Active exploration for body model learning through self-touch on a humanoid robot with artificial skin

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Abstract—The mechanisms of infant development are far from understood. Learning about one’s own body is likely a foundation for subsequent development. Here we look specifically at the problem of how spontaneous touches to the body in early infancy may give rise to first body models and bootstrap further development such as reaching competence. Unlike visually elicited reaching, reaching to own body requires connections of the tactile and motor space only, bypassing vision. Still, the problems of high dimensionality and redundancy of the motor system persist. In this work, we present an embodied computational model on a simulated humanoid robot with artificial sensitive skin on large areas of its body. The robot should autonomously develop the capacity to reach for every tactile sensor on its body. To do this efficiently, we employ the computational framework of intrinsic motivation and variants of goal babbling—as opposed to motor babbling—that prove to make the exploration process faster and alleviate the ill-posedness of learning inverse kinematics. Based on our results, we discuss the next steps in relation to infant studies: what information will be necessary to further ground this computational model in behavioral data.

Index Terms—body exploration, self-touch, goal babbling, intrinsic motivation, reaching development, body schema

I. INTRODUCTION

Touch is the first sense to emerge in the fetus [1]. Fetuses perform local movements directed to areas of the body most sensitive to touch: the face (the mouth in particular), but also for example soles of feet [2] p. 113-114. Later, from 26 to 28 weeks of gestational age, they also use the back of the hands to touch as well as touch other body areas like thighs, legs, and knees [2] p. 29-30. In addition, from 19 weeks, fetuses anticipate the hand-to-mouth movements [3] (the mouth opens prior to contact) and from 22 weeks, the movements seem to show the recognizable form of intentional actions, with kinematic patterns that depend on the goal of the action (toward mouth vs. toward eyes) [3]. Birth obviously brings about a major disruption of the equilibrium that was reached in the womb: the constrained aquatic environment is suddenly replaced by an aerial one, with gravity playing a major part. Nevertheless, hand-mouth coordination continues to develop after birth (e.g., [5]). Also, Thomas et al. [6], biweekly recording resting alert infants from birth to 6 months of age, show that infants do frequently touch their bodies, with a rostro-caudal progression as they grow older: Head and trunk contacts are more frequent in the beginning, followed by more caudal body locations including hips, then legs, and eventually the feet. DiMercurio et al. [7], following infants from 3 to 9 weeks after birth, found no consistent differences in the rate of touch between head and trunk. In summary, infants acquire ample experience of touching their body. The question remains what drives this behavior and how this experience is catalogued and used to develop first tactile-proprioceptive-motor models of the body. The dynamic brain development in this period has to be considered as well (see [8]; [9] for an account focusing specifically on the somatosensory areas).

Are the touches to the body spontaneous or systematic? If there is a particular structure—which seems to be the case [6], [7]—what drives this developmental progression? Piaget [10] theorized that in newborns, action and perception as well as the “spaces” of individual sensory modalities are separated. Until the connections (a “model”) are established, infants explore their environment (and their body) randomly. However, there is now evidence that the modalities are already connected early after birth (e.g., [11] for the visual and motor). Also, there is empirical evidence that infants perform goal-directed action right from the outset of motor learning—reviewed in [12]. Specifically related to body exploration, Rochat [13] writes: “By 2-3 months, infants engage in exploration of their own body as it moves and acts in the environment. They babble and touch their own body, attracted and actively involved in investigating the rich intermodal redundancies, temporal contingencies, and spatial congruence of self-perception.”

The goal of this work is to operationalize these observations and hypotheses using a synthetic approach, “understanding by building”, by developing embodied computational models of the phenomenon—typical for cognitive developmental robotics [14], [15]. Exploration through random movements—often dubbed body babbling [16] or motor babbling—has been employed in different models (e.g., the “endogenous random generator” in [17]). However, faced with the dimensionality of the motor and sensory spaces, trying out all the possible combinations of motor commands and observing their consequences is hugely inefficient. For example, most motor commands generate movements that do not result in any contact with the body and hence do not generate useful experience to
learn the motor-tactile contingencies. Therefore, we employ two key ideas that help the agent to channel the exploration in the right direction. First, the agent should monitor its learning efficiency—the gain in its knowledge or competence to achieve specific goals—and focus the exploration on regions of the search space that are currently most promising. This is exemplified by the computational frameworks dealing with intrinsic motivation (or artificial curiosity) [18]–[21]. Second, the agent should focus the exploration on the goal space rather than the motor space. The goal space—the skin on the body in our case—may be lower-dimensional and it is here where the “interest” of the agent lies. If it does babble, it should thus do goal babbling [22] rather than motor babbling.

This article is structured as follows. After reviewing related work in the next section, Section III presents the robot simulator and the exploration framework. After experimental results (Section IV), we summarize them (Section V) and discuss their implications and future work (Section VI). An accompanying video is available here: https://youtu.be/Zb87uTFnQZE.

II. RELATED WORK

Our focus are “mechanisms that drive a learning agent to perform different activities for their own sake, without requiring any external reward” [20]. This phenomenon has been articulated in psychology as intrinsic vs. extrinsic motivation—[23] provides an overview. Oudeyer and Kaplan [19] strive to clarify the terms of internal/intrinsic and external/extrinsic rewards and present a computational perspective as well as relationship to other computational frameworks such as reinforcement learning. As briefly outlined above, there are two key aspects of efficient exploration: (i) monitoring learning progress and (ii) focusing on the “goal space”. The former has been addressed by a number of frameworks that can be classified as knowledge-based [19]. The latter aspect has been addressed by the path-based goal babbling approach of Rolf et al. [22] or by other, competence-based approaches in which the agent self-generates goals that it tries to accomplish. The idea is best illustrated on the example of learning to reach, or, learning inverse kinematics. The motor system is known for its redundancy: there are multiple ways of reaching to a specific point in space. Knowledge-based approaches that monitor learning progress but are confined to the motor space (e.g., [24]) will discover multiple solutions to the same goal, which can often be considered inefficient. Moreover, the space of solutions in the joint space (motor space) is not convex: averaging between them will often result in wrong configurations. Rolf et al. [22] analyze this and develop a solution, goal babbling, that deals with this problem: by exploring in the goal space, the agent is not “motivated” to look for alternative solutions. Further, following continuous paths through the goal space allows to circumvent the issue of non convex solutions [22]. This architecture has been also used to model the U-shaped curve typical of infant development [25]. Baranes and Oudeyer extended their R-IAC (Robust Intelligent Adaptive Curiosity) architecture [20] to Self-Adaptive Goal Generation Robust Intelligent Adaptive Curiosity (SAGG-RIAC)—a competence-based strategy—that also handles learning inverse kinematics in redundant manipulators. Our work is employing the computational framework of [20], as embedded in the Explauto library [26].

Learning to discover the surface of the body—a 2-dimensional skin surface embedded in the 3-dimensional world and moving together with the body parts—is similar to the problem of learning inverse kinematics that is a typical showcase for many of the intrinsic motivation frameworks (e.g., [20], [22]). The motor space or joint space is identical; the goal space, or observation space, also interest space, is different: for learning inverse kinematics, these are 3D Cartesian coordinates of the end effector (the infant hand, say). For the body space, either skin activations or spatial coordinates are candidate representations, which will be explained in detail in Section III. The work of Kuniyoshi, Mori and colleagues (e.g., [27], [28]) on the fetus simulator is complementary to this work, addressing prenatal development and focusing on a lower level: first tactile-motor interactions are emerging from the musculoskeletal body model coupled to spinal and simple subcortical or cortical circuitry. In comparison, the present study focuses on how guided exploration on a higher level of abstraction can give rise to efficient body exploration.

The work most related to ours is that of Mamella et al. [29] who specifically target the body (skin surface) as the exploration target. Their architecture is rather complex compared to ours, consisting of Goal generator, Goal selector, Motor controller, and Predictor. The simulated agent, however, is quite simple, consisting of two arms in 2D with three degrees of freedom (DoF) each, and a “skin” emulated using 30 Gaussian receptive fields in a 1D topology. The motor controller is also highly complex, composed of a dynamic-reservoir recurrent neural network, a random generator, and associative memory. The “skin receptors” are phasic, as they respond to changes rather than sustained values. These changes are then relayed into a self-organizing neural map (SOM) that “clusters” them. Compared to this, our architecture is much simpler. The motor space consists simply of the robot joint space. That is, only the final configurations/postures matter—motor overlaps with proprioceptive—and the actual movement production is sidestepped.

III. MATERIALS AND METHODS

This section provides an overview of the robot simulator and the exploration framework.

A. Nao humanoid robot with artificial skin

The experimental platform was a simulated Nao humanoid robot in Gazebo 9. The model used is a variant of the publicly available nao/40 URDF model, modified to add the parts hosting tactile/pressure sensors (“skin”) using the Gazebo ContactSensor plugin. There are two variants of the skin: (i) low-resolution (Fig. 1 left) and (ii) high-resolution (Fig. 1 right). The latter mimics the physical Nao robot available at CTU, uniquely equipped with “iCub skin sensors” [30]. Low-resolution skin has 25, 24 and 27 sensors for the torso, the
head, and each wrist respectively; high-resolution skin has 250, 240 and 270 tactile sensors on the same body parts.

The code of the simulator is available at [31]. A cylindrical “pen” tool with spherical endpoint was attached to the robot’s wrist to act as a finger and facilitate localized touch. More details can be found in [32].

![Fig. 1: Nao robot model in Gazebo. (Left) Low-resolution skin. (Right) High-resolution skin.](image)

B. Explauto library

Explauto ([26], https://github.com/flowersteam/explauto) is a framework for implementation and benchmarking of sensorimotor learning algorithms, with a specific focus on intrinsic motivation: monitoring learning progress in motor or sensory (goal) spaces. The action space $Q$, represents all possible actions (e.g., joint configuration) of the robot. An action $q \in Q$ generates an outcome $x \in X$ in the observation space $X$. During exploration, a database is constructed, with every entry being a tuple: $(q, x)$.

C. Action and observation spaces

Only the upper body of the Nao robot, which hosts the artificial skin, is used. The robot uses one of its arms to touch either the torso or the face. Its action space is the robot joint space, with five degrees of freedom per arm and two DoF on the neck. To touch the torso, only the arm is used, hence $Q \subseteq \mathbb{R}^5$; to touch the head, the neck joints also contribute: $Q \subseteq \mathbb{R}^7$. The joint ranges can be found in [32].

The observation space is the robot skin-activation generated when the robot contacts its torso or face with its arm. This is a discrete space of individual taxels and their activation. Taxel activation is binary: either a taxel is activated or it is not. For the exploration methods considered here, a distance metric on this space is needed. Connecting neighboring taxels by edges and acquiring distances from an incidence graph would be a possibility. To aid the computational exploration framework, we formulated a continuous metric on the observation space. A two-dimensional observation space centered at its origin is created for each body part, using a projection of the taxels to obtain their coordinates on the new space. A simple planar parallel projection was used for low-resolution skin (Fig. 2 a and b), while a central projection on a cylindrical surface was used for high-resolution skin (Fig. 2 c and d), representing the shape of the body parts more accurately. For each body part, we thus have $X \subseteq \mathbb{R}^2$.

![Fig. 2: Projection of taxels’ coordinates. Top row: parallel planar projections used for low-resolution skin on (a) torso and (b) head. Bottom row: central cylindrical projection for high-resolution skin on (c) torso and (d) head.](image)

D. Forward and inverse models

Our focus is on inverse models: learning how to reach for particular locations on the skin (~ inverse kinematics). From the models available in Explauto, the nearest neighbor (NN) solution is the one used in our exploration strategies. Given an observation $x$, the inverse model will return the motor command $q$ that corresponds to the observation stored in the database that is closest to $x$. We do not employ forward models, with the exception of direct optimization on goal babbling (Section III-E) which uses them in a local optimization step.

E. Exploration strategies

The exploration strategies from Explauto [26] are:

a) Random Motor Babbling (RMB): a motor configuration $q \in Q$ is sampled uniformly from the action space, and then executed, generating an observation $x \in X$.

b) Random Goal Babbling (RGB): a goal $x \in X$ is sampled uniformly from the observation space and the inverse model is used to find an action $q \in Q$ best matching the goal, with added exploration noise.

c) Discretized Goal Babbling (DGB): The interest space—the observation space in this case—is discretized into $c = m \times n$ cells (or regions). We use two variants, 15x15 and 32x32 cells. Goal generation starts by selecting one of the cells with a probability proportional to the current state of an *interest value* $I$ that each cell possesses. Then, a goal $x_c$ within that cell is uniformly generated. The robot attempts to reach for $x_c$ using inverse model prediction, resulting in the
real observation $x$. $I$ is computed as the absolute value of the derivative of competence $C$. The interest value is high when competence rapidly increases or declines. $C$ is computed as follows:

$$
C \equiv d = ||x_c - x||
$$

$$
I = |\frac{dC}{dx}|
$$

(1)

DGB requires a bootstrapping phase to generate initial touches. This phase is counted towards the 1000 iteration limit. RMB with constrained joints range is used until 10 touches are observed. This is usually reached in 30 to 50 iterations.

d) Goal Babbling with direct optimization (DO): Direct Optimization is an added layer on top of Goal Babbling strategies. For each generated goal and based on the inverse model prediction, a temporary forward model using Locally Weighted Linear Regression is created and optimized using Covariance Matrix Adaptation: Evolutionary Strategy for a set number of trials $k$ (10 in our experiments). The motor command with the observation closest to the goal is used to improve the main model, replacing the prediction.

F. Learning and testing models

In each experiment, the robot uses a given exploration strategy and generates motor commands for 1000 steps. Unlike in standard cases in which every iteration of active exploration results in reaching a point in the observation space and allows for calculating an error (target vs. actual outcome—like in the case of learning to reach), in our case, the movement does not always result in contacting the skin. In that case, the step is counted toward the maximum number of iterations but does not contribute to learning the inverse model.

In addition, there is an external evaluation procedure that allows us to monitor the learning progress from the outside. Every 100 iterations, we present a testing set of taxels which the robot is asked to reach using the current inverse model. For the low-resolution skin, all taxels are included in the test set because of their already small number. For the high-resolution skin, a subset of taxels chosen to represent a grid-like pattern is tested (Fig. 3). Also here, if no taxel is contacted, no error can be measured.

![Fig. 3: Testing set for high-resolution skin – torso (left) – head (right). All skin taxels in black; testing set grid in violet.](https://youtu.be/Zb87uTFnQZE)

The right hand will be the robot’s effector and will reach either for the torso skin (Section IV-A) or for the head skin (Section IV-B). In the latter case, the action space will be larger as two neck joints are available in addition to the five arm joints. We use both versions of the skin: low-resolution and high-resolution (Fig. 1). The low-res. skin has the practical advantage that experiments are considerably faster (high-res. skin emulation is computationally expensive). However, the high-res. skin more closely models the real robot’s shape. Comparing these two cases is interesting in itself: the observation space is larger (more taxels), but due to their higher density, it is “smoother” since errors can be more accurately measured.

We will illustrate the results in the following ways: (i) Mean Reaching Error (MRE) after every 100 iterations (e.g., Fig. 4 left), (ii) number of touches generated after every 100 iterations (e.g., Fig. 4 right), (iii) projection of the generated goals with details about the reaching error for each test taxel (after 1000 iterations; e.g., Fig. 5). The results are averaged over ten trials for each exploration strategy. For projections, the observation space is presented from the point of view of an observer looking at the robot—like in Fig. 1. DO methods were not run on high-res. skin. Note that reaching errors are only available when a taxel (target or other) was reached by the movement.

A. Right hand reaching for torso

a) Low-resolution skin: When reaching for the torso, RMB and DGB with DO show the highest MRE (Fig. 4 left), while the other methods have similar performance. The MRE does not decrease over time, which is somewhat surprising, but may be caused by the fact that, initially, during performance evaluation, the skin is not reached at all and hence no error is measured for some taxels. Later, taxels other than target taxels may be reached more frequently, thus contributing to MRE. Both DGB strategies without DO have similar number of touches, like the two methods with DO, while RMB generates almost none (Fig. 4 right). Despite having a higher number of touches, DGB 32x32 with DO has higher MRE throughout the experiments than any other method except RMB.

![Fig. 4: Right hand reaching for torso, low-res. skin – comparison of exploration strategies (descriptions in Section III-E). (Left) MRE. (Right) Number of touches generated.](https://youtu.be/Zb87uTFnQZE)

To study how the methods covered the observation space and how accurate is reaching to different parts of the skin after learning, we use the observation space plots – Fig. 5. The panels also show the reaching performance to individual taxels after learning finished. Some taxels can be reached with
no error over all trials (blue); for most taxels, different taxels than asked are reached, giving rise to errors (magenta circles around target taxel). Finally, for some reaching targets, no contact with skin is detected and no error can be measured (red). To avoid mis-representing errors for taxels that are often “unreached” (i.e., no contact with skin occurs and error cannot be measured), only taxels that have been reached (perfectly or with error) in 60% or more trials have their reaching error calculated. The magenta circles displayed in their full extent are hard to interpret in some projections; therefore, circles are rendered with a radius of one fifth of the reaching error. The projection of all goals generated is uniformly sampled from the pool of goals generated by all ten trials.

For the case of right hand reaching for torso, low-res. skin, Fig. 5 shows that Random Goal Babbling (panel a) has a uniform distribution of goals. DGB methods focus the exploration best, despite some missed spots. However, better goal generation does not automatically mean that the robot was able to successfully reach for them: it might have reached for a close taxel, or even for a space between taxels, leading to no touch feedback and no learning. We can observe this by looking at the projection of individual trials, or at Fig. 5 d), where a taxel on the bottom right with numerous close goals has an on average higher error than other taxels whose neighborhood was less frequently sampled (with goals). Simple RGB displays good results: It can on average correctly reach around half of the taxels, as we can see a lot of taxels with errors so small that only a dot can be seen and not the dot and the error circle separately. DGB displays better results, with more taxels being consistently reached over the trials, and other taxels reached with small errors (often because in one or two of the trials, it reached for the closest taxel instead of the target taxel). Surprisingly, direct optimization did not improve the performance results. Over the course of the trials, it seems that only for RGB a particular taxel stayed mostly unreached. For both RGB and DGB, the taxels with the highest reaching errors are on the sides of the skin.

b) High-resolution skin: Compared to the low-res. skin, the MRE (Fig. 6 left) starts at the same levels, but shows a clear decrease of the error for DGB methods, with higher number of touches (Fig. 6 right). This may be due to the higher density of taxels: the distances between taxels are lower. There is also a small effect on the number of touches, with DGB 32x32 generating more than DGB 15x15.

Fig. 4 visualizes the observation space. As explained in Section IV-A, at least 60% trials contacting the skin—target or other taxel—are needed for average error to be calculated out of these trials. Random Motor Babbling (RMB) is not shown—no goals can be displayed as exploration proceeded in the motor space and reaching errors could not be measured for any of the taxels. DGB methods show again several consistently perfectly reached taxels or with low error. The goal generation from DGB 15x15 seems to be slightly more spread out over the skin than DGB 32x32. The taxels with the most errors are on the sides, like for the low-res. skin, and the highest errors are on the same set of taxels.

Fig. 5: Right hand reaching for torso, low-res. – observation space. Goals generated during exploration process (grey); testing after all learning iterations: Reached taxels with no error (blue); Reached with error / 5 – taxels reached (magenta dots) with error magnitude divided by 5 (magenta circles); Unreached taxels – no taxel reached during reaching attempt (red).

Fig. 6: Right hand reaching for torso, high-res. skin. (Left) MRE. (Right) Number of touches generated.

Fig. 7: Right hand reaching for torso, high-res. skin. All skin taxels shown with black dots. See Fig. 5 for details.

B. Right hand reaching for head

a) Low-resolution skin: Results on the low-res. head (Fig. 8) show similar MRE as well as number of touches as the low-res. torso results. However, DGB 32x32 with DO performs
better and is one of the methods with the lowest MRE, along with its counterpart without DO.

The projections (Fig. 9 a and b) show results consistent with the low res. torso. DGB is better than RGB, with average errors lower than the distance to the closest taxel, indicating that most of the taxels are reached perfectly in a majority of the 10 trials. DGB’s goal generation covers all taxels, with no empty spots, compared to low-res and high res. torso. DO did not show notable improvement in performance (plots not shown). Contrary to low-res. torso, no subset of taxels seems to always be perfectly reachable, but there is no taxel or set of taxels showing an overall significantly higher error than others.

The results for high resolution skin (Fig. 9 c to f) – observation space. See Fig. 5 for details.

b) High-resolution skin: The results for high resolution (Fig. 10) show the same change observed between high-res. torso and low-res torso, with a clear decrease of MRE over the course of the trials for DGB. However, MRE is higher than for the low-res. head, likely due to the cylindrical projection distortions that increase the distance between the taxels on the upper part of the head. Looking at the observation space (Fig. 9 c to f), contrary to high-res. torso skin, RMB reaches some taxels, but with high errors. RGB shows several unreach taxels, mostly on the upper-left of the head. Both DGB show the lowest errors and similar results, with again no unreach taxels.

Fig. 8: Right hand reaching for head, low-res. skin. (Left) MRE. (Right) Number of touches generated.

Fig. 10: Right hand reaching for head, high-res. skin. (Left) MRE. (Right) Number of touches generated.

V. SUMMARY AND DISCUSSION OF EXPERIMENTS

As would be expected, the most successful algorithms in learning to reach to the body in our experiments were those with a competence-based algorithm (discretized progress): monitoring the learning progress in different areas of the goal space (the skin surfaces). However, in our case, the results are less clear-cut compared to standard learning inverse kinematics (e.g., [22], [24]): goal babbling with or without discretized progress or direct optimization achieves similar performance. This has mostly to do with the measurement of the performance available to the learning algorithm and also during testing: if no contact on the skin is generated, no error is available and learning as well as “external evaluation” are compromised. For this reason, we complemented the results presentation by reaching error (MRE) with the number of touches achieved and the goal space projection. None of these provide a complete picture, but together they improve our understanding. Reaching for the head was overall more successful than reaching for the torso, presumably because the two additional joints on the neck were recruited.

VI. GENERAL DISCUSSION AND FUTURE WORK

First, the issue of motor redundancy should be discussed. The inverse model—from skin space to joint space—was learned directly from the training samples and it was best represented with the nearest neighbor algorithm. While direct inverse modeling [33] is prone to the ill-posedness of the general inverse kinematics problem and the averaging over non-convex solutions sets, our solution circumvents this by performing the exploration in the goal space: alternative solutions exploiting motor redundancy are thus not sought. Additionally, in the nearest neighbor algorithm, no averaging takes place. However, there are some trade-offs associated with this choice. The solution found will in our case be the first solution found; it may thus depend on initialization or chance and may not be the best solution. Distal learning, or learning with a distal teacher [33], as opposed to direct inverse modeling, is more versatile in that it allows the incorporation of additional constraints to channel the search for the (single) solution. However, while initially a single solution to a reaching target on the body may suffice, we know that we, adults, are capable
of alternative solutions depending on context. Distal learning allows the incorporation of a forward model and inverse model in series. Such a solution is more versatile in that the forward model, which is unique, “disambiguates” between alternatives coming from the, one-to-many, inverse mappings and can check their correctness. Human motor control in the cerebellum may be employing multiple paired forward and inverse models [24] (see the MOSAIC model [35]). Distal learning can thus in principle deal with a redundant system, but the problem is that the motor error is not directly observable [22]. A solution that would allow the agent to find one solution for every reaching target first, but add and keep alternatives later on, remains our future work. The mixed—composite forward-inverse models—can be a solution (see [56] for a survey). It is also worth considering how the task studied here—reaching to the body—differs from reaching in general. Self-touch configurations are more kinematically constrained than reaching in free space in front of the body and hence the effective motor redundancy is likely lower. This is even more the case for the experiments used here in which only five DoF of the Nao arm were employed.

Second, the use of nearest neighbor algorithm for the inverse model representation has to be discussed. It has the following advantages: (i) incremental learning is simple and requires registering pairs from input and goal space only (“lazy learning”); (ii) there is no averaging or interpolation of samples (avoiding the problem of non-convexity of the solution space). The disadvantages are: (i) computational complexity: all experience is stored in memory and upon retrieval—query to the inverse model—time is required to find the nearest neighbor; (ii) susceptibility to noise: in our scenario, “phantom” skin activation would be catalogued together with the current joint configuration and contaminate the model. (iii) mapping will not be smooth: adjoining skin receptors will not necessarily map to nearby joint configurations. Baranes and Oudeyer [20] deem nonparametric methods (like nearest neighbor) suitable for their problems (including inverse kinematics) and the complexity problem can be mitigated by efficient implementation [37]. Alternative representations of the inverse model could be local regression methods (e.g., Locally Weighted Projection Regression; Sigaud et al. [38] for a survey). How such mappings are encoded by the brain is an open question.

Third, the representations of the input and output spaces importantly influence what can be learned and how. Regarding the input, motor, space, we have discussed some alternatives from [20], [29] in Section II. In our representation, the actual execution of the movement—initiation, termination, and its dynamics—has not been addressed and such separation of movement preparation and control may not be justified [39]. Mannella et al. [29] do consider this aspect and observe for example that easy postures are acquired before hard ones. Dynamic Movement Primitives [40] seem a good candidate for such representation. Regarding the “skin space”, one could come closer to the biological reality by mimicking the non-uniform density of receptors (as done in [27], [29]). On the representation level, self-organizing maps seem like a natural candidate [29], [41]. The distance metric required for the exploration will then be distorted as is typical for homuncular representations and present an additional challenge. Finally, the motor and sensory spaces could be treated in a more integrated manner as proposed by Marcel et al. [42] who present a mathematical analysis of building a sensorimotor representation of a naive agents tactile space.

It is our ultimate goal to ground the model in biological data. The work of Schlesinger [43] is an example investigating looking patterns of infants. In our scenario, there are two concrete ways how we plan to proceed. First, in our study, the robot is learning an inverse model: which motor commands to use to reach to targets on its body. The performance for different body parts and at different stages of development can be compared with behavioral data from infants reaching for vibrotactile stimuli on the body [44]. For example, we should analyze how infants deal with the redundancy of their motor system in this particular case: during different “stages” in their development, do they use the same or distinct configurations to reach for targets on the body? If the latter were the case, the goal exploration strategies that suppress the redundancy of the motor system may not be appropriate. Also, with different initial postures, do infants tend to go to a canonical posture first? There is evidence suggesting that this may be the case in infants [45] and adults learning a new task [46]. Second, statistics obtained from studies observing spontaneous touches to the body in infants [6], [7]—such as how often infants touch particular body parts, in which sequence etc.—could be fed into the robot simulator to train the inverse model and the results in terms of reaching performance to targets on the body compared with those obtained from the computational exploration strategies. Alternatively, we could aim to model the exploration process itself and obtain similar self-touch statistics as an emergent property. Discovering signatures of curiosity-driven learning in the brain is an active research area [47]. Only behavioral data poses a greater challenge. With carefully designed experiments, one may be able to discern which cost function the “learning machine” is using [48]. Discriminating spontaneous vs. systematic exploration in naturalistic observations (like [6], [7]) remains to our knowledge an open question.

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