

Body schema in robotics: a review

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Abstract—How is our body imprinted in our brain? This seemingly simple question is a subject of investigations of diverse disciplines, psychology and philosophy originally, complemented by neurosciences more recently. Despite substantial efforts, the mysteries of body representations are far from uncovered. The most widely used notions - body image and body schema - are still waiting to be clearly defined. Not only the scientific, but also pragmatic implications of body representations are interesting. The mechanisms that underlie body representations are (co-)responsible for the admiring capabilities that humans or many mammals can display: combining information from multiple sensory modalities, controlling their complex bodies, adapting to growth, failures, or using tools. These features are also desirable in robots. This paper reviews the body representations in biology from a functional or computational perspective to set ground for the second part, where we review the concept of body schema in robotics. First, we review application-oriented research: how a robot can improve its capabilities by being able to automatically synthesize, extend or adapt a model of its body. Second, we summarize the research area in which robots are used as tools to verify hypotheses on the mechanisms underlying biological body representations. We identify trends in these research areas and propose future research directions.

I. INTRODUCTION

The basic notion of body schema encloses a group of body representations which are essential for body motion and a meaningful interaction with the environment carried out by an embodied agent. The body schema allows for integration of information from proprioception, vision, audition, the vestibular system, tactile sensing, and from the motor system in order to keep an up-to-date representation of the positions of the different body parts in space. Typically these representations are involved in movement preparation and the representation of space in different frames of reference to be used by different behaviors. Such representations are the central subject of many studies in the cognitive sciences, especially in the neurosciences. The concepts of a postural schema and a surface schema were first introduced by Head and Holmes [HH11]. In their view the postural schema represents the awareness we have of our bodies' position in space, and the surface schema represents our capacity to locate stimuli on the surface of the skin. Since then, many other classifications and taxonomies appeared, trying to structure the plethora of body representations, yet the literature has not converged to any of them up to now.

Biological agents are able to adapt seamlessly to new situations or cope with failures. To a large extent, this is because the body representations required to support their behaviors can dynamically adapt to new circumstances. These properties are also desirable in robots; today, their operation is still restricted to static or limited environments, and resilience to failure is typically absent. When trying to bridge this gap,

many roboticists look to biology for inspiration, in order to integrate some of the features of a biological body schema into their machines. While this flow of information - from biology to robotics - was dominant so far, there also exists a route in the opposite direction. Many of the mechanisms underlying the body schema are still a mystery to cognitive scientists. Although there is rapid progress, to a large extent thanks to the neurosciences with their imaging techniques, the investigation of some mechanisms requires whole brain-body-environment systems as test-beds. Here, robots can qualify as useful tools to test hypotheses that computational neuroscience has put forward up to this day.

This paper will be structured as follows. First, we offer a review of body representations in the context of biology. After discussing the taxonomies and how these are supported by studies on disorders, we will focus on topics that we consider of greatest relevance for robotics: plasticity of body representations (development, adaptation, extension), coordinate transformations, and the relationship between body schema and forward models. Second, we provide an overview of the engineering-oriented work in which a body schema serves to control a robot and to improve its behavior when faced with unexpected circumstances. In theory, an enormous part of research in robotics and control could fall into this section, since models (plant models) used to control robots are ubiquitous. However, we will show how this representation is different from the ones that take inspiration from biology and further concentrate on the latter. There are many axes according to which the research in robotics could be structured. For us, the principle axis will be the nature of representation: explicit vs. implicit. Third, a section on robots employed as tools to model biological body representations is presented. We think that this body of work - investigating whole brain-body-environment systems - is a necessary complement of computational neuroscience. We conclude by identifying the major trends and suggesting future research directions.

II. BODY REPRESENTATIONS IN BIOLOGY

It is clear that there are representations of the body in the brain. It is also very likely that there is no single unitary representation, but rather several, partial representations that serve different purposes. We will discuss the basic taxonomies and clarify what we will mean by body schema and body image in the rest of the paper. Disorders and dissociation studies are useful to get insight into the structure of the putative body representations. We will discuss two in detail and present an overview of those that we consider relevant for robotics. Body representations are plastic over time. It is this property that is largely responsible for many of the capabilities that animals

display. We will discuss the developmental time scale first. How does an infant acquire its body representation? How does it develop a sense of body ownership and agency? Then, we will review the plasticity of body representations over short time scales, minutes for instance. We will discuss the “rubber hand illusion” and extension of body representations on tool use. The next topic of undisputed direct relevance for robotics are coordinate transformations. Finally, we have included a section which demonstrates the notions discussed on a concrete scenario. In addition, we explicitly establish a relation to forward internal models - a closely related concept. The idea is to provide enough information for a roboticist to get an initial functional understanding of the topic and to equip him with initial pointers to the literature. We have to admit that this section is strongly biased toward body representations in humans and primates. Other animals remained out of the scope of this review. However, studying body representations in simpler animals than humans can provide no less valuable insights for roboticists.

A. What is a body schema

Two main taxonomies form a first attempt to differentiate the variety of body representations: the dyadic and the triadic taxonomies [dV10]. Both draw a line between representations that are used for action and those used for perception; the former are called a body schema. This functional division is grounded on the hypothesis that visual as well as somatosensory processing is carried out in two distinct nervous pathways: one for action and another for conscious perception and object recognition [Gal05], [DdH07], [Pai99]. In visual processing, these are the “what” and “how” streams as suggested in [MG95] (earlier distinction between “what” and “where” pathways was suggested in [UM82]). The visual pathway for action, the “how” or dorsal stream, goes from the occipital lobe to the motor cortex through the parietal cortex. The pathway for perception, the “what” or ventral stream, goes from the occipital lobe to the temporal lobe. A similar separation can be observed in somatosensory perception. The pathway for action involves the anterior parietal cortex (APC), eventually the secondary somatosensory area (SII) and terminates in the posterior parietal cortex (PPC) [DdH07]; the pathway for perception involves a similar route but terminates at the insula rather than the PPC. The right PPC might also be involved when integration of spatio-temporal information is required for the recognition of objects as well as body configuration (see also [CP01] and [MG95], [DdH07] for a comparison between the two pathways for action and perception in the somatosensory processing and visual and auditory processing).

On these grounds, the *dyadic taxonomy* distinguishes between *body schema* and *body image*. The former are sensorimotor representations of the body used to guide movement and action, the latter representations are used to form our perceptual (body percept), conceptual (body concept) or emotional (body affect) judgments towards our body [Gal05]. However, especially the concept of body image is problematic, lacking a positive definition; it seems that once we are done with a body schema, everything else can fall into body

image [dV10]. Therefore, the *triadic taxonomy* further splits the representations belonging to the general concept of body image [SC05]. One of these representations, the body structural description, entails a topological representation (mainly visual) of the position of the different body parts in relation to each other (e.g. the forearm extends the upper arm via a hinge joint). The other representation, body semantics, comprises a semantic representation of the body which includes the names of the different body parts, their functions as well as potential relations to external artifacts (e.g. shoes are used on the feet, and feet can be used to kick a football).

The functional axis (action vs. perception) is nevertheless only one possible criterion to distinguish between various body representations, and an oversimplifying one too. Other features used to classify body representations are availability to consciousness (unconscious vs. conscious), and dynamics (short-term vs. long-term). However, the weight of the criteria varies relative to the author and sometimes even the same notion is ascribed opposite properties (see [dV10] for more details). While these additional axes are useful, they still do not give rise to any clear taxonomy of body representations. Perhaps, such an endeavor cannot be successful, because we are not faced with two or three distinct representations, but rather with a plethora of many interacting partial representations.

Nevertheless, there is definitely some agreement that there is something like a body schema - a sensorimotor representation of the body used for action. Typically, it would not be available to consciousness¹ and would encompass both short-term (e.g. position of a limb at a given instant) and long-term dynamics (e.g. biomechanical properties and size of limbs). Since our motivation is robotic, this notion will be our primary focus. Our decision is motivated by the following reasons: (1) As stated above, there is certain consensus on the existence of a body schema; (2) The fact that it is a representation for action finds a natural counterpart in robots which can then be employed to perform tasks; (3) We think that robots have not yet reached the level of competence where notions like semantic or conscious representations can be investigated in a grounded fashion.

The notion of body image - as a perception-based representation - will not be excluded from our investigation; however, we will restrict it to the body structural or topological representation, leaving apart the domains of body concept or body affect.

B. Disorders

What are the grounds on which the body representations are classified into the taxonomies we have come across? Underpinning these taxonomies are a variety of studies which analyze the functional impact of some impairment on the behavior of a subject (see [DdH07]). It is the fact that some subjects are able to perform normally on some body-related tasks but not on others that allows to distinguish between the different representations.

¹Though it may become conscious under certain circumstances, such as during motor imagery [SC05].

Probably the most mentioned disorder in the context of research on body schema is that of deafferentation. Deafferentation in general is the (total or partial) deterioration of afferent signals, i.e. signals that go from the periphery to the central nervous system. When applied to body-related representations, deafferentation is the (complete or partial) loss of proprioceptive and tactile signals whether their origin is in the periphery or in more central areas. Paillard [Pai99] reported two cases of deafferented patients with very different behaviors. In one case, the patient G.L. was able to perceive a signal applied to her body, report verbally the location of the stimulus as well as to point to the correct location of the limb part stimulated on a body sketch. However, when asked to point with her right hand to the part of her own body which had been stimulated, she was unable to do so. In the other (somehow more bizarre) case, patient R.S. was unable to consciously perceive tactile stimuli, joint positioning, temperature or pain in her own body; she could for example cut or burn herself without noticing. R.S. failed to locate verbally a given tactile stimuli on her own body but curiously (even to herself) she could point flawlessly to the body part stimulated. According to Paillard, these two cases provide a case for an intact body schema with an impaired body image (R.S.) and a case for an impaired body schema with an intact body image (G.L.); i.e. they provide a case for the distinction between the two body representations in the brain as mentioned in the previous section [Gal05].

Cases showing a further distinction between body structural description and body semantics can also be found in the literature. In a large group study, Schwoebel and Coslett [SC05] analyzed subjects on three types of measures: one accessing the integrity of the body schema, one accessing the integrity of the body structural description, and another accessing the integrity of the body semantic representation. Each performance measure involved a set of different tasks [SC05]. In the first measure, aimed at accessing the integrity of the body schema, subjects were required either to (1) imagine or execute different finger movements, or (2) to indicate the laterality of a hand in a picture (i.e. left or right hand). The second measure, aimed at accessing the body structural description, included three tasks: (1) to point to the location in one's own body of a body part depicted in an image, (2) to point to the location of a stimulus applied to a given body part, and (3) to point to one of three pictured body parts that were closer to a given target body surface. The third measure, aimed to access the integrity of the body semantic description, involved two tasks: (1) to match one of three pictured body parts with another functionally-related target part (e.g. the elbow has as similar function as the knee; they are both joints), and (2) to match a pictured item of cloth with one of four given pictured body parts. They found out that 13 of the patients analyzed failed on tasks involving the measure of body schema integrity but performed normally on the other two measures. Three of the patients failed to carry out successfully the tasks involved in the body structural description measure, but were able to carry out normally the tasks involved in the other two measures. Finally, two of the patients failed to execute the tasks related to the body semantic measures but performed normally in the

other tasks. These results provide grounds to support the triadic taxonomy.

If robots are to be used as models of biological (in this case human) body representations, they can eventually be also subject to such tests - failures in robots can be compared to disorders in humans. A list with main disorders related to body representations is given in Table I. This list is a short version of the one offered in Vignemont [dV10]. The original table was pruned in order to give only the most relevant information for roboticists; the disorders removed were basically related to eating disorders or emotional responses related to body representations.

C. Plasticity of body representations

1) *Development, body ownership, agency*: How do the various body representations originate? They arise during the process of development immediately after birth (or even before - in the womb). We have to rely more on psychological rather than neurophysiological data here, since brain imaging techniques are not readily applicable on infants. As reported by Rochat [Roc98], infants spend substantial time in their early months observing and touching themselves. Rochat calls it the visual-proprioceptive calibration of the body. Through this process of babbling, intermodal redundancies, temporal contingencies and spatial congruences are picked up. Environmental stimulation (single touch) can be distinguished from self-stimulation (double-touch + proprioceptive stimulation) [RH97]. If we treat this process as relying mainly on perception, we can view it as the acquisition of the body image. However, the infants not only observe, but actively involve their motor apparatus in the explorations (e.g., [BB93]). Hence, the development of body schema probably takes place at the same time. Hand in hand with the development of the body representations, the infants acquire a notion of *body ownership* and *agency*. We mean here agency in a low-level sense - pre-reflective, sensorimotor, and functional, rather than in a phenomenological sense (see e.g. [DNO8] for a disambiguation). Basically, a sense of body ownership would be disrupted by a sensory experience that does not match the previously learned regularities between modalities (i.e. mismatch with body image); sense of agency would be disrupted by a sensory-motor mismatch (i.e. a mismatch with a body schema).² However, as it is hard to separate body image from body schema, it is also hard to separate sense of body ownership from sense of agency (see [TSBG07] for details and experimental treatment of this issue). The above-mentioned low-level capabilities constitute the basis for action recognition in self, action recognition in others, and self-other discrimination. This is further related to action mirroring (where the mirror neurons are active) and imitation (see Rizzolatti et al. [RSA07]). This is a natural extension

²In more concrete terms, this means there will be a mismatch between the sensory feedback predicted by a forward model from a motor command (efference) copy and the actual sensory input (reafference). This is also referred to as the "comparator model". However, for both body ownership and agency, the situation is more complicated and involves a top-down component as well - knowledge about the context [DNO8], [TSBG07].

TABLE I
DISORDERS RELATED TO THE BODY SCHEMA (EXTRACTED FROM [DV10]).

Alice in Wonderland Syndrome	Distorted awareness of body size, mass, or its position in space
Allochiria	Mislocation of sensory stimuli to opposite half of the body
Anarchic hand sign	Unintended but purposeful and autonomous movements of the upper limb and intermanual conflict
Autoscopy	Experience of seeing one's body in extrapersonal space
Autoprosopagnosia	Inability to recognize one's own face
Autotopagnosia	Mislocalisation of body parts and bodily sensations
Body form agnosia	Deficit of recognition of body parts
Body-specific aphasia	Loss of lexical knowledge of body parts
Deafferentation	Loss of tactile and proprioceptive information
Dysmorphophobia	Distorted perception of one's self-appearance
Fading limb	Lack of awareness of the presence and position of the limb if not seen
Finger agnosia	Inability to individuate and recognize the fingers
Gertmann's syndrome	Finger agnosia, agraphia, acalculia and left-right confusion
Heterotopagnosia	Designation of parts of the body of another person when asked to point towards one's own body
Ideomotor apraxia	Inability to execute or carry out skilled movements and gestures
Macro/microsomatognosia	Distorted awareness of the size of the whole body or of body parts (bigger or smaller)
Mirror sign	Inability to recognize one's own image in the mirror
Motion sickness (or kinetosis)	Vestibular balance disorder
Motor neglect	Underutilisation of one side of the body
Numbsense	Tactile deficit with preserved tactually guided movements
Out of body experience (OBE)	Visual awareness of one's own body from a location outside the physical body
Personal neglect	Lack of attention towards one's side of the body
Phantom limb	Awareness of an amputated limb
Pusher syndrome	Postural deviation towards the contralesional side
Prosopagnosia	Deficit of face recognition
Supernumerary limb	Awareness of non-existing limbs
Tactile extinction	Lack of awareness of tactile stimuli on the contralesional limb during simultaneous bilateral stimulation

of our topic, but will remain largely out of the scope of this review.

2) *Rubber hand illusion*: The body representations are not only plastic during development. They can also respond to large changes in the body, such as limb loss (see e.g., Ramachandran and Blakeslee [RB98]). Moreover, body representations can also adapt over much shorter time scales. Let us first look how this can happen on the perceptual side, modifying the body image. Holmes and Spence [HS05] made an extensive review on different behavioral, neurophysiological and neuropsychological studies regarding evidence on the possibility to "incorporate" objects not connected directly to the body by multisensory integration. A prominent series of studies involves the "rubber hand illusion". Botvinick and Cohen [BC98] first introduced the idea of the "incorporation" of a rubber hand in the bodily representation by simultaneous tactile stimuli, and congruent visual and proprioceptive feedback. That is, because of the rapid adaptation of the body image, the rubber hand enters our sense of body ownership. More recently, other studies ([PC04], [AR03], [ESP04], [Ehr09]) further explored the rubber hand paradigm, also in the case of hand amputees [HBA⁺08]. The appropriation of the external object as part of the body representation of the person goes to the extent that if the rubber hand is threatened, the person shows a similar level of activity in the brain areas associated with anxiety and interoceptive awareness [EWW⁺07]. This effect can be found in the appropriation of virtual bodies too [HEHR⁺08].

3) *Tool use*: Tsakiris et al. [TSBG07] pointed out that the basic rubber hand illusion setup lacks ecological validity, because it does not involve bodily movement. In other words, it is not a usual situation for primates or humans not to actively perform actions, but rely on multi-sensory integration only. Efferent information may play a key role, bringing us back to the difficulty of separation between body schema and image, resp. body ownership and agency. This leads us to another prominent experimental paradigm: *body schema extension on tool use* (body schema because now we are concerned with representations for action). Primates can manipulate objects in different ways and some can use tools to achieve a particular goal. How is the tool reflected in their body representations? Maravita and Iriki [ITI96] investigated this in a macaque monkey that was retrieving food with the help of a rake. Neuronal activity of bimodal neurons (i.e. neurons that react to both somatosensory and visual stimulation) was recorded from the intraparietal cortex. Two groups of neurons were identified: 'distal type' and 'proximal type'. The former responded to somatosensory stimuli at the hand and visual stimuli near the hand. The visual receptive field (region of space in which the presence of a stimulus will alter the firing of that neuron) of these neurons followed the hand in space. After the monkey had used the tool for about five minutes, the visual receptive field of some neurons expanded to cover the entire length of the tool. The visual receptive field of the latter neuron group - the 'proximal type' - was not centered around the hand, but spanned the whole space within reach. We call this space *peripersonal space*. As the body and the space

immediately surrounding it are always in close interaction, the same seems to hold for their representations. Therefore, the representation of the body and of peripersonal space - space within reach - have to go hand in hand [HS04]. In the monkey, this space was expanded accordingly after working with the tool to accommodate the whole space that can be accessed with the tool. Several studies ([MSD03], [JF03], [MI04], [Ats09], [BF00], [HCS04]) followed that show the ability of the primate brain to incorporate tools into its body representations and use them for a coordinated action. The visual receptive field was extended by the tool when it was used for retrieving food, but not when the monkey just held the rake passively in its hand. This confirms the hypothesis that action context plays a key role. It is also probable - unlike in the rubber hand illusion scenario - that the subject is not fully 'deceived' to think that the tool is part of her body - the tool does not look like the hand - but only incorporates it into the representation in order to be able to use it as a "body auxiliary" [TSBG07].

4) *Intelligent tools*: The tool - or artifact that is extending our body - can be much more than a passive rake. It can be an artifact with intelligence of its own. Here we are moving away from the simple parallel between biological body representations, such as a body schema/image in a primate, on one hand, and their counterparts in an artificial system, such as a robot on the other, to two interacting systems which both possess some intelligence and plasticity. We think that this is an area with a lot of potential. There is evidence that the "incorporation" of "intelligent" tools is possible. Slater et al. [SPMESV09] show how it is possible to induce the incorporation of virtual bodies in the body representation. The advances in Brain-Computer interfaces ([MR03], [LN06], [MW08]) have made it possible to use biological signals to control robotic devices, enabling their users to perform activities otherwise out of their reach. These interfaces allow direct interaction with cortical processes that the user can control. So far evidence with monkeys ([CLC⁺03], [VPS⁺08]) show how they can "incorporate" these devices into their body representation. Other studies with amputees ([HKY⁺06], [HADD⁺08], [CAB⁺09]) present evidence of changes in the cortical activation due to the interaction with an "intelligent" prosthetic hand. The evidence described above presents the possibility of "incorporation" of artificial limbs in the body representation, thus opening the possibility of having two intelligent systems interacting together. Di Giovanna [DMF⁺09] explores the idea of having a system that taps into the brain plasticity with an artificial system that learns from its user using reinforcement learning. Sanchez et al. [SMDP09] performed experiments with rats, who have electrodes implanted on the motor cortex, and control a robot hand to perform a goal oriented task. The result of these experiments give the first steps into having symbiotic systems, where the artificial limb is "incorporated" in the body representation of its user, and at the same time, the artificial system develops its own representation to adapt to its user.

It is not hard to imagine, how the features of biological body representations - development, adaptation, extension - can be useful for robots. A robot that can automatically acquire its model that can then be used for control will save a lot of work of programmers. If it is able to automatically adapt the model

to new circumstances - body extensions, wear and tear or even substantial failures - it will lead to a new generation of robots that can leave their restricted domains.

D. Coordinate transformations

A key issue that is often mentioned in the context of the body schema is the one of coordinate transformations. The problem is simple to formulate but hard to tackle. Imagine you see an orange at some location in space and you want to grasp it. It might seem trivial for you to simply stretch your arm and reach it, but how is the brain successful at it? The orange falls on some location in the retina, which is dependent on the position of the eyes, the head, and the torso; if you move either of them (or all, as far as their movements do not cancel out) then the location of the orange in the retina will change accordingly. To perform a particular movement the brain has to have (in principle) at least one stable frame of reference (FoR), i.e. a FoR which is invariant to changes in the position of some of your limb parts (say, the eyes or the head). A stable FoR for reaching is the torso frame of reference, since all the movements of the hand have necessarily to be executed in relation to the torso - due to the physical structure which connects the two limb parts. However, to have the position of the orange encoded in relation to the torso, the brain has first to convert the retina coordinates into eye coordinates using the location of the orange in retina, then transform the position in eye FoR to the head FoR using the current orientation of the eyes with respect to the head, and finally transform the location of the object with respect to the head into torso FoR using the orientation of the head in relation to the torso (see Figure 1).

The brain areas which are often mentioned in the context of body schema are: the lateral intraparietal area (LIP), which encodes information relevant for saccadic eye movements [ABB⁺90], the ventral intraparietal area (VIP) which is connected to premotor areas responsible for head movements [DBBG97], the parietal reach region (PRR) which encodes reaching information [BBSA99], and the anterior parietal area which encodes grasping information. Each of these areas seems to use different frames of reference. This would be expected as different behaviors might benefit from a different encoding. For example, neurons in the LIP area have been reported to respond according to a head FoR [ABB⁺90], whereas neurons in the PRR should have the eye as their reference frame [BBSA99]. Interestingly, other neurons in the PRR have also been found which seem to encode the difference between a target in eye FoR and the current position of the hand also in eye FoR [CPS09]. Such neurons seem to be particularly suited to output an error signal with the distance between the hand and the target [CPS09]. Similar neurons have also been found in area 5 of the posterior parietal cortex, which is adjacent to the PRR (see [BJBA02]).

But how does the brain compute these coordinate transformations? In the classical view (coming from geometry and applied in robotics, for instance), coordinate transformations are computed explicitly and applied sequentially; for example to pass from eye FoR to hand FoR, the brain would compute

all the required transformations in series between the eyes and the head, then between the head and the torso, and finally between the torso and the hand. We will see examples of this approach throughout the robotic part of the paper, in particular in Section III-C. However, in a novel view, coordinate transformations can be computed implicitly and in parallel [BC09]. The above mentioned neurons which encode for the difference between the hand and the target are a good example of such a view. In this particular case the only modality used for the coordinate transformation is vision; the positions of the hand and the target are both acquired from the visual input. In fact, relatively little is known about the influence of proprioception for computing coordinate transformations.

One of the most relevant findings in brain research on coordinate transformations is that of gain modulation (also called gain fields, or fields of gain). Gain modulation consists of “a change in the response amplitude of a neuron that is not accompanied by a modification of response selectivity” [SA01]. It is a nonlinear way of combining information from two or more sources, let them be sensor, motor, or cognitive. Typically gain fields are used within a population based encoding, in which several neurons respond to a region of space. The use of a population based encoding combined with gain fields for coordinate transformations is depicted in Figure 1. The plots show the reconstruction of the signal obtained from a population of five neurons (circles below the plots). As can be seen when the stimulus (the star) is on the left side of the fixation point, the neurons in the left part of the plot are more active than the ones on the right part (A and C); when the stimulus is located on the right side of the fixation point the neurons on the right part of the plot are more active than those on the left part (B). The plots on top show the response selectivity of each particular neuron in retina frame of reference; in A and C the response of the neurons to the respective stimulus is very similar as the stimulus falls on the same location of the retina. However, in the neurons that encode the stimulus in head-centered frame of reference, the amplitude of the neural responses changes with respect to (i.e. is modulated by) the current position of the eyes. While in A the eye position increases the amplitude response of the active neurons, in C it does not. This result can be achieved by multiplying the responses of eye position signal with the position of the stimulus in retina frame of reference [PDD02].

E. Body schema and forward models

While the taxonomies (Section II-A) help us to roughly define the landscape of body representations, they still stop short off a concrete enough characterization that would allow one to build a computational or robotic model. The goal of this section is to illustrate some of the concepts put forth in the previous section on a simplified, but concrete enough, scenario and to clarify the relationship of body schema to the closely related concepts of peripersonal space and forward models.

Figure 2 presents a didactic biologically motivated scenario, where a humanoid robot is interacting with an object on the table. The top part of the figure shows the robot and its visual field on the right, and a corresponding hypothetical neural

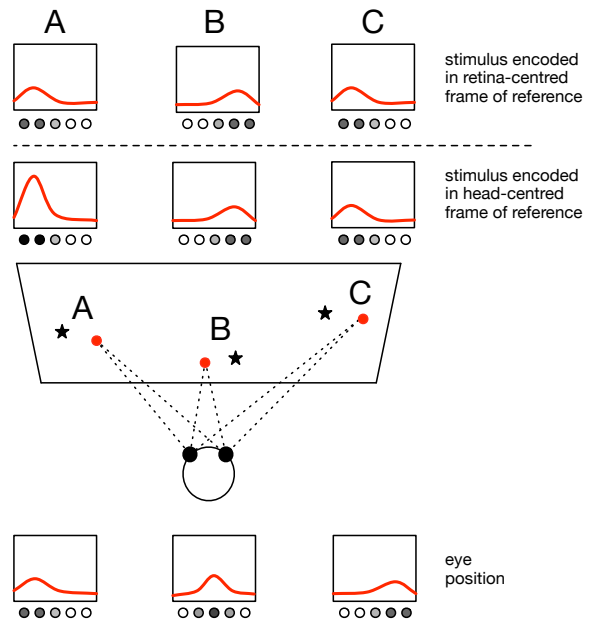


Fig. 1. Population based encoding combined with gain fields to achieve coordinate transformations between a retina-centred FoR and a head-centred FoR (see text for details).

architecture on the left. We have included three modalities: visual, proprioceptive, and tactile. In the visual modality, there are two hypothetical neural ensembles: one corresponding to the image on the camera (retina), and another which represents the same image in a body-centered reference frame. The position of the object as well as the hand is displayed in the activation. The transformation to the body-centered view is achieved by combining the camera image with the position of the eye and the head. Whereas regarding the position of the object, there is only visual information available, the location of the hand can also be obtained from proprioception in arm and hand.

Where is the body schema in this schematics? We offer the following interpretation: the activations in the individual neural fields are the short-term body schema - they represent the position or configuration of the body at one particular instant. The links between the neuronal ensembles, on the other hand, belong to a long-term body schema³. They are relationships between modalities that hold, at least over the here-and-now time-scale, and that can be used to perform coordinate transformations and to combine redundant information, such as regarding position of one’s hand, in an optimal fashion.

Until now, only sensory modalities were involved. However, to move from one configuration to another, a motor action is required. A particular activation of arm and hand muscles can bring the robot to the situation at the bottom part of Figure 2. However, in order to know which action is the right one, the motor modality has to enter our representation. This brings us to the concepts, which originally come from control theory but

³For reasons of simplicity, there are direct cross-modal mappings in our scenario. However, multimodal neural ensembles, i.e. those that fuse multiple modalities, were also reported in the brain. Similar connectivity could nevertheless apply to them as well.

were adopted by the field of human motor control, forward and inverse models (e.g. [Kaw99], [DW05]). Given current sensory state and a motor command (or its copy - efference copy), a *forward model* can predict the next sensory state (or predicted sensory feedback - corollary discharge, bottom-left in Figure 2). This can have several advantages. For instance, the predicted sensory signals can be delivered before the real ones and can be exploited for control, or they can be compared with the real reafference and integrated to give a more reliable state estimation, or used to separate the expected effect of the agent's actions from unexpected intervention from the environment. A very useful mapping is also the so-called *inverse model*. Given a target (goal) state, and the current state, this model will provide the motor command needed to reach the goal state. As Grush [Gru04] points out, the forward or inverse model (Grush uses the term emulator) can be either a look-up table storing previous input-output sequences, or it can be an *articulated model* - a model that includes some variables corresponding to their counterparts in the musculoskeletal system (e.g. elbow angle, arm angular inertia, tension on quadriceps). Some of these variables can be measured (e.g. by stretch receptors) and these sensors can also be simulated in the emulator.

It should be clear by now that a body schema involves relationships between sensory modalities (such as coordinate transformations or integration of redundant information from modalities) and relationships between sensory and motor modalities. In our didactic scenario, these two components were separated - cross-modal mappings were between sensory modalities, whereas a separate forward model was dealing with a mapping between two sensory states, given a motor action. Such a division is very tempting and convenient for a robotic implementation. However, the biological reality may be more complex and it may not be possible to dissect the sensorimotor loop like this (see e.g. O'Regan and Noe [ON01] for a detailed account). Finally, the body schema has to involve not only spatial, but also biomechanical information, and it has to be plastic over time.

III. IMPROVING ROBOT BEHAVIOR THROUGH A BODY SCHEMA

Like natural agents, artificial agents can also acquire sensorimotor representations of their bodies and use them to guide their actions. Or, to use the engineering/robotics terminology, a model of the plant is needed for control. However, before we discuss the character that such a model can have, we will discuss whether the models or representations are in fact needed altogether. Afterwards, we will classify the various forms that a body schema of a robot can take. We have used the nature of representation (explicit vs. implicit) as a primary axis to divide the spectrum of body representations. Regardless of the representation, the key issue will be automatic acquisition and adaptation of a body schema. In particular, the application scenarios will include: recognition of own body, acquisition of its model, and its extension or adaptation when using a tool or on failure.

A. Does a robot need a model?

The necessity for models of the world as well as of the robot itself comes as natural both to followers of Traditional Artificial Intelligence or GOFAI (Good Old-Fashioned Artificial Intelligence") [Pyl87] as well as to control engineers. This stance - that models, or representations, are necessary to produce useful behaviors - was challenged by the so-called new AI, behavior-based AI, or embodied cognitive science [Bro91], [PS99]. New AI demonstrated the potential of robots that do not rely on representations, but rather on embodiment, and that exploit the interaction with the environment [PLI07]. Relating back to our topic and paraphrasing Brooks, to what extent can it hold that "the body is its own best model"?

1) *Intelligence without representation*: It has been shown by the proponents of behavior-based AI that many remarkable behaviors can be achieved without a model. Examples are the achievements of Grey Walter [Wal53], and Valentino Braitenberg [Bra86] with purely reactive agents - agents that have no internal states, but only direct connections between sensors and motors. Another case in point that illustrates that a lot can be achieved without representation is the subsumption architecture of Rodney Brooks [Bro86], [Bro89]. Inspired by biological evolution, Brooks created a decentralized control architecture consisting of different layers. Every layer is a more or less simple coupling of sensors to motors (responsible for obstacle avoidance, for instance). While in this architecture the individual modules may have internal states (as they are Finite State Machines), Brooks argues against even implicit representation here [Bro91]. The 'insect' robot Ghenghis [Bro89] or the control architectures used by Cruse [CKS+98] demonstrate how a reflex-like controller can give rise to a walking pattern. There is no plan or model for the behavior in the robots' control architectures - walking arises only through the interaction of the body with the environment and simple sensor-actuator connections.

2) *Model - benefits and costs*: Before we ask ourselves the question, what is the best body representation for a particular robot, following up on the the previous section, we propose to ask another question first: what are the benefits and costs of having a model of the robot's body?

The benefit number one typically is that the model of a robot (or plant) can be used for control. For instance, while multi-DOF robotic manipulators can be precisely controlled using the models and associated control techniques that were developed [SSS00], to our knowledge, it is not feasible to control such a plant without a representation of any sort. With a precise representation of the robot's body - its kinematics and dynamics, including the actuation mechanism - it can be used for precise open-loop control, i.e. without feedback. In controlled environments, such as industrial settings, this is sufficient. If feedback is present, the mappings from motors to sensors can also be learned, giving rise to a forward model (see Section II-E). Such a model can also be used to improve closed-loop control: sensory feedback can be predicted in advance - before it is actually received - and control action can be adapted (see e.g. [DG00]). This is especially useful when the feedback comes with a significant delay. The fact

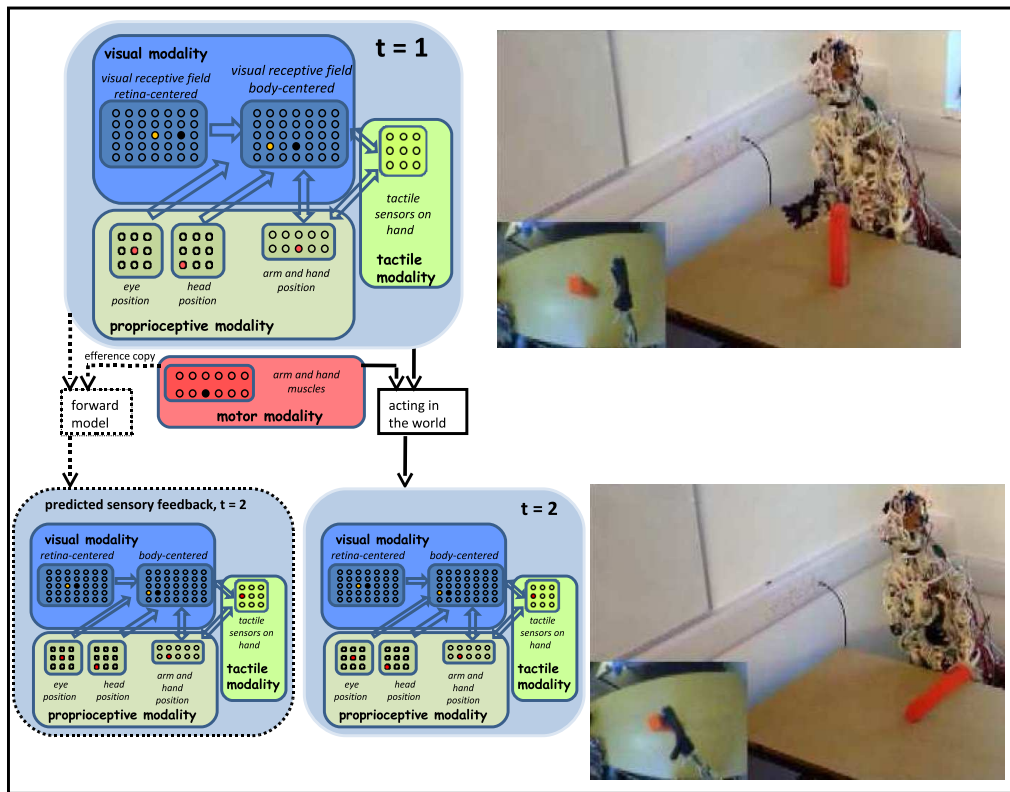


Fig. 2. Long-term and short-term body schema, and forward models. This figure presents a simple biologically-inspired scenario to illustrate the concepts. An agent, in our case a humanoid robot, is depicted on the right at two different time steps, while trying to poke an object. The small window in the bottom-left of each picture shows the view from the robots camera. The left part depicts hypothetical neuronal ensembles of different modalities, their connections, and activations. Let us look at the initial situation (top). The robot sees an orange object in the center of its visual field (orange activation) and its hand slightly right from it (black activation). However, with respect to the robots body, the object is to the left and slightly down. Based on proprioception from the eye and head muscles, this frame of reference (or coordinate) transformation can be performed. Regarding the position of the hand, there is additional information from proprioception in the hand. The coordinate transformation between the visual modality (where the hand is seen) and the proprioceptive can also be performed and the two sources of information can be combined. The bottom part of the figure depicts a situation where the robot has moved the hand to the object and hit it. The corresponding activations in the modalities are updated and there is a new activation in the tactile modality. The left-most part illustrates the concept of a forward model: based on the multi-modal map at $t=1$ and a copy of a motor command, a prediction of the sensory map at $t=2$ arises.

that the expected feedback can be predicted can be also used to distinguish self-generated sensory information from sensory input generated by the environment, leading to detection of changes in the environment. An account of similar scenarios in biology, in insects, is provided by Webb [Webb04]. A more elaborate and decoupled forward model, i.e. a model that can be executed without actually sending the motor commands, can be used for planning of whole action sequences [MH09], [Sut90]. Based on the predicted consequences, an appropriate action can be selected. As the last benefit we want to mention here, if the model includes a temporal dimension and uncertainty, using probabilistic terminology, it can be used to perform not only prediction, but also filtering (computing the belief state - posterior distribution over the current state)

However, we should not forget that there are costs associated with having models or representations. Such a model needs to be developed and that has costs attached to it. Heikkonen and Koikkalainen [HK97] report that robot programming - a substantial part of which is development of the model for the robot - accounts for about one third of the cost of an industrial robot system. The model is developed by engineers and given to the robot. This may be acceptable if the job has to be done only once - before the robot is put in operation.

However, problems arise if the conditions change over time; this can be due to deformations of body parts from wear and tear, but it can also be due to more dramatic changes such as change of topology of the robot or the robot using a tool. In such situations, a significant part of the model would have to be reprogrammed, giving rise to additional costs - model maintenance costs. This motivates the research in automatic model acquisition and adaptation.

B. What is body schema in a robot?

It seems that in order for a robot to be able to perform a goal-directed action, two components are essential. First, to perform the action itself, it is often necessary to know at least some of the parameters of the system to be controlled. Second, if the robot relies on its own sensory system and if the goal is expressed in one of the sensory modalities (such as an object to be grasped in sight of a camera), a mapping between the sensory and motor modalities has to exist [Mas95]. These two components can be almost completely separated or they can be completely intertwined. In robotics and control theory, the separation is typically clear. However, even in the biological realm, there are indications that sensorimotor representations operate on kinematic variables, while

the details that are necessary to perform a particular movement (an inverse dynamics model of the 'plant' which needs to include masses, inertia, stiffness, actuator dynamics etc.) can be delegated to other control structures (such as cerebellum and the spinal cord [WMK98]) and to the body itself.

Let us first look at a prominent scenario, a multi-DOF robotic manipulator. The typical goal is to make the end-effector reach a certain point in the workspace. While the goal is typically expressed in Cartesian or visual space, motor commands will be issued in joint space. Thus, a coordinate transformation between the two spaces is essential (confront with Section II-D and with the notion of peripersonal space in Section II-C3). An example of such a mapping is inverse kinematics, i.e. the manipulator joint angles needed to achieve the desired position and orientation of the end-effector in Cartesian space can be obtained. In industrial settings, a manipulator can often operate based solely on the kinematic model - without sensors. The dynamics (forces/torques needed to achieve desired positions) can be delegated to another subsystem (e.g. feedback controllers within servo motors), or a plant dynamics model can complement the kinematic model. The model used in this case is *explicit*. The kinematics (and dynamics) are described by equations and the parameters, such as segment lengths and orientation of joints, are measured and filled in the equations. The platform and its model are then carefully calibrated. The model is also *objective* - the parameters that correspond to the physical parameters of the robot are given from the outside. Yet, we are dealing with a representation of the robot's body that can be used to guide actions, and thus it can be classified as a body schema. However, for us, it will lie on one end of the spectrum of research and we will discuss it only briefly. First, because we feel that such a model departs too far from the properties that we attribute to a body schema - contrary to its biological counterpart, this model is typically fixed, explicit, precise, and centralized. Perhaps even more importantly, it involves minimal or no perception - it is given from the outside and thus relies on information that biological agents cannot access. Second, modeling and control of robotic manipulators (e.g., [LAD93], [SSS00], [Cra89]), or robots in general (e.g., [SV89]), is already an enormous research field in itself.

Articulated models come closer to the notion of body schema as we know it from biology. Recall from Section II-E that an *articulated model* is based on state variables (such as manipulator joint angle positions) that interact according to the laws of dynamics and mechanics [Gru04]. This time, however, the variables have to be measured by the robot's own sensors. Thus, the model is not objective anymore. Hersch et al. hence use the term *subjective body schema*. Usually, the definition of state variables comes from the outside - with prior knowledge of the problem. The model can still have a form of equations, as in [HSB08]. However, we will regard even a body schema that does not have a mathematical form as explicit, if there is a one-to-one correspondence between the body parts of the real robot and those in the model, as in [SPB09]. Articulated models will be discussed together with explicit models.

Explicit models have a number of advantages. The senso-

rimotor mappings as well as plant models are governed by explicit equations, and hence it is possible to calculate the behavior of the system even in previously unseen situations. Also, as they are more transparent, it may be easier to debug them and to assess their performance. However, as the plant and sensorimotor mappings become nonlinear (imagine a compliant pneumatically driven robot with multiple modalities), a closed-form solution may not exist. Platforms that cannot be modeled explicitly will be addressed by *implicit models*. Such a body representation can be a simple look-up table with previously encountered sensorimotor relationships, or, neural networks often serve as the substrate for an implicit body schema. These models are typically more bio-inspired and will close the section on improving robot behavior through a body schema. At the same time, they will provide a natural transition to Section IV - that deals with robots as tools to model biological body representations.

The representations of the robot's body, as discussed above, contain the long-term properties of the plant and hence correspond to the notion of a long-term body schema (cf. sections II-A and II-E). However, what is no less important is a short-term representation of the body - where it is in space right now, for instance. Current sensory readings have to be mapped onto some states (if there are states) in the long-term body schema and can then be used to plan future actions, for instance. The short-term body representations can have a "winner-take-all" form, or they can have a probabilistic form, where alternative states are possible, with given probabilities (cf. gain fields and population based encoding in Section II-D). The most prominent studies - using both explicit and implicit models - are summarized in Table II.

C. Explicit models

Fixed kinematic models will start off the section concerned with explicit representations of robot bodies. Then we will continue with adaptive modes - models that can self-calibrate or that can even learn the topology of the body structure. These models are inferred using the robot's own sensors and hence are subjective, even though the perception is typically simplified. Finally, we will discuss models of the robot's body that also include dynamics.

1) *Fixed kinematic models*: Let us briefly look at a multi-DOF robotic manipulator again. It operates based on its forward and inverse kinematic functions that ensure the coordinate transformation between the workspace (a Cartesian coordinate system in which the goal for the end-effector is expressed), and the joint space. The joint positions can be directly used as target commands for servomotors⁴. If the manipulator is accompanied with a fixed camera that is observing the environment, an additional frame of reference transformation from the camera frame reference to the Cartesian or task space has to be defined.

What are the limitations of this architecture? First, the model is designed from the outside and is not adaptive. New

⁴This is often the case in robotics: proprioception from joints can at the same time act as a motor command - it is the target position sent to a servomotor. However, although this simplification may be convenient, we have to be aware that it departs from biological reality.

calibrations have to be done in response to plant drift (e.g. robot’s wear and tear). A change in the robot’s geometry or the addition of a tool might require a new model. Second, this approach is not easily extensible to include more modalities (such as touch). Additional nonlinear sensorimotor mappings and their integration cannot be dealt with with the current analytical machinery. Third, since the dynamics was not addressed by the kinematic model, this solution has variable performance in different tasks, where the end-effector has to apply force, or with plants that cannot be position controlled (e.g. pneumatic actuators). All these shortcomings will be addressed in the following sections.

2) *Self-calibration of a parametrized kinematic model:*

Self-calibration of a parametrized kinematic chain can deal with changes in geometry over time (such as changes due to material fatigue). Automatic calibration is only possible when the system receives information from more than one source. For instance, the calibration of a camera-manipulator system can be achieved automatically by comparing the position of an end-effector as observed by the camera with the one from the forward kinematic function (after they have been converted to a common, typically Cartesian, reference system). Leaving the human engineer out of the loop can reduce costs. As a special case of self-calibration, we include body schema extension in this subsection. Automatic calibration of a model is addressed by some traditional methods from machine learning [Alp04], system identification [Koz98],[Lju99], or probability theory [RT99]. More specifically, there is a number of solutions to the automated calibration of a kinematic chain [BGH91], [HW96], [GLWS07] or a hand/eye setup [TL88]. Typically, a sampling period in which different configurations are visited is followed by an optimization procedure. This is not the case for the exploration-estimation algorithm [BL05] though, where the exploration strategy is more sophisticated and intertwined with the model evaluation stage.

Hersch et al. [HSB08] present an extension of the self-calibration approach. Taking advantage of prior knowledge of its kinematic structure (number, arrangement and type of DOFs), a simulated 24 DOF humanoid robot is able to learn the missing parameters of the kinematic chain - position and orientations of joints - by observing its body with a camera. A gradient descent algorithm is then applied, the efficiency of which increases when additional joints, not only the end-effector, can be observed. On a real robot (Hoap3, see Fig. 3), it was demonstrated that the algorithm can cope with the incorporation of a stick as an extension to the body within 2 or 3 minutes (cf. Section II-C3). In [Her09] this system is complemented by learning the neck-eyes kinematic chain using optical flow, and the whole system is demonstrated on the iCub humanoid robot. There are a couple of features that bring this work closer to the biological notion of body representations. First, contrary to the standard calibration approaches in which a phase of sampling and optimization precedes the actual use, the algorithm of Hersch et al. [HSB08] works online. Second, it is a case of a ‘subjective body schema’. The system is self-contained, or situated, in the sense that the sensorimotor mappings that are learned are solely based on the information

acquired from the robot’s own sensory and motor signals. The physical properties of the robot, such as the segment lengths, of course mediate the sensorimotor relationships, but cannot be accessed directly. The correspondence between the different reference frames, e.g. from end-effector to head with the camera, is given by the kinematic chain parameters which are subject to learning. Thus, there is no pre-coded transformation given from the outside, such as one from a camera to Cartesian frame.

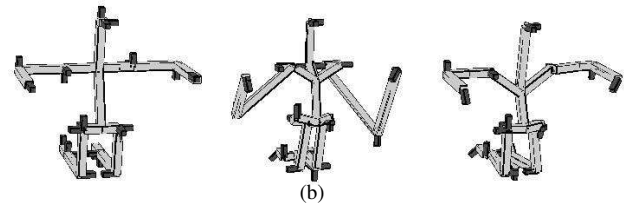
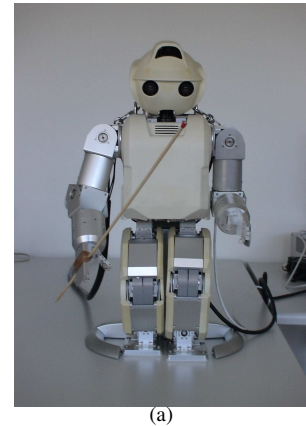


Fig. 3. Robot and its body schemata. (a) Hoap3 robot. (b) Body schema. Left: ‘real’ schema. Middle: body schema learned by looking at hands and feet only. Right: body schema learned when looking at additional joints. Hersch et al. [HSB08]

Nabeshima et al. [NKL06] also employ a traditional kinematic controller. However, the problem they address is not self-calibration, but specifically body schema extension and the detection of such a change. An upper humanoid torso is used to reach for objects. Apart from proprioception (joint angles) and vision, a third modality, touch, is involved. When the robot hand touches a target, a learning process - spatiotemporal integration of the multimodal information that preceded the contact - is triggered. This can be retrieved later from an associative memory and used to drive a controller. When the robot arm is extended with a stick (a primitive tool), contacts occur in new situations, and a new kinematic controller is learned in response. Neural networks are employed to implement the spatiotemporal integration and learning. This work is much more bio-inspired than what we have encountered and will encounter in this section. However, as no explicit correspondence with biology is established, we do not classify the work as biological modeling (an example of which, Hikita et al. [HFOA08], will be presented in Section IV).

3) *Automatic model synthesis including topology:* In this section we review robot kinematic models that can be syn-

thesized automatically with little prior knowledge. Contrary to the previous section, no parametrized form of the model is necessary. As a result of that, not only parameters like segment lengths, but also the robot's topology can be learned. Therefore the work reviewed in this section does not only address body schema extension, but can cope with more dramatic changes in the robot's body, such as the loss of a limb or a blocked joint, leading to resilient machines. We will focus on two case studies: (1) the work by Sturm et al. [SPB09], who show how a robotic manipulator can synthesize and adapt its kinematic model from self-observation and can then use it for reaching; and (2) the work by Bongard et al. [BZL06b], in which a quadrupedal robot continuously models itself and generates new locomotion patterns.

Let us first point out what the two models have in common. First, both models are explicit in the sense that there is a one-to-one match between the components (e.g. body parts) in the body schema (or model) and their counterparts in the physical robot. The number of joints and body parts presents the prior knowledge. Second, the dynamics is offloaded to position-controlled servo motors and only static configurations (i.e. not the dynamics of behavior to reach that configuration) are used to assess the match between the model and the physical robot. Third, both present a case for a 'subjective' schema, as the signals from the robots' own sensors are used to validate the model. And fourth and last, there is a population of candidate models involved.

Let us start with the work of Sturm et al. [SPB09]. Here, different robotic manipulators are used (4, 6 and 7 DOF). The robot observes the pose of its body parts (with special visual markers) using an external monocular camera (see Fig. 4). The goal is that the model of the manipulator is learned through exploratory actions and self-observation. In Hersch et al. [HSB08] described previously, the parameters of the kinematic chain were learned, providing a coordinate transformation between two sensory modalities - visual (camera) and proprioceptive (joint space). On top of that, different, also classical, approaches to control can be used, and will have to provide a mapping between motor commands and joint angles. Thus, although their body representation could be used for action, it does not contain the motor modality directly. Sturm et al., on the other hand, directly include the action commands. As we will see, their architecture thus also provides a forward and inverse model of the robot (cf. Section II-E).

The body schema in Sturm et al. is the joint probability distribution of available actions signals (target angles sent to individual joints), self-observations (as obtained from the camera), and true poses of the body parts (hidden states). The body schema is modeled as a Bayesian network, where the nodes correspond to body parts, action signals and model components. The structure of the network reflects the kinematic chain. For example, the 6D pose of a body part of the manipulator depends on the pose of its predecessor and one of the action signals. This is represented as dependencies in the Bayesian network. The learning problem is then factorized into two parts: First, local models that describe the relationship between pairs of body parts are learned using Gaussian processes regression. Local models that do not explain data

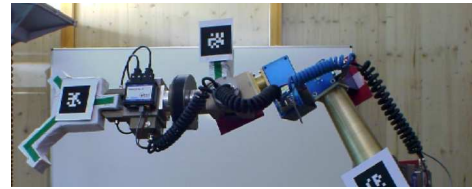


Fig. 4. A 6-DOF robotic manipulator arm learns and monitors its own body schema using an external monocular camera and visual markers. Sturm et al. [SPB09]

well are discarded. Second, a graph is built from the valid local models. Under the assumption that the manipulator has no cycles, the problem of finding the kinematic structure of the manipulator corresponds to the minimum spanning tree of this graph. The cost function is defined as the combination of the marginal data likelihood and a complexity penalty for each local model. Instead of using joint encoders, the relationship between motor commands and positions of the body parts of the manipulator is learned directly, circumventing the mapping between the target motor commands and the angle actually assumed by the joints. In order to control the manipulator, an inverse model is needed, i.e. a mapping from desired pose to action commands. While this can be obtained by searching for the motor commands that maximize the likelihood of generating the desired pose, it results in a high-dimensional optimization problem. Therefore, a different approach is used: the representation of the model allows to apply differential kinematics, in particular, it is possible to compute the Jacobian of the forward model and thus a gradient-descent algorithm is used for selecting suitable motor actions.

In their experiments, Sturm et al. demonstrate that: (1) the robot can learn its kinematic model from scratch; (2) the robot can adapt the model to blocked joints as well as to deformations. This presents a solution to automatic model synthesis, calibration, body extension as well as recovery from damage. Furthermore, the model provides additional benefits thanks to its probabilistic nature. First, information from the robot model is combined with the sensory data in a statistically optimal fashion, and the model also contains uncertainty of the estimates. Second, each model candidate has an associated likelihood, and thus multiple candidate models explaining data can be kept in parallel. Classical control, which assumes a single model, can thus be extended to take the uncertainty into account. Third, extending the model in time will allow to perform prediction, or filtering (computing the belief state). Therefore, the Bayesian framework encompasses both long-term (structure and parameters of the network) and short-term body schema (current belief), and a forward and inverse model, including a measure of the reliability of the information.

Bongard et al. [BZL06b] used a different platform, a quadrupedal robot, whose body schema is to serve the syn-

thesis of locomotor behaviors. Compared to the manipulator arm scenario, the interaction with the environment is much more profound here. A model of the dynamics (mass and inertia) of the robot, as well as of the ground and their interaction (friction model) is indispensable. The robot's self-model is split into two parts here. The first part consists of an externally designed model of the robot and the environment in a physics-based simulator. This is a special form of an explicit model - equations of motion for the mobile robot are not specified analytically, but they are embedded in the physics-based simulator and numerically integrated. This first part of the model contains the robot as a chain of rigid bodies connected by servomotors, and remains fixed during experiments. The second part is the kinematic structure of the robot in the simulator. This part is subject to adaptation. To validate the model, the information obtained from the sensors on the real robot is compared with the one from simulated sensors in the simulator (cf. with the notion of emulator and articulated model of Grush [Gru04] in II-E).

What is the procedure to synthesize or adapt the model? A set of 15 candidate self-models is kept. In every (static) configuration of the robot, the sensor readings are taken and compared with the readings from the simulated robot in the same configuration. In [BZL06b] only orientation sensors are used, but in [BZL06a] more modalities are employed and their relevance is also assessed. However, these configurations - or action that lead to them - are not selected at random. It is the action that is expected to best disambiguate between the candidate models that is executed on the real robot. Behavior synthesis on the model pool thus precedes and only when the information expected to gain is maximum, actions are executed on the real robot. On damage (lower leg part breaks off), a mismatch between the predicted and real sensory signals is detected, and exploration, modeling, and testing is re-initiated until a new model which reflects the change is found.

This architecture also encompasses a forward model. Whole action sequences can be executed in the simulator, and their outcomes observed. New behaviors can thus be synthesized in the model first - which would otherwise be a lengthy process on the real robot. This is an advantage of an explicit model. Unlike an implicit model, which allows to interpolate between actuation-sensation patterns that were seen before, an explicit model allows to extrapolate, and to generate qualitatively new behavioral patterns. Nevertheless, the (explicit) interaction with the environment is very hard to model in this case - contact modeling with the ground is a notorious problem - and there is always going to be some discrepancy (the reality gap). While the parameters describing this interaction (such as friction) were fixed in the physics-based simulator and represented prior knowledge in the cited work, in principle, they could also be adaptive.

4) *Models including dynamics*: Apart from the physics-based simulation used by Bongard et al. [BZL06b], so far we have dealt with kinematic models only - the forces and torques required to cause a particular motion were not addressed. Nonetheless, these are essential to finally execute an action. This gap is filled by (inverse) dynamics models of the robot or plant. This can be viewed as a relatively independent module

and there are indications that a similar strategy is used in biological motor control [Kaw99]. Therefore, the models of robot dynamics do not lie at the center of our interest and we refer the reader to many textbooks on the topic, e.g. [LAD93] [SSS00] [Cra89].

Having drawn this parallel between inverse dynamics in biological and robotic motor control, let us also point out the important differences. It is probably fair to say that the basis of the field of control in robotics is largely formed by engineered models (e.g. computed-torque control [LAD93] [SSS00]). While model adaptation and dealing with uncertainty is also addressed (by robust and adaptive control [LAD93]), adaptation to dramatic changes in the robot dynamics lies still outside of the scope of these methods. Similarly, the platforms that can be modeled are still largely restricted (mostly stiff rigid bodies). On the other hand, we know that biological motor control can deal with both significant changes to the dynamics or to the kinematics, and with compliant platforms, for instance. Therefore, if we want to deal with such robotic platforms, we may need to resort to implicit models - which leads us to the next section.

D. *Implicit models*

This section reviews work where an implicit representation of the robot's body is used. This can take a form of a simple look-up table or it can be a neural network, for instance. We will also review work that deals with self-recognition - how does the robot find its body and separate it from the environment. Finally, we will look at models that address the issue of delays in the effects of robot's actions. Compared to the explicit models, much less prior knowledge enters the implicit representations.

1) *Representations of sensorimotor mappings*: To derive analytical equations representing the kinematics and dynamics of a controlled system is not always possible. In situations where this is not feasible (in highly nonlinear systems with compliant actuation composed of deformable bodies, for instance), these mappings can still be learned using different function approximation techniques. Such mappings can either aid standard control schemes (as in the case of neural networks for control), or they can be control schemes in their own respect.

If a model of a plant cannot be obtained analytically, it is still valuable to obtain a model that treats the target system as a black-box. Its input-output behavior can be learned by a system identification process. By observing the responses of a system to different inputs, a forward model can be learned. For control, however, an inverse model is typically required. This can be either obtained by inverting the forward model (which is possible only in special cases), by directly learning the inverse mapping, or by the so-called distal supervised learning approach [JR92]. *Inverse kinematics* can be approximated by various approaches: locally weighted regression [DVS01], multilayer perceptrons, or radial basis functions [PG96][ML07]. Over the past decades, connectionist approaches have been integrated into numerous control architectures (for instance model reference adaptive control, model

TABLE II
BODY SCHEMA TO IMPROVE ROBOT BEHAVIOR - AN OVERVIEW.

Study	Key issue	Platform (S:simulated, R:real)	Body representation
Hersch <i>et al.</i> [HSB08]	automatic kinematic chain calibration	humanoid robot (S,R)	kinematic chain
Nabeshima <i>et al.</i> [NKL06]	body schema extension	humanoid torso (R)	kinematic chain
Bongard <i>et al.</i> [BZL06b]	body schema synthesis and adaptation	quadrupedal robot (R)	kinematic chain
Sturm <i>et al.</i> [SPB09]	body schema synthesis, adaptation and extension	robot arm (S,R)	Bayesian network
Yoshikawa <i>et al.</i> [YHA03]	body-nonbody discrimination	humanoid torso (R)	cross-modal map
Dearden & Demiris [DD05]	body schema synthesis	camera and grippers (R)	Dynamic Bayesian Network
Grimes <i>et al.</i> [GCR06]	body schema synthesis	walking humanoid (S,R)	Dynamic Bayesian Network

predictive control, internal model control [HD99]), where they form one or more of the building blocks: plant model, inverse plant model, or controller. One of the earliest architectures that is still being developed is the Cerebellar Model Articulation Controller (CMAC) [Alb75][JW03]. We will refer the reader to the abundant literature on the topic of neural networks in traditional control schemes [MSW90][HSZG92][PG96]. Interestingly, unsupervised (or self-supervised) neural network architectures can also be used. Barreto *et al.* [BAR03] demonstrate the use of self-organizing maps and some of their advantages. For instance, the topological arrangement of network nodes ensures that a redundant manipulator is well-behaved. A 'lazy' cost function is implicitly coded - while looking for an adjacent target point, an adjacent joint configuration is automatically selected.

The big advantage of implicit approaches is that almost arbitrary sensorimotor mappings can be represented. For instance, *inverse dynamics* does not present a problem with different characteristics, assumptions and complexity than inverse kinematics, as is the case with explicit modeling. If dynamic instead of kinematic variables are fed to the learning algorithm, inverse dynamics can be learned in the same manner (e.g., [KFS87]). Similarly, platforms that were outside of the scope of analytical modeling, such as pneumatically driven robots, can now be treated equally easily [ZSS97]. The problems of coordinate transformations and forward modeling do not have to be addressed as separate building blocks anymore.

To further illustrate the case of sensorimotor mappings, let us look at visually guided reaching. This is a hand-eye coordination problem and there are two basic strategies to tackle it: (1) Open-loop control, in which a sensorimotor map that relates the hand visual location and the arm position from proprioception is needed; (2) Closed-loop control, where the visual Jacobian of the manipulator is needed. The open-loop strategy can be realized through a combination of classical explicit frame of reference transformations that involve the hand, body, and camera reference frames. As mentioned in Section III-C2, these maps can be obtained through automated calibration procedures (kinematic chain [BGH91], [HW96], [GLWS07], hand/eye setup [TL88]). However, a highly structured environment is typically required for these calibration procedures (see [NNMS07] for more details). The Jacobian that is needed for the closed-loop strategy (or visual servoing [HHC96]) can be derived analytically, or estimated ([MLSVC06]). The Jacobian is a good example that sensorimotor maps may also involve derivatives. The two strategies, open-loop and closed-loop can also be combined, as demonstrated by Natale *et*

al. [NNMS07], for instance, where reaching in 3D is possible without prior knowledge of the kinematic model.

The mappings needed to perform visually guided reaching can also be coded implicitly. For instance camera calibration and triangulation can be learned in an implicit manner [JV94][Kup91]. Moreover, interestingly, the open-loop component which requires a sensorimotor mapping can be turned into a motor-motor coordination problem, as demonstrated by [RK98][MSK99][GC03]. Rather than learning the mapping between visual space and arm motor space directly, the eye-head system is exploited. A camera is let to fixate on the target (this can be pre-coded or learned separately) and the appropriate motor variables of the eye-head plant are extracted and used to learn the relationship with the hand motor plant variables that represent reaching to the target. This relationship can be represented by a look-up table [MSK99] or by a self-organizing map [GC03]. The learned mapping reduces the dimensionality of the problem, and is an instance of a body schema which allows to reach to a certain point in space - the target to which the eyes are looking - in an open-loop fashion.

2) *Self-recognition*: In the works that we have described so far, the goal was to acquire or adapt a body representation. The representation itself has taken various forms - an explicit kinematic chain, a model in a physics-based simulator, or a cluster of implicit sensorimotor mappings. However, it was assumed that a robot knows which signals come from its body. For instance, in the work of Hersch *et al.* [HSB08] or Sturm *et al.* [SPB09] (see Sections III-C2 and III-C3), all the body parts of interest were visible and easy to distinguish. In reality - if we take a developmental perspective and assume that the robot does not have this prior knowledge - the robot first needs to 'find itself' in the stream of sensorimotor signals (cf. Section II-C1).

Yoshikawa *et al.* [YHA03] address the problem of how a robot identifies its arms in a visual image. Unlike objects in the environment, the arms remain at fixed positions, and due to this invariance, they can be extracted from the visual scene and identified as belonging to the body. Hebbian learning is employed to pick up this invariance between the visual modality (disparity after the eyes fixate on an object), and proprioception (position of cameras - pan, tilt). The work of Yoshikawa *et al.* [YTHA04] is an extension of this strategy to multiple visual attributes (disparity, luminance, chroma, edges). Since the arms are not allowed to move, the procedure is dominated by perception and we can talk about *acquisition of body image* (cf. Section II-C1). However, the fact that the robot's arms are in a fixed position is an unrealistic

assumption. If they were allowed to move, the arms' posture would have to be included into the body representation that was established. It is not clear how the method will scale up though.

A largely converse strategy is employed by Fitzpatrick and Metta [FM02], Natale et al. [NOMS07], and Gold and Scassellati [GS09]. It is the active behavior of the robot that is used to self-recognize. Kemp and Edsinger [KE06] can perhaps be viewed as a transition between the two strategies. The robot's arms are allowed to move, but it is *spatial contingency* - mutual information between salient patches in the visual scene and expectations on appearance and position of the robot's parts - that allows self-recognition. On the other hand, it is temporal contingency that is utilized in [FM02], [NOMS07], [GS09]. The robot learns to recognize its body parts *because* they are moving. However, since external objects can be moving as well, it is the correlation between the visual input (optic flow) and the motor signal that facilitates the body identification [FM02]. Natale et al. [NOMS07] improve the robustness of this procedure by using periodic hand motions. Then, the robot's hand could be segmented by selecting, among the pixels that moved periodically, only those whose period matched that of the wrist joints. Gold and Scassellati [GS09] use probabilistic reasoning and examine the likelihood of three alternative models: (1) robot's own motors generated the movement; or (2) something else generated the movement; or (3) irregular movement. Case (1) would correspond to the robot's own body. Unlike the case of Yoshikawa et al., action plays a key part in these methods. Therefore, it is more appropriate to talk about *body schema acquisition* and *sense of agency* (cf. Section II-C1 again). We also want to point out that this strategy can be naturally extended action recognition in others and imitation (see [GS09]), tool use, or interaction with objects (see [NOMS07]).

3) *Temporal models*: The sensorimotor mappings that were discussed so far were largely relationships between various modalities in *static* configurations. Some architectures encompassed a forward or inverse model and thus allowed to iterate a body state in time. However, in reality the actuator commands cannot be expected to take effect immediately - there are always delays involved. The same counts for sensory signals. A body schema unfolded in time can be nicely represented with a Dynamic Bayesian Network (DBN). Dearden and Demiris [DD05] used a similar approach to Sturm et al. [SPB09], but included the motor delays into the body schema. The problem of model selection among competing candidate body schemata (as represented by the DBN) has thus grown to include the temporal dimension. Hidden states are discrete and represent the states of two grippers (open/closed). Observables are based on optic flow in the visual scene; visual blobs are extracted and clustered with a k-means algorithm. The prior knowledge that enters the body schema is the 'template' for the structure of the Bayesian network: from motors to hidden states to observables. While this approach is more general than Sturm's [SPB09], the toll that needs to be paid is that the system has much fewer DOF (essentially 2).

The work by Grimes et al. [GCR06] uses a similar approach, but addresses a different problem: bipedal locomotion. Hu-

manoid walking is a much more difficult problem than robotic manipulation. Balance becomes a key issue, modeling dynamics become inescapable, and we are dealing with a floating-base system. Traditionally, explicit modeling is performed based on CAD data, followed by further parameter estimation. The most famous control scheme in use is the zero-moment point (ZMP) control [VV04]. While this is commonly applied in walking humanoids ([HHHT98], [YSIT99], [NKK⁺07]), it has not yet been possible to extend it to rough terrain ([BKM⁺09] is an attempt in this direction, but on a quadruped platform). Therefore, Grimes et al. [GCR06], instead of using an explicit physics-based model of the robot and a control scheme on top of this, adopted a model-free, or implicit, approach. The kinematic and dynamic states are represented in a Dynamic Bayesian Network (DBN), together with action commands and observables. The problem of balance is addressed by a relationship between sensors (gyroscope and pressure sensors), which is, again, an instance of a subjective or situated body schema. Parameters for the model are learned with Gaussian processes. Implementations with Bayesian networks have the usual benefits that they allow for prediction, planning, or filtering, all that with measures of uncertainty. Moreover, both Dearden and Demiris [DD05] and Grimes et al. have shown how to utilize their architectures in an imitation scenario.

IV. ROBOTS AS MODELS OF BIOLOGICAL BODY REPRESENTATIONS

Although direct recordings from the brain have revealed relevant facts about body representations in biology, as described in previous sections, the mechanisms underlying the working and the development of body schema (and body image) in animals and humans are still far from clear. A difficulty in understanding such mechanisms from the observation of neural activity is that the recorded data cannot be disambiguated from a variety of factors inside the brain as they result from the interaction among brain, body, and environment. A synthetic approach - investigating the phenomena of interest by implementing them in robots (e.g., [PS01]) - is a promising methodology to overcome the difficulties that computational neuroscience alone faces. Not only the mechanisms underlying a mature body schema, but also its development in infants can be addressed by synthetic modeling (Asada et al. [AHK⁺09] provide an excellent review). The implementations feature more biologically realistic architectures and mechanisms. Hebbian learning, self-organizing map (SOM), or spike timing-dependent plasticity (STDP) are often employed. In some cases, it is possible to establish a correspondence between the proposed models and neural firing patterns in the cortex [HFOA08], [FOA09]. While it is probably fair to say that this body of research is at its nascent stage, there are a couple of relevant cases that will be described below. The scenarios we will come across will resemble the ones from Section III, but this time, the architectures will not merely draw inspiration from biological body representations, but will explicitly attempt to model the mechanisms.

We will structure this section as follows. Many synthetic studies have been made to understand multi-modal body

representations which, in primates, are found in the parietal cortex. Here, we categorize them into two groups: non-action-oriented body representations and action-oriented ones. First, we will review the former body of work. Cross-modal maps are often acquired through Hebbian learning applied on individual modalities [FOA07], [HFOA08], [FOA09], [YHAH02], [PAK09]. Second, we will review studies, in which the acquired body representations are utilized to coordinate the robot’s behavior [MS95], [Sto07], [PMKK09]. Third, we will review the work by Kuniyoshi and Sangawa [KS06] where the emphasis is placed on the physical interaction between body and the environment and on the effect of low-level (spinal) control. On top of these, low-level sensorimotor representations can emerge.

A. Non-action-oriented body representations (body image)

Many synthetic studies have focused on how to integrate information from tactile, visual, and proprioceptive sensor spaces. The ‘body maps’ that are acquired are used for recognition of the agent’s own body (cf. Section III-D2). Yoshikawa *et al.* [YHAH02] focused on correlations in the activation of tactile, visual, and proprioceptive modalities. Through an experience of self-touching, maps linking the modalities were associated by Hebbian learning. While Yoshikawa’s study allows to represent only body parts that are visible to the robot, Fuke *et al.* [FOA07] proposed a model in which the invisible parts - the robot’s face - can also be incorporated into the body representation. This was done via learning a Jacobian from the motor (joint) space to the visual space. Integrating the velocity, position in visual space can be estimated for invisible parts as well. Then, while the robot was touching its face with the arm, the position in the visual modality could be estimated and matched with the touch modality - learning a cross-modal map. It is then hypothesized that a fetus establishes this correspondence while touching its face in the womb and this may explain why a newborn is able to respond to faces immediately after birth.

Another important topic is the body schema adaptation, to tool use for instance (see Section II-C3). While we have encountered implementations of this behavior in the section on applications (e.g., [HSB08], [NKL06], [SPB09]), the mechanisms employed were only inspired by biology. The approach of Hikita *et al.* [HFOA08], on the other hand, models the mechanisms hypothesized to be used in humans. In particular, they focus on the role of the attention system in detecting body extension by a tool. Based on a neurobiological model by Itti *et al.* [IP04], a model that enables a robot to detect its own end-effector by associating proprioceptive information with visual information during visual attention, a saliency map, is proposed. Tactile sensation on the robot’s hand is used to trigger the association⁵. The representation enables a real robot to recognize its own body and there is an analog to the findings in parietal cortex during use of a tool, as described in [ITI96] (see Fig. 6).

⁵This work resembles the experiments by Nabeshima *et al.* [NKL06] that we have encountered in Section III-C2. However, unlike Nabeshima, Hikita’s work is a more direct attempt at modeling the putative biological mechanisms

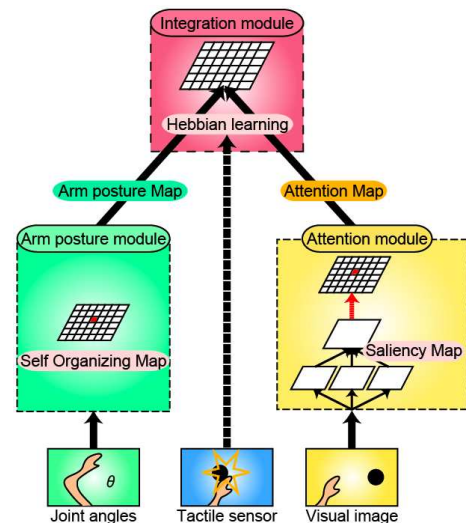


Fig. 5. Overview of the model proposed by Hikita *et al.* [HFOA08]. The association between the posture of the robot’s arm and position in the visual field is triggered by tactile stimulation. A saliency map makes a robot fixate a point of contact between its end-effector and an object, since more salient features are observed at that point.

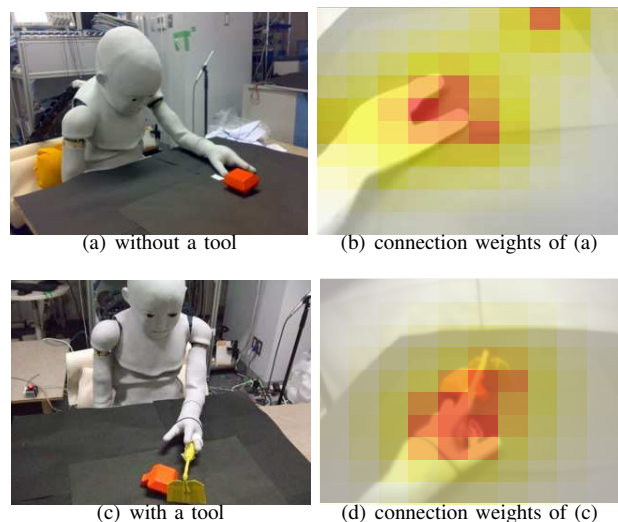


Fig. 6. Body schema extension during tool use. The connection between visual and proprioceptive fields: (a) and (b) without a tool; (c) and (d) with a tool (from Hikita *et al.* [HFOA08]). The red areas show a strong connection between visual and proprioceptive spaces in each setting.

Fuke *et al.* [FOA09] extended the problem of integrating tactile, visual and proprioceptive modalities by addressing the frame of reference transformation that needs to occur between an eye-centered and a head-centered reference frame. In human and primate brains, the lateral intraparietal area (LIP) is hypothesized to represent the position of a visual target in both eye-centered and head-centered coordinate systems [MGCG05]. The LIP area connects to the adjacent ventral intraparietal (VIP) area [BAS90], which includes neurons that encode both visual and somatosensory information [DCG98], [SH06]. Based on studies on infants [RSA07], this integration is assumed to be achieved through hand regard behavior:

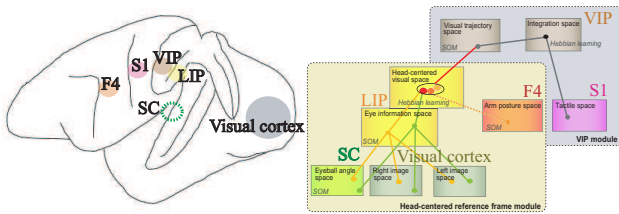


Fig. 7. Correspondence between brain regions and representation spaces proposed by Fuke *et al.* [FOA09]. Eye information space is combined with arm posture space into a head-centered visual space. This process bears similarity to connections among F4 and LIP areas. Integration of the head-centered visual space and tactile space produce neural activities similar to the ones observed in VIP area.

human infants gaze at their own hands in front of their face at around four months of age. A robot first acquires a head-centered visual space representation by associating ocular angles and camera images while gazing at its hand moving. Then, it integrates tactile sensations with visual stimuli by touching its face. Experimental results with a simulated human-like robot show that the activities of the acquired maps are similar to the ones of the VIP neurons as observed in [DCG98]. The correspondence of the model with brain regions is shown Fig. 7.

B. Action-oriented body representations (body schema)

This section deals with models of biological body representations used to guide actions. In some studies, cross-modal maps are first acquired and then exploited to plan the behavior of robots. Morasso and Sanguineti [MS95] have proposed a model of body schema for motor planning that is presumably carried out in area 5 of the posterior parietal cortex in association with the basal ganglia. The model is called SO-BoS (Self-Organizing Body-Schema) and consists of two components: a sensorimotor mapping (forward kinematic model), and inverse sensorimotor mapping (inverse kinematic model). The former is first acquired through motor babbling. Then, the latter is tuned depending on the task constraints such as the target position and the posture to reach a target. Results of a simulation of a 3-degree-of-freedom arm show that the proposed model can realize different reaching behaviors that satisfy the constraints. However, the platform used is rather simplistic and the work has a more computational than synthetic modeling flavor.

Stoytchev [Sto03] extended this model to a tool use scenario. An offset vector was added that represented the distance in the visual field from a position of an end-effector to the tip of a tool attached to the end-effector. Results with a simulation of a 2-degree-of-freedom arm showed that the proposed model can extend the body representation and successfully approach a visual target using the tool. The author has also shown that this model can acquire an extended body representation that allows the robot to guide its arm movements through a TV image. The robot detects its own body part based on the

synchronization between its own movements and the changes of visual features on the TV screen [Sto07].

Pitti *et al.* [PMKK09] have encoded body representations as a spatiotemporal pattern of neural activities in sensorimotor networks. Coordinated behavior, induced by morphological properties, was produced. Spiking neural networks were used to acquire mappings from a log-polar representation combined with a saliency map to motor commands for controlling the neck and the camera's orientation. Connections were regulated by spike-timing-dependent plasticity. Interaction among the body, environment, and the nervous system enabled a robot to self-organize the fixation behavior and the saccade behavior to a salient object. Analysis of the neural activities in the networks revealed a distinction between movement caused by the agent itself and that caused externally, thus representing a sense of agency (cf. Sections II-C1 and III-D2).

C. Development of a low-level body schema

Kuniyoshi and Sangawa [KS06] investigated the role of tight coupling between a body and its environment and how consistent dynamical patterns can emerge from this close physical interaction. They proposed a model of a neuro-musculo-skeletal system that consists of biologically realistic components such as a skeleton, muscles, spindles, tendon organs, spinal circuits, and medullar circuits (CPGs). On top of that, a basic cortical model from self-organizing maps was constructed. The connections were modulated by Hebbian learning rule during spontaneous movement driven by the activities of the lower circuits. Self-organized body movement was observed in a simple musculo-skeletal model which consisted of two rigid objects connected with a free joint and multiple muscle fibers. This mediated the acquisition of low-level body representations, such as the relations between agonist and antagonist muscles. Further experiments with a human fetal model showed that simple movements, such as crawling and rolling, can emerge. The cortical maps displayed a separation into areas corresponding to different body parts shown Fig. 8. Related to this work, a real robot that has anthropomorphic features is currently developed in the context of the ECCEROBOT project, where the development of a body schema will be subject to investigations [Hol10], [ECC].

V. CONCLUSION AND FUTURE PROSPECTS

The research in cognitive sciences deals with many body representations that are short-term or long-term, conscious or unconscious, perception or action-oriented. Body representations are also crucial for robots. However, their body representations cover only a subspace of their biological counterparts so far. They can be long-term or short-term, but they can hardly be considered conscious and they are largely action-oriented (since we are usually interested in the robots performing some tasks). This is also why our review focuses more on body schema than body image in robots.

To have a model of a robot in order to control it comes as natural to most control engineers or roboticists. A model of a plant (or robot) indeed is a representation that is used to guide the robot's actions and can thus be considered a kind of body

TABLE III
MODELS OF BODY REPRESENTATION IN BIOLOGY - AN OVERVIEW.

Study	Key issue	Platform (S:simulated, R:real)	Body representation
Yoshikawa <i>et al.</i> [YHAH02] Fuke <i>et al.</i> [FOA07] Fuke <i>et al.</i> [FOA09] Hikita <i>et al.</i> [HFOA08]	multimodal representation representation of invisible body integration of reference frames finding self body body extension	humanoid (R) humanoid (S) humanoid (S) humanoid (R)	neural network with Hebbian learning SOMs, Hebbian learning SOMs, Hebbian learning SOMs, Hebbian learning
Morasso & Sanguineti [MS95] Stoytchev <i>et al.</i> [Sto03], [Sto07]	representations that guide actions representations that guide actions body extension	robotic arm (S) robotic arm (S,R)	Self-Organizing Body-Schema Self-Organizing Body-Schema
Pitti <i>et al.</i> [PMKK09]	representations that guide actions finding self-body	robotic head (R)	spiking neural networks with STDP
Kuniyoshi & Sangawa [KS06] Holland <i>et al.</i> [Hol10], [ECC]	low-level representation low-level representation	humanoid (S) humanoid (R)	SOMs, Hebbian learning, CPG -

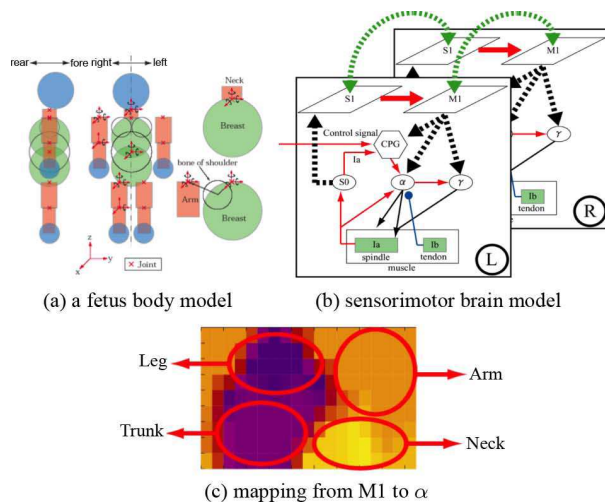


Fig. 8. Low-level body representations in a fetal model (Kuniyoshi and Sangawa [KS06]) (a) A fetus body model. Its physical properties such as size, mass and joint angle limitations were based on biological findings. (b) Cortico-medular-spinal-muscular model. (c) Self-organizing map from M1 to α , which displayed separation into areas corresponding to different body parts through spontaneous movement driven by the activities of the CPGs.

schema. However, this largely remained outside of the scope of this paper for two reasons. First, it is already dealt with by an enormous field of control. Second, such a model has very different characteristics than a biological body schema: typically it is fixed, explicit, precise, centralized, and objective. These very characteristics of a classical model of a plant restrict the domains in which robots can be successfully applied to very restricted, precisely controlled, environments. There are also costs associated with the development of such a model. Therefore, it is desirable that robots can develop, calibrate and adapt their models automatically. We have reviewed work that departs from the traditional robotics field and extends it toward automatic self-calibration. Beyond self-calibration, architectures that can also cope with topological changes are analyzed, paving the way for the adaptive and the resilient machines of the future. Apart from body representations that have an explicit nature, the body schema of a robot can also be represented in an implicit manner. While this traditionally meant a connectionist (neural network) implementation, mod-

els using Bayesian networks are gaining popularity.

The mechanisms underlying the working and development of body schema (and body image) in animals and humans are still far from clear. Uncovering them has been largely the task of neuroscience. Many findings were obtained by direct recordings from brain. However, even though the recording/imaging techniques are improving, there is still a lot of difficulties associated with 'live' recordings from experimental subjects. Empirical studies have been supplemented by computational modeling. However, in many situations, a whole brain-body-environment system is indispensable. This is when robots and simulated robots come into play as tools to investigate biological body schema. While it is probably fair to say that this body of research is at its nascent stage, there are a couple of relevant cases that we have reviewed.

We want to conclude by identifying the trends and also the weak spots in the research that we have just summarized and also propose areas for future research. First, the work on models in robotics is heavily biased toward manipulator arms, observed by a camera. At the same time, the platforms are typically very stiff. This holds not only for traditional, but also for bio-inspired research. Therefore, a future research challenge is to deal with other behaviors and platforms: locomotion and compliant robots, for instance. Second, the integration of multiple modalities as demonstrated by biological agents, is still largely lacking - visual modality is often the only one that complements proprioception (joint angles). Third, next to traditional analytical methods from control theory, Bayesian networks are becoming a prominent tool to represent a body schema, with the additional benefits of integrating uncertainty in them. Fourth, most of the research discussed is demonstrated to work in rather simple scenarios (limited number of degrees of freedom, for instance). The extent to which the individual solutions can be scaled up is an open question.

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