wiesel, J. N. (1970). The period of susceptibility to the physiological effects of unilateral eye closure in kittens. *The Journal of Physiology*, *206*, 419–436.

Ijspeert, A. J. (2001). A connectionist central pattern generator for the aquatic and terrestrial gaits of a simulated salamander. *Biological Cybernetics*, *84*(5), 331–348.

Imamizu, H., Miyauchi, S., Tamada, T., Sasaki, Y., Takino, R., Putz, B., et al. (2000). Human cerebellar activity reflecting an acquired internal model of a new tool. *Nature (London)*, *403*(6766), 192–195.

Johansson, R. S., & Flanagan, J. R. (2009). Coding and use of tactile signals from the fingertips in object manipulation tasks. *Nature Reviews. Neuroscience*, *10*, 345–359.

Jones, L. A., & Lederman, S. J. (2006). *Human hand function.* New York: Oxford University Press.

Kawato, M. (2008). From “Understanding the Brain by Creating the Brain” towards manipulative neuroscience. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *363*, 2201–2214.

Kording, K. (2007). Decision theory: What “should” the nervous system do? *Science*, *318*, 606–610.

Lederman, S. J., & Klatzky, R. L. (1987). Hand movements: A window into haptic object recognition. *Cognitive Psychology*, *19*, 342–368.

Lin, C.-H., Erickson, T. W., Fishel, J. A., Wettels, N., & Loeb, G. E. (2009). Signal processing and fabrication of a biomimetic tactile sensor array with thermal, force and microvibration modalities. *ROBIO 2009 IEEE international conference on robotics and biomimetics*.

Loeb, G. E., Levine, W. S., & He, J. (1990). Understanding sensorimotor feedback through optimal control. *Cold Spring Harbor Symposia on Quantitative Biology*, *55*, 791–803.

Loeb, G. E., Peck, R. A., Moore, W. H., & Hood, K. (2001). BION system for distributed neural prosthetic interfaces. *Medical Engineering & Physics*, *23*(1), 9–18.

Loeb, G. E., White, M. W., & Merzenich, M. M. (1983). Spatial cross-correlation. A proposed mechanism for acoustic pitch perception. *Biological Cybernetics*, *47*(3), 149–163.

Marks, L. E. (1983). Similarities and differences among the senses. *The International Journal of Neuroscience*, *19*(1–4), 1–11.

Marr, D. (1982). *Vision*. New York: W.H. Freeman & Co.

McCrea, D. A., & Rybak, I. A. (2008). Organization of mammalian locomotor rhythm and pattern generation. *Brain Research Reviews*, *57*(1), 134–146.

Mitchell, E. E., DeMoyer, R., & Vranish, J. (1986). A new metglas sensor. *IEEE Transactions on Industrial Electronics*, *IE-33*, 166–170.

Oddo, C. M., Beccai, L., Felder, M., Giovacchini, F., & Carrozza, M. C. (2009). Artificial roughness encoding with a bio-inspired MEMS-based tactile sensor array. *Sensors*, *9*, 3161–3183.

Ohka, M., Mitsuya, Y., & Takeuchi, S. (2004). Sensing characteristics of an optical three-axis tactile sensor under combined loading. *Robotica*, *22*, 213–221.

Pan, Z., & Zhu, Z. (2005). Flexible full-body tactile sensor of low cost and minimal output connections for service robot. *Industrial Robot: An International Journal*, *32*, 485–491.

Pastor, P., Hoffmann, H., Asfour, T., & Schaal, S. (2009). Learning and generalization of motor skills by learning from demonstration. *IEEE International Conference on Robotics and Automation*.

Pratt, J., Torres, A., Dilworth, P., & Pratt, G. (1996). Virtual actuator control. *IEEE/RSJ international conference on intelligent robots and systems*.

Puig, J. E. P., Nestor, E. N., Rodriguez, N., & Ceccarelli, M. (2008). A methodology for the design of robotic hands with multiple fingers. *International Journal of Advanced Robotic Systems*, *5*(2), 177–184.

Raphael, G., Tsianos, G., & Loeb, G. E. (2010). Spinal-like regulator facilitates control of a two-degree-of-freedom wrist. *The Journal of Neuroscience*, *30*(28), 9431–9444.

Sachs, N. A., & Loeb, G. E. (2007). Development of a BIONic muscle spindle for prosthetic proprioception. *IEEE Transactions on Biomedical Engineering*, *54*(6), 1031–1041.

Schaal, S. (2006). Dynamic movement primitives—A framework for motor control in humans and humanoid robotics. *Adaptive Motion of Animals and Machines*, 261–280 Part 6.

Schaal, S. (2007). The new robotics—Towards human-centered machines. *HFSP Journal*, *1*, 115–126.

Smitsman, A. W., & Schellingerhout, R. (2000). Exploratory behavior in blind infants: How to improve touch? *Infant Behavior & Development*, *23*, 485–511.

Soechting, J. F., & Flanders, M. (1989). Sensorimotor representations for pointing to targets in three-dimensional space. *Journal of Neurophysiology*, *62*(2), 582–594.

Todorov, E., & Jordan, M. I. (2002). Optimal feedback control as a theory of motor coordination. *Nature Neuroscience*, *5* (11), 1226–1235.

Upasani, A. V., Kapoor, C., & Tesar, D. (1999). Survey of available sensor technology for robotic hands. *Proceedings of the DETC 99, ASME design engineering technical conferences*.

Wettels, N., Fishel, J., Su, Z., Lin, C.-H., & Loeb, G. E. (2009). Multi-modal synergistic tactile sensing. *Tactile sensing in humanoids—Tactile sensors and beyond workshop, 9th IEEE-RAS international conference on humanoid robots*.

Wettels, N., Santos, V. J., Johansson, R. S., & Loeb, G. E. (2008). Biomimetic tactile sensor array. *Advanced Robotics*, *22*(8), 829–849.