the Alignement Paradigm for Modeling the Self

Alexandre Pitti

***Abstract*—We propose to develop the notion of Alignment as one general design principle to understand how to model the Self. Alignment encompasses the temporal contingency detection between sensors and motors to calibrate the self, the spatial alignment between sensors of different reference frames to represent the physical limits of the body for ego-centered representation. and the memory construction and alignment for the design of a worknig memory and the construction of the autobiographical self. Behind this concept of alignment we identified three complementary neural mechanisms that may serve to achieve this autonomous construction, namely spike timing-depent plasticity, gain-modulation and predicitive coding. We review several robotic researches performed to answer this question in this perspective.**

***Index Terms*—Alignment, Contingency, STDP, Multimodal Integration, Gain-Field, Body Image, Predictive Coding, Working Memory**

I. INTRODUCTION

I propose to review in this manuscript different robotic researches I have done in the last decade to understand the development of agency and of self-other differenciation in robots as infants might do and to find which design principle should be replicated in robots in my viewpoint. Although it is now well admitted that the notion of Embodiment is linked to intelligent and autonomous systems, the design principles behind the very idea of what it means for an autonomous system to have a body –, agency, self-recognition, self-other representation, awareness, sensorimotor expectaction, action observation – are still in a current research investigation state by roboticists.

In so far, no robot can even roughly recognize itself on a mirror, really grasp an objet, understanding where its own hand is or learn to predict internal or external events and be surprised if they did not occur as expected. If sensorimotor learning in robots is still poorly achieved by cognitive architectures, any changes in the sensorimotor configuration or in the environment achieves to ruin it as any contextual changes modify just slightly sensorimotor contingencies (like perceptual illusions, tool-use, changes of reference frame) and perturb the mapping across the senses.

Thus, it appears that the imprinting of the body in a neural representation in silico should follow some design principles and mechanisms to be robust to changes. In this attempt, we would like to emphasize the concept of *Alignment* as a paradigm to understand (and create) a notion of Self in a robot. For instance, the Alignment Paradigm (AP) incorporates the idea of body calibration by that has been enounced by Rochat [1], [2] and Meltzoff [3], [4], temporal synchronization and timing contingency by Watson [5], [6], as well as of spatial contiguity and dissonance studied by Heed [7], [8], [9].

We propose that Alignment can be one unity measure that can be quantified, ever causal (unidirectional) or mutual (bi-directional) and multidimensional. Furthermore, AP is not necessarily centered to physical interactions, it conveys also aspects seen in social interactions: as we interact with others, we can align ourself to the partner as well as to its motion and to its intention. The social alignment can be in the opposite way with the partner adjusting its actions to our owns. And finally, AP can be bidirectional between oneself and its partner, together aware of the joint motions. In this case, the mutual alignment cannot be easily separated as it becomes one joint motion or one joint intention. I suppose this last stage is at the root of communication with the development of joint attention, empathy, ethics and theory of mind, which may be the ground for even broader cognitive skills like abstract representation, language.

Another dimension of this Alignment hypothesis is 'Memory' Alignment, which I define as the recursive and cumulative capacity to compare current actions to old ones experienced in the past and stored in the working memory and to decide either to explore new tracks or to follow old paths that were advantageous in the past. We possess some intrinsic mechanisms of predictive coding, reinforcement learning, novelty detection important for the developping of an auto-biographical mind. Hesslow and Adolph called this autothelic force the capacity of Learning-to-Learn [10], [11]. As we acquired more information about our environment, we can form some intuition about the success or failures of our own actions, our working memory can select which actions to choose; that is, to align to old memories or to search for new ones. Some examples are the A-not-B problem or the mirror test as exemplified in [12], [13], they are constitutive of a conscious notion of Self in the human brain. The dynamical comparison between old memories and new actions, knoswn as predictive coding, permits to construct habits and to form memory sequences.

All-in-all, I suggest three bio-inspired mechanisms potentially interesting to develop this idea of Alignment for the construction of the Self, namely (1) the Hebbian learning mechanism of Spike Timing-Dependent Plasticity (STDP) which permits to neurons at the neuron level to learn causally dependent temporal rules, (2) topographic networks based on the mechanism of Gain Modulation for multimodal integration, body representation and sensorimotor transformations at the population level, which can serve for learning a body ego-centered spatial representation as well as for changing it into an allocentric perspective, (3) a hierarchical memory system based on predictive coding for a rule-based episodic memory at the brain level.

All these three alignment mechanisms underlying Tem-

A. Pitti is in the Laboratory ETIS, UMR CNRS 8051, the University of Cergy-Pontoise, ENSEA, France.
E-mail: alexandre.pitti@u-cergy.fr

poral Contingencies, Body Space and Top-Down Prediction are compatible with each other and have been investigated elsewhere by many researchers already. It is not clear however how they can be combined in the brain to give rise to a seeming unity to oneself.

II. TEMPORAL ALIGNMENT

One key mechanism for integrating different modalities into a cohesive neural representation appears to lie in the temporal encoding done by the synapses. Recent advances in neurosciences two decades ago have permitted to find the regulation mechanism based on timing known as Spike Timing-Dependent Plasticity (STDP, cf. [14], [15]) responsible for the functional integration in cortical neurons. Similar to the Hebbian rule of associative learning, STDP reinforces the synaptic links of the most congruous neurons as well as their temporal delays. STDP consists on the bidirectional adaptation mechanism which dynamically regulates the long-term potentiation (LTP) and long-term depression (LTD) in synaptic plasticity readjusting the synaptic weights to the precise timing interval between the initiating and the targeting neurons [14], [15].

Information processing in distributed neural networks is performed at a precise temporal resolution of several milliseconds. Over time, the most congruous neural pairs aggregate themselves into coherent neural patterns whereas the less congruous ones delete their links. Thus, STDP extends the hebbian rule to the temporal domain and can be defined as follows: `if` $neuron_{pre}$ `fires at time` t_{pre} `, then` $neuron_{post}$ `is expected to fire at time` t_{post}.

Keysers proposed that STDP could shape the specific connectivity and structural organization of the multi-sensory neurons in parieto-motor circuits to represent actions with millisecond order precision [16]. It is proposed that the contingent and redundant multimodal information learnt in the sensorimotor circuits sustain then a neural representation of the body in action [17], [18].

At reverse, various perceptual experiences in the environment with temporal discrepancies can modulate differently the levels of integration in the sensorimotor circuits with the disrupting of sensorimotor integration. For instance, perceptual illusions like the McGurk effect or the rubber-hand illlusion may be based on this timely-based mechanism. Rochat in [19] and also Shimada and colleagues in [20] performed some visual-delay based contingency detection tests for measuring self-perception in infants and showed that temporal synchrony was effective early at birth. Interestingly, their capabilities for self-perception cover the temporal horizon over 200 and 300 milliseconds above which the feeling of agency was not perceived. These discoveries give some indications on the level of temporal binding in sensorimotor coordination.

In several robotic researches, my colleagues and I have employed the STDP learning rule with spiking neural networks for temporal binding to study visuo-tactile anticipation during prehension and action observation in [21], during visuomotor coordination of a robot head and self-recognition on a mirror in [22] and recently with Sotaro Shimada to replicate the rubber-hand illusion with an artificial skin in [23]. In these experiments, we associate the level of synchrony within the network to the level of agency, which means the prediction across the neurons related to temporal events detection. Depending on the robotic experience, the incoming information was from vision (camera), touch (artificial skin) or proprioception (motor activity) combined at the same time scale with synaptic delays within the interval range between $0\,ms$ and $30\,ms$. We showed that multimodal integration was quite robust to temporal delays over $200\,ms$, which were ten times higher than the capabilities of each neural pairs and that temporal binding was done at the population level. In all the experiments, the study of the networks structural organization presented interesting topologies following the functional organizations of complex networks such as the small-world networks. These types of networks, similar to archipelagos with few interaction between the sub-clusters, have interesting information processing properties for sparse coding.

One hypothesis is that, depending on timing, temporal alignment permits to switch the functional organization from the *Self*-network into *Other*-network.

III. BODY ALIGNMENT

Perceiving objects in space is one of first tasks babies have to deal with during infancy. It is a rather difficult problem since infants have to represent one object with multiple sensory modalities (vision, sound, tactile) encoded in different reference frames (e.g., eye-centered, head-centered or hand-centered). This curse of dimensionality requires to construct some mapping between the reference frames relying on multiple coordinates transformation between the senses. One brain mechanism I found important is the one of Gain-Field (GF) modulation, which addresses this problem of spatial transformation and multi-sensory representation. The gain-field modulation mechanism describes the phenomenon where the motor and the sensor signals (resp. A and B) mutually influence the amplitude activity of their afferent parietal neurons (resp. C) [24] such that the corresponding mathematical function is similar to a multiplication: $C = A \times B$. This result is surprising because most neurocomputationnal models rely on classical summing or integration function. Yet, there some advantages to use multiplication to integrate easily information, like estimating probabilities from two density proabilities or computing matrix-like 3D transformation.

For instance, multiplicative GF neurons have been found to monitor nearby objects in the peripersonal space [25], [26]. These neurons combine diverse incoming information from multiple modalities to process multiple body-centered coordinate systems invariant to motion. Similarly, multimodal GF neurons have been found in the motor cortex to be activated with respect to where the hand is moving in the visual space [27], [28] or the wrist orientation [29]. In both regions, we observe a neural field activity sensitive to both the preferred motor activity and the preferred visual orientation [30]. Thus, these neurons may participate to the construction of a body image and of the peripersonal space.

Since GF neurons construct body-centered representations based on the integration of body posture, tactile information and vision, we believe its mechanism is important not only for self-perception but also for any kind of sensorimotor transformation such as those during social interaction such as imitation or joint attention. Based on these considerations, I propose that the GF mechanism is at the ground of the Mirror Neurons System (MNS) also.

Their modeling corresponds to multiplicative Radial Basis Functions (RBFs) or sigma-pi networks [31], [32] to learn sensorimotor transformations. In image processing, these networks are known as gated networks, which have been recently re-investigated by [33], [34] for affine transformations and in developmental robotics [35], [36], [37] for multimodal integration. These multiplicative networks can serve to learn nonlinear transformations, which are common problems in robotics to compute direct mapping and inverse kinematics.

In recent researches, we proposed to exploit the properties of these GF neurons to construct neural networks that process spatial transformations in body-centered coordinates based on body posture, tactile information, sound and vision for self-perception. Sensorimotor coordination was done either in head-centered coordinates with the binding of audiovisual signals and of the camera motor position [35] or in arm-centered coordinates with a robotic arm from visual and tactile inputs [36], [38].

We showed that GF networks can map efficiently nonlinear transformations from one reference frame to another. This feature was used to learn the effects of motor activity on different sensor maps and to construct correspondences. By doing so, the GF units serve to learn the sensorimotor mapping necessary to predict the sensory changes based on the motor activity. One result was for instance the construction of an ego-space around the body based on the integration of tactile, visual and motor activity. Another result was the learning of the visual transformation necessary for mapping the motion of one person in front of the robot camera with its most probable actions selected from its motor repertoire. These two results describe how self-other representations and the correspondence problem may be resolved based on the Alignment across the modalities.

IV. MEMORY ALIGNMENT

Previous sections emphasized the modeling of the present Self with candidate neural mechanisms that can support temporal binding and multimodal integration. We consider in this section auto-biographical memory cite Dominey and incremental learning as an important component and complementary to the two previous ones.

Auto-biographical memory relies on the idea that we have the capability to scrutinize our own past actions and to judge them in comparison to current ones cite Neisser / de Waal. Based on our self-judgment, the human working memory (WM) has the ability to initiate flexible decision-making[39] and to incrementally learn to optimize its actions in order to perform better later. Stated like this, it is as if the Self brain was monitoring its own activity online with regard to its past performances.

One interesting framework that has emerged recently to describe this Self brain is the one of Predictive Coding (PC) [40] and of the related mechanism of Free-Energy Minimization (FEM) [41], [42]. According to PC, the brain is continuously attempting to minimize the discrepancy or prediction error between its inputs and its emerging models of the causes of these inputs via neural computations approximating Bayesian inference[43]. Therefore, its architecture has to be hierarchical so that one neural circuit makes inferences about the causes of another circuit's own incoming signals. One network (top layer) anticipate what is expected to be seen in another network (bottom layer) and minimizes the prediction errors for controlling it. According to Seth, One such Self memory system may display the introspective capabilities of the human brain to learn interosceptive signals and to infer hidden causes (active inference) as well as errors (error-learning) when they can(not) be predicted [43]. Seth identified the Anterior Insular Cortex (AIC) as a comparator circuit to be engaged in interoceptive inference usefull for error learning. We modeled also the AIC system for error learning [44].The aim of the study was to describe how recursive and online learning could be done based on negative reinforcement learning. We attached the network behavior with the capability of learning-to-learn because the error detection served for interoceptive comparison of old memory and the indirect selection of new actions and therefore the indirect learning of new memories.

AIC is of course not the only place for interoceptive inference and several overlapping sub-networks appear to participate to the realization of the Predictive Brain [45] that could constitute the Self. In previous researches, we modeled the cortico-hippocampal system in order to investigate the development of predictive coding and of an autobiographical memory [46], [47], [48] with the rapid categorization of novel memories and the consolidation of old memories [49]. Based on previous developmental studies and neuro-functional analysis [50], [51], we simulated how the gradual activation of the neuromodulator Acetylcholine (ACh) activated the functional re-organization of the hippocampal system to start to detect novelty and to code sparsely old memories. We could show that a novelty detection mechanism in combination with habit learning could create a flexible working memory. The resulting system was capable to solve the A-not-B problem, which is a marker during the first year of cognitive development and of flexible action selection.

We extended our research on predictive coding with a recent model based on the iterative free-energy optimization of recurrent neural networks, which is the acronym for INFERNO [52]. It consists on two learning systems coupled each other that attempt to diminish their mutual prediction errors. The result is the active control of one system on the other (active inference). In sensorimotor tasks, the coupled system is similar to a forward model and an inverse model, which attempt to dynamically optimize their models to reduce error prediction to better reach one goal and to better learn one body dynamics. In memory sequence tasks, we showed that INFERNO was capable to retrieve long-range sequences of spikes above 200 iterations which is above the state of art.

In the perspective of modeling one working memory, to learn and retrieve memory sequences, we believe that it encompasses also some important aspects beind designing the Self and autobiographical memories in one artificial system.

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