Stable kernels and fluid body envelopes

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Abstract

Recent advances in robotics leads us to consider, on the one hand, the notion of a kernel, a set of stable algorithms that drive developmental dynamics and, on the other hand, variable body envelopes that change over time. This division reverses the classic notion of a fixed body on which different software can be applied to consider a fixed software that can be applied to different kinds of embodiment. Thus, it becomes possible to study how a particular embodiment shapes developmental trajectories in specific ways. It also leads us to a novel view of the development of skills, from sensorimotor dexterity to abstract thought, based on the notion of a fluid body in continuous redefinition.

1 Incorporation

Our skin is not the limit of our body. When we interact with tools and technical devices, our body extends its boundaries, changes shape. The stick, the hammer, the pen, the racket, the sword extend our hand and become, after some training, integral parts of our body envelope. Without thinking about it, we bend a bit more when we wear a hat and change the way we walk when we wear special shoes. This is also true for more complex devices. We are the car that we are driving. It took us many painful hours of training to handle it the right way. At the beginning it was an external body element, reacting in unpredictable ways. But once we got used to the dynamics of the machine, the car became like our second skin. We are used to its space occupation, the time necessary to slow down. Driving becomes as natural as walking, an unconscious experience.

Our body envelope is extensible, stretchable, constantly changing. If we want to fix a nail on wall, we will first pick a hammer. At this stage, the tool is *abstracted* from the environment. A few second later, when we pick the hammer, we temporally extend our body envelope to include the tool in our hand. It disappears from our attention focus as a direct extension of our hand. It is *incorporated*. Once our goal has been reached, we put back the hammer and the tool becomes again an external object, ready to be used, but separated. This is the fundamental and misunderstood process of *incorporation*.

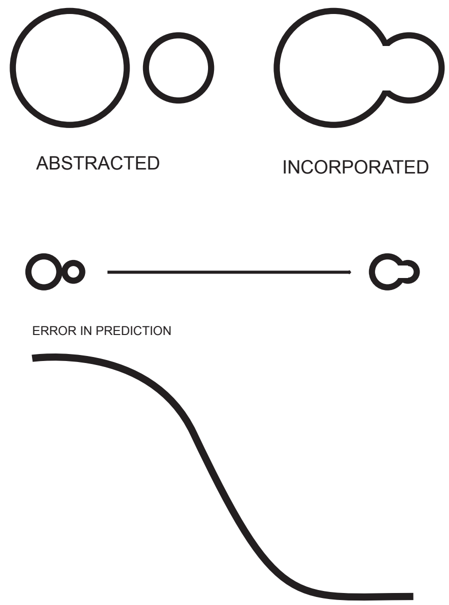

Figure 1: Illustration of the incorporation process. Objects can either be abstracted from the environment or incorporated as extension of our body. The process of incorporation takes time. Surprise or failure causes an incorporated objet to be abstracted again. When one learns to use an object, error in prediction corresponds to disincorporation of the object. The fewer the errors the more the object is incorporated.

The first time we use a hammer, we fail to fail to control it perfectly. Every time we fail to predict where the hammer will be, the tool becomes again abstracted, back in our attention focus. It takes time until we can successfully predict the consequences of our action with this "extended" hand and it is only when prediction errors are very low that the object is fully incorporated (figure

1).

Before picking a hammer, we must first choose it among the other tools abstracted from our toolbox. Once picked, new objects, nails, become relevant for the pursuit of our goal. We don't think anymore of our extended hand, we focus on these new abstracted objects. In general, incorporation is a recursive process. At a given state of incorporation, certain objects are abstracted from the environment and become affordants. When one of these objects starts to be controlled and therefore incorporated, our attentional space changes and new objects get abstracted (figure 2). As we will later argue, this recursivity is a fundamental component that permits not only hierarchical compositional behaviour but also higher-level cognitive processes.

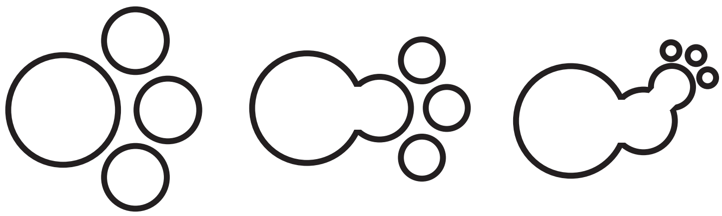

Figure 2: Incorporation is a recursive process. At a given state of incorporation, certain objects are abstracted from the environment and become affordants. When one of these objects start to be controlled and therefore incorporated, new objects get abstracted

There is a long tradition of research that discusses the notion of body schema, body map, body image as if it was some stable notion that the child needs to discover or model. Such approach to the body does not give a good account of the flexibility of our embodiment. The relevance of considering the body not as a fixed, determined entity but as a fluid perceptually changing space has been argued by several philosophers [Merleau-Ponty, 1945], psychologists [Schilder, 1935], ethnographers [Warnier, 1999] and neuroscientists [Head and Holmes, 1911]. However, we are still far from having a precise model of the process of incorporation and its relationship with attention, memory and learning. In this paper we will argue that recent experiments with robots permit to progress in this direction.

The argument developed in this article is the following. Since the 1950s, robots were essentially seen as fixed bodies in which different programs could be plugged, like the software and hardware parts of a computer. This dualism has led to a prejudicial divergence between artificial intelligence researchers building intelligent programs and roboticists building sophisticated bodies. In the last 1980s, a handful of researchers tried to escape from what appeared to be a technological dead-end and pushed forward a reunited view of intelligence, under the name of embodied artificial intelligence or new A.I. [Brooks, 1991, Steels and Brooks, 1994, Pfeifer and Scheier, 1999]. They argued that physical bodies and control systems should be intrinsically linked, like two sides of the same coin. The return to the design of complete agents undoubtedly led to some successes, notably for locomotion, sensorimotor learning and navigation in unknown complex environments. However, if such kind of holistic approaches proved to be efficient for designing complex adapted behavior, they were not sufficient to articulate a clear view of developmental processes. For instance, in just a few months, children learn to crawl, stand, walk, jump, hop, run, etc. As they learn these new skills in a continuous incremental manner, their sensorimotor space changes, permitting them to investigate novel domains of exploration. This is even clearer with the use of tools or the acquisition of communication skills. This has led researchers in developmental and epigenetic robotics to present models in which an agent is essentially constituted on the one hand of a *kernel*, a set of stable processes that drive developmental dynamics and, on the other hand, of *variable body envelopes* that change over time. This new view reverses the classic notion of a fixed body on which different software can be applied to consider a fixed software that can be applied to different kinds of embodiment, potentially changing over time. The rest of the paper gives a more detailed account of this important conceptual evolution.

2 The divided body

The *Flute Player* automaton built by the French engineer Jacques de Vaucanson in the 18th century could play up to twelve different tunes. Unlike most of the machines of that period which were conceived in a holistic manner, i.e. built as complete integrated systems, this automaton introduces a separation between stable body mechanics and programmable process for animation. Improving on such kind of mechanism, the *Writer* from Pierre and Henri-Louis Jaquet-Droz was equipped with forty "cams" controlling the movement of the automata's hand. With such a system, the same body could perform different sequences of independently programmed movements. These kinds of systems continuously improved in the following years taking various shapes, wax cylinders, punch-cards used for instance in machines meant to produce various fabric designs, progressively creating each time a larger independency between the body mechanics and the animation process.

Near the middle of the 20th century, with the advent of the digital computer, physical bodies and animation processes seemed definitively separated. The automaton, now named robot, was conceived as a physical body equipped with sensor and actuator controlled by a computer program, abstract digital description of its behavior. With such a separation it was natural to have various kinds of software "applied" to the same robotic body.

Two complementary fields emerged. On the one hand, research in artificial intelligence focused on designing algorithms for classifying data, prediction sequences and taking decision autonomously. On the other hand, robotic engineers were busy creating new sensors and actuators, thus expanding the boundaries of the "world" in which robots could perceive and act.

As one could have guessed, these two disciplines diverged. Many AI researchers stopped considering embodiment as an important part of their research. They tended to prefer focussing their effort on building complex models of human cognitive behavior, concentrating on tasks like medical diagnosis, mathematical proof of theorems or strategic board games. These algorithms were supporting a disembodied view of intelligence consisting essentially in complex symbol manipulation [Haugeland, 1985]. Cognitive psychology researchers used these new symbolic models to support the hypothesis that such kind of information processing processes were giving more relevant account of human behavior than the behaviorist theories very influential in the US at that time. Progressively, the cognitivist and computational views, stipulating that thinking can be equated to symbolic computing, took grounds (see [Churchland and Sejnowski, 1996, Fodor, 1999] for a review). The body was forgotten, irremediably separated from the mechanism of intelligence.

Symmetrically, as one entire field of research explores the promises of intelligence without bodies, another one develops bodies with not much intelligence. The first industrial robots are installed in predictable, carefully arranged environments. In workshops, they perform precise, calibrated, standardized movements. Control theory made many important advances on how to control such complex devices. Unfortunately, as soon as one tried to adapt these machines to less constrained environment, changing or unknown in advance, the behavior of such robots seemed very difficult to program.

Between the 1950s and the 1980s, the gap between the builders of robotic bodies and the researcher trying to model "intelligence" has some direct consequences on the performances of the machines produced. The AI algorithms, designed to manipulate predefined unambiguous symbols show clearly their inadequacy when it comes to deal with the complexity and the unpredictability of the real world. Consider for instance the problem of programming the walking behavior of a four-legged robot using a classical AI algorithm. The set of joints of a robotic body are not a set of abstract symbols but rather a complex system that can easily end up being in out of equilibrium positions especially if it is made of rigid parts, like most robots are. The type of ground and the degrees of friction have a direct influence on the behavior of the machine. With a symbolic AI approach, but also with many approaches in control theory, it is important that the system is equipped with precise model of the robot body but also on the environment in which the robot evolves. It many cases this is just impossible. Viewed from this angle, walking on four legs can reveal itself to be a harder problem than demonstrating mathematical theorems.

3 The reunited body

To go out of this dead-end, a new school of thought emerged at the end of the 1980s, with the work of researchers like Rodney Brooks, Luc Steels and Rolf Pfeifer. The so-called embodied artificial intelligence, or new AI, strongly criticized the disembodied and symbolic approach of the "classical" artificial intelligence, claiming that intelligence could not be considered without reference to the body and the environment [Pfeifer and Scheier, 1999]. Rodney Brooks added that bodies and environments are impossible to model and that therefore research should not try to build models of external reality but on the contrary concentrate on direct situated interaction: "the world is its own best model" [Brooks, 1999, Steels, 1994].

This change of perspective introduced a renewal of robotic experiments and in someway a return to conception and experimentation methods that were characteristics of robotics *before* the advent of the digital computer. Grey Walter's cybernetic "tortoises" built in 1948 are taken as canonical example of what a good conception is, integrating seamlessly the physical design of the machine to the targeted behavior. These entirely analogical robots were capable of complex behavior, without the need of any internal "representation" [Grey Walter, 1953].Their design was taking into account that they were physical machines, on which many kinds of "forces" had an influence, from gravity to frictions and that perception itself was primarily the result of their own movement and behavior (a concept later known as "enaction" [Varela et al., 1991]). The nature and positioning of their sensors enabled them to solve complex tasks, like returning to their charging station, without the need to make any kinds of complex "reasoning".

Inspired by von Uexkull's writings [von Uexkull, 1909], research of the new AI defined the behavior of their robot taking into account their "Umwelts: the very nature and structure of their body immersed them in a specific ecological niche where certain stimuli are meaningful and others not. This research was also supported by the reappraisal of a non-dualistic philosophical trend which in the tradition of Merleau-Ponty views cognition as being situated and embodied in the world [Merleau-Ponty, 1942, Merleau-Ponty, 1945, Varela et al., 1991].

To try to convince the cognitivists to view intelligence only as a form of sophisticated computation, researchers in embodied AI tried to define the kind of *morphological computation* realized by the body itself [Pfeifer and Bongard, 2007].To solve a problem like four-legged walking, it is easier and more efficient to build a body with the right intrinsic physical dynamics instead of building a more complex control system. One can replace the rigid members and powerful motors of the robot by a systems of elastic actuators inspired by the muscle-tendon dichotomy that is typical of the anatomy of quadruped animals. With such a body, one just needs a simple control system producing a periodic movement on each leg to obtain a nice elegant and adapted walking behavior. Once put on a given ground the robot stabilizes itself after a few steps and converges towards its “natural” gait. With such a system, the walking speed can not be arbitrary defined but corresponds instead to attractors of this dynamical system. Only an important perturbation can enable the robot to leave its natural walking gait and enter another attractor corresponding for instance to ”trotting” [Pfeifer and Bongard, 2007].

Thus, in an attempt to suppress the gap inherited from the post-war field division, embodied artificial intelligence emphasized the crucial importance of the body and illustrated its role for the elaboration of complex behavior: body morphological structure and animation processes must be thought as a coherent whole.

4 Stable kernels

In the beginning of the 1990s, robotic experiments from the new AI perspective focused essentially on reenacting insect adaptive behavior, examples strategically far from the classical AI programs playing chess. In the following years, some researchers tried to extend this embodied approach to build robots capable of learning like young children do. The idea what not to address one particular step in children development (like learning how to walk or how to talk), but to capture the open-ended, versatile, nature of children learning. In just a few months children incrementally learn to control their body, to manipulate objects, to interact with peers and caregivers. They acquire everyday novel complex skills that open them to new kinds of perception and actions. How could a machine ever do something similar? The objective of children-like general learning capabilities was not new as it was already clearly articulated in one of Turing’s founding article of artificial intelligence [Turing, 1950]. However, the sensorimotor perspective developed by the embodied approach gave to this challenge a novel dimension.

In asking how a machine could learn in an open-ended manner, researchers in epigenetic or developmental robotics [Lungarella et al., 2003, Kaplan and Oudeyer, 2006] partially challenged the basis of the embodied artificial intelligence approach and introduced a methodological shift. The importance of the body was still central as the focus was on developing sensorimotor skills intrinsically linked with a specific morphology and the structure of a given environment. However, while following an holistic approach, it seemed logical to identify inside a robotic system, a process independent of any particular body, ecological niche or task. Indeed, by definition, a mechanism that could drive the learning of an open-ended set of skills, cannot be specific to a particular behavior, environment or body. It must be general and disembodied.

Thus, the just reunited body must again be divided. But the division is not the one inherited from the punch-cards and the digital computer, the software/hardware gap. In this new methodological dualism, the objective is to separate (1) a potentially changing body envelope corresponding to a sensorimotor space and (2) a kernel, defined as a set of general and stable processes capable of controlling any specific embodied interface. By differentiating a generic process of *incorporation* and fluid body envelopes, the most recent advances in epigenetic/developmental robotics permit to consider the body from a new point of view. Contrary to the traditional body schemata, grounded in anatomical reality, body envelopes are ephemeral spaces associated with a particular task or skill. Contrary to easily changeable animation programs used in robotics, we now consider a stable kernel, acting as an engine driving developmental processes. It is not the body that stays and the programs that change. It is precisely the contrary: the program stays, the embodiment changes.

Several kinds of kernels can be envisioned. Some of them lead to open developmental trajectories, others don't. Let's imagine a control room equipped with a set of measurement devices, a panel of control buttons, and most importantly, *no labels* on any of these devices. Imagine now an operator trying to guess how the whole system works despite the absence of labels. One possible strategy consists in randomly pushing buttons and observing the kind of signals displayed on the measurement devices. However, finding blindly correlation between these inputs and outputs could be very hard. For the operator a better strategy is to identify the contexts in which he progresses in his understanding of the effects of certain buttons and to explore further the corresponding actions.

It is possible to construct an algorithm that drives such kind of smart exploration. Given a set of input and output channels, the algorithm will try to construct a predictive model of the effect of the input on the output, given its history of past interactions with the system. Instead of trying random configuration, the algorithm detects situations in which its predictions progress maximally and chooses the input signal in order to optimize its own progress. Following this principle, the algorithm avoids the subspaces where the outputs are too unpredictable or on the contrary too predictable in order to focus on the actions that are most likely to make it progress (figure 3). We call these zones: "progress niches". The use of such an algorithm results in an organized exploration of an unknown space, starting with the simplest subspaces to progressively explore zones more difficult to model. The term "kernel" is relevant for several reasons to describe the behavior of this algorithm. It is a *central* process, stable, unaffected by the peripheral embodied spaces. It is also the *origin* and the starting point of all the observed behavior.

Details of one version of this progress-driven kernel can be found in [Oudeyer et al., 2007]. However many variant of such kind of intrinsic motivation systems have been or are currently being explored (see [Oudeyer and Kaplan, 2007] for a taxonomy). One of the first computational system exploring progress-driven exploration was described by Schmidhuber in 1991 [Schmidhuber, 1991]. He articulated the idea that in order to learn efficiently a machine should try to reduce pre-

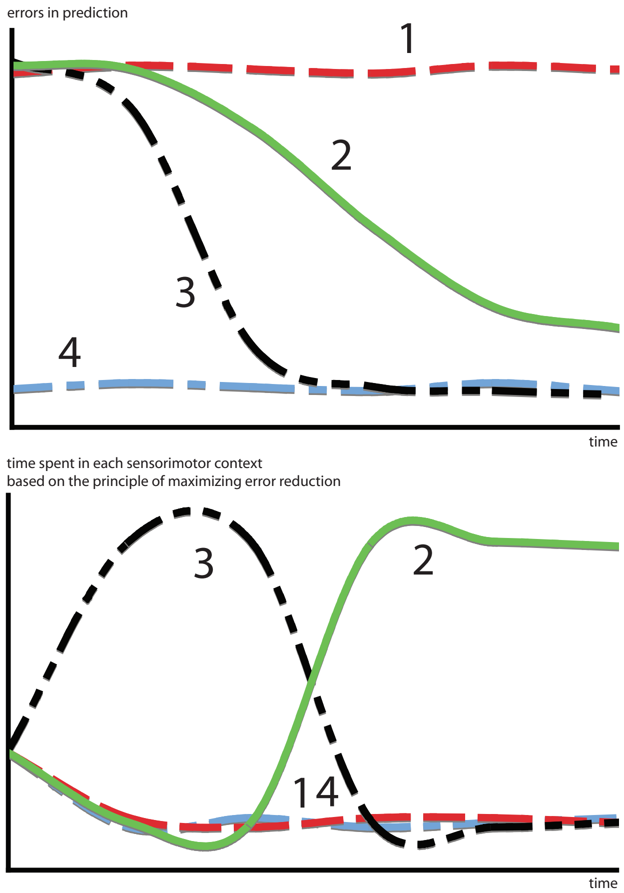

Figure 3: Confronted with four sensorimotor contexts characterized by different learning profiles, the exploration strategy of a progress-driven kernel consists in avoiding situations already predictable (context 4) or too difficult to predict (context 1), in order to focus first on the context with the fastest learning curve (context 3) and eventually, when the latter starts to reach a "plateau" to switch to the second most promising learning situation (context 2).

diction error instead of maximizing or minimizing it. More recently, different types of intrinsic motivation systems were explored, mostly in software simulations [Huang and Weng, 2002, Marshall et al., 2004, Steels, 2004]. Technically, such control systems can be viewed as particular types of reinforcement learning architectures [Sutton and Barto, 1998], where rewards are not provided externally by the experimenter but self-generated by the machine itself. The term "intrinsically motivated reinforcement learning" has been used by Barto in this context [Barto et al., 2004]. Interestingly, the mechanisms developed in these papers also show strong similarities with mechanisms developed in the field of statistics, where it is called "optimal experiment design" [Fedorov, 1972].

From a larger perspective, it should be noted that Artificial Intelligence has a long tradition for trying to build generic, universal, open-ended, meta-learning algorithms. Almost since its beginning, certain A.I. researchers have tried to build programs that can solve many different problems. In 1957, Herbert Simon and Allen Newell created the General Problem Solver (GPS) that aimed at solving any formalized symbolic problem, like strategic games, theorems proofs, geometric problems, etc. It was probably the first implemented program which separated its knowledge about problems and its strategy on how to solve them [Newell et al., 1959]. More recently, theoretical so-called optimal architectures have been explored. Several optimal but difficult to implement systems (with existing computing architectures) have been recently described like the AIXI universal learning algorithms [Hutter, 2005] or the Goedel Machines [Schmidhuber, 2006]. What appears when you look back at this history of research attempts towards universal learning algorithm is that Artificial Intelligence is not so much about solving problems but about *framing problems* in the right way so that they can be solved in a general manner.

Coming back to our walking case study, let us now consider an experiment where a progress-driven kernel controls the movement of the different motors. For each motor, it chooses the period, the phase and the amplitude of a sinusoidal signal. The prediction system tries to predict the effect of the different set of parameters in the way the image captured by a camera placed on the robot's head is modified. This indirectly reflects the movement of its torso. At each iteration the kernel produces the values for the next parameter set in order to maximize the reduction of the prediction error (figure 4).

When one starts an experiment like this one, several sets of parameters are explored for a few minutes. The robot legs wobble in an apparently disorganized manner. Most of these attempts have very predictable effects: the robot just doesn't move. Errors in prediction stay at a minimal level: these situation are not interesting for the kernel. By chance, after thirty minutes or so, one movement leads the robots to make a slight move, in most cases a step backward. This new situation results first in an increase of the error in prediction but, as the robot experiences similar movements again, this error tends to decrease: the kernel has discovered a "progress niche".

Then the robot will start exploring different ways to move backwards. Dur-

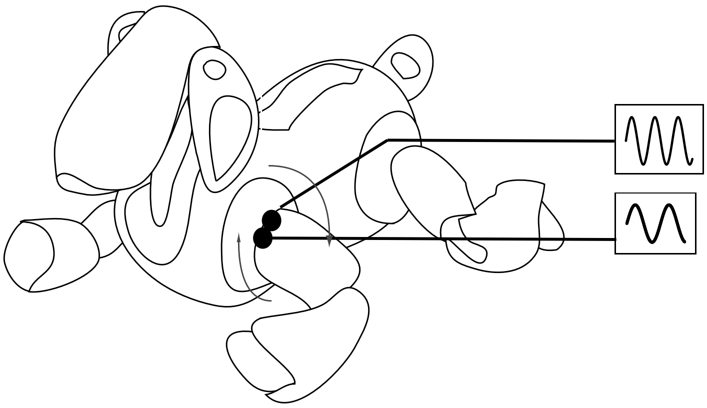

Figure 4: A robot can learn to walk just by exploring smartly a sensorimotor space. In the experiment. a progress-driven kernel controls the movement of the different motors of a four-legged robot. For each motor, it chooses the period, the phase and the amplitude of a sinusoidal signal. The prediction system tries to predict the effect of the different set of parameters in the way the image captured by a camera placed on the robot's head is modified. This indirectly reflects the movement of its torso. At each iteration the kernel produces the values for the next parameter set in order to maximize the reduction of the prediction error.

ing this exploration, it is likely that it discovers that certain modification of the parameters could lead to some sort of rotation movement, at least from an external observer's point of view. This is a new set of progress niches that the robot will learn to exploit when the skills for walking backwards will be essentially mastered.

In most experiments, it takes typically three hours for the kernel to find several subsets of parameters resulting in moving forward, backwards, sideways and to turn left and right. At no time in the process the robot was given the objective of learning to walk. Guided by the principle of maximizing the reduction of error in prediction, the robot ends up developing versatile locomotion skills. Actually, this versatility is the result of the unspecific nature of the kernel. A robot artificially motivated to go towards a specific object may not have learnt to walk backwards or to spin.

The fact that walking backwards revealed itself to be a parameter subset easier to discover was not easy to foresee. Given the morphological physical structure of the robot and the kind of ground the robot was placed on during the experiments, the walking backward movement happened to be the first to be discovered. To know whether this progress niche is actually an attractor for most developmental trajectories, it is necessary to set up a bench of experimental trials, changing systematically the initial conditions, including the morphology of the robot itself. With such an experimental approach it becomes possible to study the developmental consequences of a physical modification of the body. A longer leg or a more flexible back can change importantly the structure of the progress niches and therefore the trajectory explored by the kernel. From a methodological point of view, the body becomes an *experimental variable.*

These robotic experiments naturally lead to novel questions addressed at other fields, including neurosciences (Can we identify the neural circuits that act as a kernel ? [Kaplan and Oudeyer, 2007a]), developmental psychology (Can we reinterpret the developmental sequences of young children as progress niches ? [Kaplan and Oudeyer, 2007b]) or in linguistics (Can we reconsider the debate on innateness in the language learning by reconsidering the role of the body in this process ?[Kaplan et al., 2007]).

5 Fluid body envelopes

A simple way to change the body envelope of a robot is to equipped it with a tool. Figure 5 shows how the body of four-legged robot can be simply extended by a helmet that plays the role of a prosthetic finger.With this simple extension the robot can now push buttons, press on hard surfaces, even switch on or off other devices. This is a new space to explore.

Figure 6 shows the same idea with a pen holder. With this simple extension, the robot can now leave traces and use the environment as an external memory. A drawing is the temporal integration on a paper of a sequence of gestures. This

Figure 5: A helmet-finger extension. Design : ECAL / Stephane Barbier-Bouvet Photo : ECAL / Milo Keller

simple pen holder opens a whole new space of exploration where the machine can learn to predict the relationship between a sequence of actions and particular kinds of representations. Such kind of anticipation is likely to be a fundamental milestone on the road towards higher-level cognition [Steels, 2003].

Figure 7 presents a small scooter adapted to the morphology of the robot. Learning how to move with this device is not very different form learning how to walk. Like in all the other cases, the progress-driven kernel discussed in the previous section can be applied [Kaplan et al., 2006]. The body changes but the program stays the same.

The progress-driven kernel does only give a partial understanding of the general process of incorporation. We illustrated how it could act on a single space, a single body envelope, like the parameter space resulting in versatile walking skills, but we have not shown how it could be used to shift between them. Incorporation as we described in our introduction involves complex sequences of body envelopes transformation. It involves recursive and hierarchical processes. Typically, once a robot would have learnt how to control its body to walk, it should be able to use these newly discovered walking primitives as basic elements for performing exploration of new spaces. A walking robot will certainly discover new objects, new environment for learning. Let's take for instance the case of the graspable blanket of figure 8. This blanket is equipped with a special

Figure 6: A pen holder extension. ECAL / Meynet Bndicte, Burgisser Olivier, Xavier Rui,Wildi Sbastien et Reymond Simeon Photo : ECAL / Milo Keller

Figure 7: A scooter. Design : ECAL/ Clement Benoit and Moro Nicolas Photo : ECAL/ Milo Keller

handle adapted to the robot's "mouth". Learning to grasp the blanket is pretty similar than learning to grasp the pen holder we just mentioned. Once the robot would have learnt how to grasp this object, it could explore the specific space corresponding to walking with a blanket. This compositional process could continue endlessly.

Figure 8: A blanket with a special handle. Design : ECAL / Meynet Benedicte, Burgisser Olivier, Xavier Rui,Wildi Sbastien et Reymond Simon Photo : ECAL / Milo Keller

Going from the exploration of a single envelope to a generic kernel capable of easily switching between hierarchical envelops is a difficult issue. In particular, it involves a mechanism permitting the formation of habits. The possibility of implementing these different features in a single generic kernel remains to be shown. However, several state of the art methods permit to move towards this goal and envision how such a kernel could work. Multilayer recurrent neural network architecture like the ones considered in [Tani and Nolfi, 1999, Tani, 2007] or the option framework [Sutton et al., 1999] permit hierarchical learning where chunks of behavior can be compiled and continuously adapted to be used later on. When a sensorimotor trajectory becomes easily predictable it becomes implicitly or explicitly associated with a dedicated expert predictor, responsible for both recognizing this specific sensorimotor situation and automatically choosing what do do. In other words, when a part of the sensorimotor space becomes predictable it is no longer necessary to explore it at a fine grained level, a higher level control is sufficient. In our walking example, routines for moving forward or backward, turning left or right could likewise become higher-level habits. When this is the case, the progress-driven kernel could focus on other parts of the space, assuming these basic behavior routines to be in place.

6 Concluding remarks

Paradoxically, robotics often associated with jerky movement of rigid mechanical bodies, sets the stage, both theoretically and experimentally, for a new conception of the embodiment process that views the experience of the body as a fluid, constantly changing space. Viewing the body as an experimental variable permits to approach the idea of a variable body.

More than a technology of animated body, robotics appears to be a science and practice of the embodiment process. By extracting, on the one hand, the concept of generic and stable kernel, origin of the movement and action, and, on the other hand, the notion of changing body envelopes, robotics offers a novel framework for considering deep and complex issues linked with development and innateness. Indeed, what is development if not a succession of embodiment: not only a body that changes physically but the discovery of novel embodied spaces. Each new skill acquired changes the space to explore. Walking is one clear and illustrative example. Once a child has learnt how to walk, he discovers a whole new space of exploration. Therefore, viewing the body as fundamentally variable permits to reconsider the phenomena of incorporation we introduced at the beginning of this article. Through incorporation, the body extends temporally including objects, tools, musical interfaces or vehicles as novel envelopes to explore with no fundamental differences with their biological counterpart [Warnier, 1999, Clark, 2004].

By pushing further this notion of fluid body envelopes, couldn't we consider symbolic reasoning and abstract thought as merely special forms of body extension? Lakoff and Nunez suggested very convincingly that there is a direct correspondence between sensorimotor manipulation and very abstract notion in mathematics [Lakoff and Nunez, 2001]. Metaphorical transfer, one of most fundamental process to bootstrap higher-level of cognition, can be relevantly considered as a process of incorporation [Lakoff and Johnson, 1998]. Eventually, couldn't we consider linguistic communication itself as just one particular case of embodied exploration [Oudeyer and Kaplan, 2006]? All these spaces could be explored relevantly by progress-driven kernel like the one we presented.

Robots introduce both technological and philosophical questions. This has always been the case [Kaplan, 2004, Kaplan, 2005]. Robotics offers now a framework and an experimental methodology to start exploring issues very difficult to address otherwise. Robots help us think about ourselves by difference. Studying the development of robots with embodied spaces very different from our own, is probably the most promising way to study the role of our body in our own developmental processes. In that sense. robots are not models. They are physical *thought experiments*. That's why they can permit to consider apparently impossible splits, like the ones separating the body from the animation processes or, more recently, the distinction between a stable kernel and fluid body envelopes.

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