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Neural learning of embodied interaction dynamics

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Abstract

This paper presents our approach towards realizing a robot which can bootstrap itself towards higher complexity through embodied interaction dynamics with the environment including other agents. First, the elements of interaction dynamics are extracted from conceptual analysis of embodied interaction and its emergence, especially of behavioral imitation. Then three case studies are made, presenting our neural architecture and the robotic experiments on some of the important elements discussed above: self exploration and entrainment, emergent coordination, and categorizing self behavior. Finally, we propose that integrating all these elements will be an important step towards realizing the bootstrapping agent envisaged above. © 1998 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Behavior is attributed by an observer to the dynamics of a coupled agent–environment system. The dynamics cannot be statically decomposed so that each component corresponds to a physical constituent clipped out from the agent–environment system (Beer, 1997). The nervous system is no exception. If we clip it out of the agent's body and observe its activity patterns by giving a static set of test stimuli, there is no way we can relate such observation to the natural behavior of the agent. This is because the (cyclic) causal relationship (i.e. dynamics) between the stimuli and the neural activity (and its output) is broken. The tight coupling between the neural system and the body–environment system is called embodiment.

Early approaches with the interactionist robotics discipline, such as the behavior based approach (Brooks, 1990), successfully realized insect-like robot behaviors (e.g. locomotion and navigation). However, their limitation is now widely recognized; it is extremely difficult to scale up the systems to handle complex tasks or to make them adaptive enough to quickly create/acquire novel behavior to meet variations in the situation.

The above difficulty mainly arises from the fixed and decomposed realization of the low level behavior, as in insects. This makes it difficult to achieve higher level behavior without destroying the underlying dynamics as the newly introduced dynamics gets more and more complex and intertwined with others.

Many attempts have been made to extend or modify the behavior based architecture to make it more adaptive and capable of complex tasks. However, their success was still mainly around locomotion and navigation level behavior. Embodied and interactionist approach towards human level intelligence, pioneered by Brooks (1997), may require a new set of disciplines.

Humans are extremely flexible and continuously learn new skills and concepts. Even newborns are found to have rather powerful adaptivity and learning ability (Meltzoff and Moore, 1997). What we need is an interactionist framework unifying the abilities for robust stable behavior, quick 'on-the-fly' adaptation to novel situations, bootstrapping learning by exploring for novel dynamics and creating higher structures which support it.

This paper presents our current approach towards designing an adaptive agent with a neural architecture which has the above discussed properties. The architecture must meet seemingly contradicting requirements; it must be adaptive to quick changes in the dynamics, but it must not drastically destroy the pre-existing behavioral capabilities, and it should coordinate and maintain the integrity of the whole set of interactions, while exploring and creating new global structures to acquire a higher level integrity.

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In our current approach to the above issues, we focus on a particular class of interaction dynamics, i.e. adaptive imitation of physical behavior. As discussed in the next section, imitation is a perfectly suitable class of behavior which contains all the above issues without losing clarity or becoming too general and arbitrary in problem formulation.

Building an 'architecture of an imitating robot' per se is not our goal. Rather, our approach is to analyze the concept of imitation and focus on important interaction dynamics issues behind it, expecting that they apply to more general cases of adaptive interaction.

In this paper, we investigate the above discussed issues through three case studies. Case Study I is about self exploration and entrainment for a single interaction dynamics. There we describe our neural architecture for spatiotemporal information processing along with the basic experimental framework, which is currently under our investigation towards integration of exploration, quick adaptation and persistence in a uniform framework. Case Study II is on-line adaptation and emergent coordination of distributed motion controllers, experimented on a real robotic head system. This shows that coordination can emerge from interaction through embodiment without any explicit neural coordinator. Then the issue of categorization of such coordination patterns is discussed in Case Study III, with the presentation of our neural architecture (similar to the one in Case Study I) which learns the categorization of self behavior patterns. This is a step towards autonomous creation of higher level structure and bootstrap learning while maintaining the pre-existing dynamics. Then we summarize the conceptual elements of learning of embodied interaction dynamics in the discussions section. All the work in the above case studies assume a particular robotic setup, a binocular active vision head, which is described below.

1.1. ESCHeR: a binocular robotic head system

ESCHeR (Etl Stereo Compact Head for Robot Vision) (Kuniyoshi et al., 1996) is the platform for our experiments (simulated in Case Studies I and III, and a real experiment carried out for Case Study II). It is a four-DOF (degrees of freedom) binocular active vision mechanism: as shown in Fig. 1, it has two CCD cameras which rotate independently ('vergence') in a common horizontal plane which can be tilted, and the whole platform can rotate around the vertical axis ('pan'). All joints are driven by DC servo motors equipped with rotary encoders. The mechanism partially mimics the eye mobility of human vision system. ESCHeR is provided with a high performance gaze mobility (close to humans), which is sufficient for tracking a moving object ('smooth pursuit') or to quickly change the focus of attention ('saccade').

The lowest level control (such as achieving a commanded velocity) of the motors is done at 500 Hz cycles by a servo controller, a dual Transputer (IMS T805) system, which communicates motion commands and proprioceptive data with higher level controllers via 20 Mbps serial communication channels. Real time image processing is implemented using a DataCube MaxVideo system, a pipeline architecture which does fast preprocessing, a Shamrode Multi-DSP system which does high speed floating point signal processing, and a KIWIVision system, a distributed transputer system (9 CPUs) which does post processing and communication with the servo controller. They are connected via MaxBus image data bus, and controlled by a MVME167 Motorola 68040 based CPU board running LynxOS, a real time UNIX. The learning programs presented in Case Study II were implemented in part (which requires real time operation) on the servo controller CPUs, and the rest (which does not need strict real time operation) on a workstation connected with the above system via Ethernet. Currently we

Dimensions			
Width	222mm	Height	187mm
Depth	160mm	Baseline	180 mm
Weight	2.0 kg		
Performance			
Axis	Range	Max. Vel.	Resolution
Pan	200°	$140^{\circ s^{-1}}$	0.0044°
Tilt	090°	$350^{\circ s^{-1}}$	0.0145°
Left	100°	$400^{\circ s^{-1}}$	0.0125°
Right	100°	$400^{\circ s^{-1}}$	0.0125°

Fig. 1. ESCHeR: ETL Stereo Compact Head for Robot Vision.

Focal length (fovea)	10.7[mm]
Focal length (60[deg])	1.39 [mm]
View angle (2θ)	120[deg]
F No. (fixed)	4.0
Configuration	10 groups 11 lenses

$$y = f_1 tan(\theta), \quad 0 \leq \theta \leq \theta_1 \quad (6)$$

$$y = log_a(f_2\theta) - p, \quad \theta_1 \leq \theta \leq \theta_2 \quad (7)$$

$$y = f_3\theta + q, \quad \theta_2 \leq \theta \leq \theta_{max} \quad (8)$$
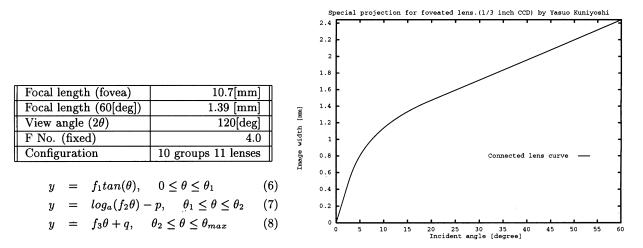
Fig. 2. Characteristics of the foveated wide angle lens equipped on ESCHeR. The optical characteristics (left top), the projection curve equations (left bottom), and the projecting curve (right).

have real time implementation of integrated motion detection and binocular fixation processes based on optical flow and an extended zero disparity filter (Rougeaux and Kuniyoshi, 1997).

The most significant part of ESCHeR is its 'foveated wide angle' lenses (Kuniyoshi et al., 1995). They simulate human visual system's compromise between a wide but low resolution field of view for peripheral detection and a tiny high resolution fovea[1] for precise observation. Our lens seamlessly combines the above two extreme characteristics in a single special optics which implements a nonlinear projection curve (Fig. 2). It has a 120° field of view and a maximum magnification of 7.7 in the fovea versus the periphery.

The projection curve is a combination of three parts: (1) the fovea (with incident angles between 0° and 2.5° from optical axis) adopts a standard projection, (2) the periphery (from 20° to 60°) adopts a spherical projection, and (3) the intermediate range (2.5° to 20°) adopts a log-of-spherical projection. The log component can be combined with a polar transformation, which has many useful characteristics (Sandini and Tagliaco, 1980). It enhances the lock-on effect in stereo fixation, simplifies the analysis of optical flow and introduces image invariance to rotation and scaling (a powerful characteristics for 2D identification).

The above system imposes a particular embodiment to our system which is similar to human vision system to some degree: the foveated lens introduces nontrivial motor image mapping. Moreover, it imposes a non-uniform weight function to the perceptual stimuli by enhancing the foveal view. The redundancy in motor degrees of freedom (i.e. the vergence and neck pan rotation) introduces a nontrivial control problem which requires appropriate dynamic coordination of the motors.

2. Imitation as adaptive interaction dynamics

The class of behavior we are currently exploring with the ESCHeR system is spontaneous and imitative head swinging accompanied by gradual improvement in visual tracking/saccading.

Imagine a two-month-old baby lying on the bed. One commonly observed behavior is it spontaneously and repetitively swings its head. When it is calmly alert, if an adult comes and swings one's head sideways in front of the baby, it watches it first, then after the adult stops, the baby starts to swing its head (Piaget, 1962). This way the baby gets involved in agent interaction, and boosted up in the development of its unified sensory-motor and social interactions.

2.1. Why imitation research?

In the interactionist endeavour to understand and create human level intelligence, imitation is a very important and appropriate phenomenon for investigation. It is no doubt a complete form of embodied agent–environment interaction. Particularly, it is an interaction with another agent acting in the shared environment, which introduces the interactive emergence and cultural scaffolding (Hendriks-Jansen, 1996), or cultural learning (Tomasello et al., 1993) aspect. This is crucial in understanding human level intelligence, including emergence of symbols, sense of self, communication, understanding intentions, cooperation, etc (Meltzoff and Moore, 1995).

Naive conception of imitation is behaviorally deined: 'Doing a similar thing'. So it is often quite straightforward to decide whether an agent is imitating the other or not. In a stricter cognitivist analysis, such as in Tomasello et al. (1993), definition of imitation must account for internal cognitive process of the agent, as whether it was goal directed or not, whether the imitator 'understands' the 'intention' of the modeler, or whether the imitated action was novel and

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[1] The fovea is the rodless part of the human retina. It covers about 0.5° (in diameter) of the average 160° of entire field of view.

delayed. However, we think it is more appropriate to have a broader view; that it is more beneficial to treat those different 'kinds' of imitation in a uniform framework. One reason is that the same neural architecture shows quite different behaviors depending on the situation it is placed in, according to the interactionist framework.

A more careful speculation about what 'similar' means reveals an important twist that this observational definition of imitation holds because of embodiment and social grounding of all the involved agents, i.e. the modeler, the imitator, and the observer. And each agent often plays all three roles simultaneously, e.g. in mutual imitation, which has the property of interactive emergence. Imitation is a unique interaction dynamics which bridges the internal observer and the external observer so that they share a common meaning, i.e. the structure of 'similarity'. Here, an internal observer is an observer who is participating in the observed dynamics by the very act of doing the observation. An external observer means an observer who is independent from the observed dynamics.

Although it is often easy to define clearly, imitation is quite open ended. In contrast to an arbitrary task learning, there is no need for an externally provided specific goal for each case. The target behavior can be anything. Therefore, an account for imitation ability can have a great generality but not too vague as it is already constrained to be 'doing a similar thing'.

Moreover, imitation covers many levels of cognitive abilities, ranging from direct motion matching to symbolic or intention level matching, as pointed out by Piaget (1962), Meltzoff and Moore (1997) and Kuniyoshi (1994). Therefore, an investigation exclusively focused on imitation ability can traverse all the different levels of cognitive abilities in the context of interaction dynamics.

2.2. What are the issues in imitation?

There are several works in robotic imitation to date, each dealing with a specific class of actions; block manipulation (Kuniyoshi and Inoue, 1993; Kuniyoshi et al., 1994), mobile robot navigation (Demiris and Hayes, 1996; Dautenhahn, 1995), dynamic arm motion in a *kendama* play (Miyamoto et al., 1996), and head motion (Berthouze et al., 1996; Demiris et al., 1997).

For a fixed pair of sensory and motor modalities, and for a fixed class of actions and a fixed situation, constructing a behavioral imitation system is the matter of selective attention and classical adaptation (i.e. adaptation to a fixed or very slowly changing external conditions) at best. Both are only with regard to fixed criteria, such as choosing which features to match based on predefined rules and achieving explicitly specified action results in the presence of bodily and environmental difference.

As discussed before, we believe that the importance of imitation research is not in realizing a specific behavioral imitation system, but in getting insights about general

mechanisms of adaptive interaction dynamics. Therefore, we avoid a direct approach to build any specific imitation ability for its sake. Rather, we support either (or both) of the following approaches:

1. assume general mechanisms/principles for adaptive embodied interaction. Then show that imitation functionality is already there; and/or
2. assume a mechanism for imitation, which includes learning of novel imitative behavior. Then explore its role and interactions with other mechanisms in the general adaptive behavior (Mataric, 1994).

The work presented in this paper is on the line of approach 1. The above approaches do not exclude that there may be innate mechanisms dedicated for a specific class of imitation abilities (Meltzoff and Moore, 1997). It may be the case that such functionality appears as the most basic behavior of a general adaptive interaction dynamics situated in appropriate conditions. Even if it is not the case and there are such innate special-purpose mechanisms, they can never act independently of other interaction dynamics. It is important to reveal how they interact with ech other.

2.3. Piagetian view of imitation

J. Piaget (1945) claimed that the imitation ability of humans is not innate, but is acquired through various developmental stages from pure reflexive behaviors to symbolic tasks. This development is started just after the birth and is completed within about 18 months. These stages are summarized as follows:

1. use of reflexes: the basic mechanisms built in innate reflexive behaviors serve as a basis for development of imitation. They include: circular response, reinforcement of continuous reactions, reactions to stimuli given by other agents;
2. sporadic imitation: when a known stimulus pattern is given by others, it is occasionally imitated involuntarily. This process is driven by the mechanisms of assimilaton and adaptation. And occurs only when the corresponding pattern is currently active within the imitator;
3. organized imitation of directly perceived known patterns: voluntary imitation of known stimulus reaction patterns. The pair must be comparable within one sensory modality. Novel patterns are ignored;
4. imitation of known patterns which are not directly perceived: acquires a class of imitation in which the target action and self action cannot be directly compared within a single perceptual modality, e.g. imitating someone scratching his/her nose. Implies multisensor fusion and the use of body image. No structural recognition;
5. organized imitation of novel patterns: acquires an ability to imitate novel actions by combining known actions. Begins to use means–ends adjustments; and
6. symbolic imitation and delayed imitation: generalized

imitation, e.g. open/shut a mouth while trying to open a match box. Explained by internalized imitation. Also, begins to reproduce previously perceived actions after long time intervals.

Piaget's essential thesis was that imitation is composed of a set of simple mechanisms. These mechanisms interact with each other, and the environment, to produce a predictable stagewise progression.

The major Piagetian mechanisms underlying imitation are summarized as follows (Bakker and Kuniyoshi, 1996):

1. exploration: the child acquires novel sensory-motor patterns experienced during the use of reflexes. These patterns persist within the child as schema;
2. assimilation: the child maps a perceptual stimulus to the closest sensory-motor pattern (schema) it has experienced before. Since a schema is a unified sensory-motor pattern, this results in generating behavior as a selective response. If the child has a small repertoire of schema, a stimulus might be assimilated to one that seems quite different to an observer;
3. accommodation: adaptation of the activated schema towards the external events or objects. In effect, the generated motion is adjusted;
4. circular reactions: in a very early stage, the result of a reflexive behavior acting as a triggering stimulus for the same behavior. A typical example is repetitive empty sucking (i.e. when a stimulus is given on its lips, a baby starts sucking; even after the stimulus is removed promptly, this behavior persists without anything to suck in; the sucking motion itself generates a stimulus which releases the sucking reflex). Later, it has a tendency to maintain interested perceptual event by repeatedly invoking the associated motion and even adjusting the generated motion. An observer may attribute a motivation to it; and
5. index system: a mechanism for correspondence between self and other's body, and between locations in the space around self.

2.4. Renovated view of imitation

Piagetian stage theory of development has been refuted by many findings about infant competence which appear much earlier than or irrelevant from the assumed stages (e.g. Thelen and Smith, 1994). A drastic example is imitation of facial and manual gestures by neonates (Meltzoff and Moore, 1977).

It is clear that the distinct, rigid and orderly Piagetian stages do not hold, and his static decomposition of competence into elements is not appropriate. However, his essential claim that novel structures emerge from intertwining of interaction dynamics still remains a plausible hypothesis. But the modern view should be more dynamic.

It has been found that even neonates' imitation is not a fixed action pattern. Many observations confirmed that there is adaptivity and even goal directed correction to match the target behavior.

It is quite reasonable to assume that babies have innate 'hard-wired' mechanisms for imitating a specific set of gestures, namely facial imitation; they have quite high evolutionary value. However, the fact that the neonates have abilities to imitate quite unusual facial imitation (e.g. tongue-protrusion-to-the-side), and that similar adaptive imitation abilities have been observed for other modalities, such as various manual gestures, suggests that such abilities are supported by somewhat general mechanism.

As a candidate for such a mechanism, Meltzoff and Moore (1997) propose an architecture called AIM, which explains the adaptive intermodal matching process. It compares the endstates of 'organ relationship' (the endpoint bodily configuration) extracted from exteroceptive and proprioceptive/somatosensory information, and if there is a non-overlap, it is translated into a corrective motion by looking up the directory mapping organ relationship states to coordinated actions. This process is repeated as long as the non-overlap is detected. The mapping directory is created through 'body-babbling' partly done during the fetus period. This theory has much in common with the essence of Piagetian mechanisms, i.e. the integration of assimilation, accommodation and schemata acquired through exploration.

Our current working hypothesis is that static decomposition of the imitation ability into distinct elements, as in both Piaget's and Meltzoff's models, may not be appropriate. Particularly when we design an agent architecture, this may lead to a typical conceptual error of assigning each such functional element to an independent module (as pointed out by Brooks, 1991; Pfeifer and Scheier, 1996b). The apparent function may be decomposed into elements by the observer. However, the underlying process and mechanisms may be more uniform.

Currently we are developing a model of imitation process by reinterpreting the above discussed elements in terms of dynamical systems and emergent structures. Following is the current organization of our hypothetical model:

1. entrainment dynamics: assimilation, accommodation, circular reactions (Piagetian) and matching and correction (Meltzoff) can be partly captured by the notion of entrainment dynamics. Assume a simple attractor dynamics; perception and motion are now inseparable, and thus assimilation and accommodation are two flip sides of the same coin. Together they have a natural tendency to approach toward one of the potential attractors. Circular reactions and resulting repetitive actions are the most typical behavior of such a system. Point attractor dynamics is a standard concept in neural model of memory functions (Hopfield, 1982), which exactly does a kind of assimilation. Use of a single limit cycle attractor has been experimented in robot

motion control (Taga et al., 1991; Rizzi and Koditschek, 1993). An important issue would be allowing many distinct attractors in a closed-loop embodied interaction dynamics (as contrasted with the pure internal dynamics in case of memory models) and enabling it to migrate from one to another;

2. spontaneous dynamics and spatiotemporal patterns: in Piaget's stage theory, the initial schemata are created through exploration by reflexes. Then they are used for dealing with novel sensory-motor patterns. Our view is (1) not to discriminate the two stages but treat them as a mixture, and (2) not entirely resort to reflexes but take into account the spontaneous dynamics, i.e. 'body-babbling', in Meltzoff's term. Exploration may be interpreted as a combination of spontaneous dynamics and spatiotemporal pattern learning. An example of spontaneous dynamics can be spontaneous firing of neuronal cells driving the intrinsic dynamics of the body (Thelen and Smith, 1994). The effects of reflexive and learned dynamics are important in enriching while constraining the spontaneous behavior, preventing it from degenerating to trivial patterns or diverging into randomness;

3. emergent coordination and quick adaptation: coordination and cross-modality can be attributed to the emergence of ordered structure from many intertwined interaction dynamics, combined with a neural mechanism which quickly adapts to and stabilizes the emergent structure of dynamics. Our current hypothesis is that coordination emerges from interaction between many sensory-motor processes through embodiment and in the context of existing behavior patterns such as reflexes (see Case Study II). This coordination may be transient and not stable, but a spatiotemporal association network may be able to quickly adapt to this coordination pattern and start to drive the system, thereby stabilizing the pattern;

4. sense of self as spatiotemporal patterns: the index system and sense of self may be attributed to the above created novel spatiotemporal pattern (which at the same time drives the system). The pattern is basically about self in terms of its embodied interaction; and

5. attentional dynamics: real actions are never exactly the same. The similarity can only be defined if we focus on some important features. Assuming the assimilation by entrainment dynamics as discussed above, attention may in part be just an attribution by an external observer to the dynamics of the system. However, it is very likely that there is an explicit correspondent to attention in the internal neural mechanism. For example, the lateral inhibition mechanism in our spatiotemporal net (Case Study I) gives rise to a dynamic activation pattern which moves around the layer. This may constitute an internal dynamics which affects the embodied interaction dynamics by selectively enforcing particular dynamics, which then affects the attentional dynamics.

3. Case Study I: self exploration and entrainment

This case study takes up the issue of self exploration and emergence of a quasistable embodied interaction dynamics. It is conceptually related to the exploration and circular reaction discussed earlier.

First, we introduce a temporal coding neural net model, and show a simple experimental setup (simulation based) for a closed-loop robotic experiment. We chose this neural net model because we believe that it has the potential to integrate all the elements of imitation discussed in the previous section, e.g. exploration, entrainment, quick 'on-line' adaptation, emergent coordination, spatiotemporal pattern categorization, and attentional dynamics.

Then we present an experimental result which may be interpreted as an example of self exploratory behavior reaching a quasistable state by self entrainment. This is an ongoing work and we present only preliminary results.

3.1. The neural model

In conventional robotics application of neural networks, static cell models have been used. In order to deal with temporal patterns, recurrent connections or time delay elements have been commonly used. So far most applications used separate training phase which is disconnected from the interaction dynamics.

A dynamic cell model with a temporal learning rule can handle spatiotemporal patterns and the learning is embedded in the operation of the network itself. This is a suitable property for quick on-line adaptation. We adopted SAM model (Shigematsu et al., 1996) with its temporal learning rule. This model will be used also in Case Study III.

3.1.1. SAM model

SAM stands for 'Spike Accumulation and delta-Modulation'. It consists of three parts:

1. leaky integration of the input pulses:

$$U_i(t) = \sum_j W_{ij}(t).X_j(t) + \alpha.V_i(t-1) \qquad (1)$$

where j is the index of each synapse of the ith cell, $V_i(t)$ is the internal potential of the ith cell at instant t (see descrption below) and $X_j(t)$ is the activation of the jth input cell;

2. binary thresholding for pulses generation:

$$Y_i(t) = g[U_i(t) - T] \qquad (2)$$

where $g[z] = 1$ if $z > = 0$; $g[z] = 0$ otherwise; T is the firing threshold and $Y_i(t)$ is the generated pulse; and

3. subtraction of constant from internal potential at spike firing:

$$V_i(t) = U_i(t) - p.Y_i(t) \qquad (3)$$

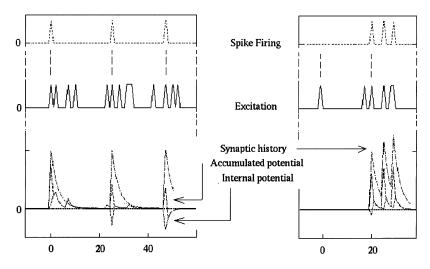where p is a constant that controls the loss of internal potential after spike firing.

Fig. 3. SAM model behavior under various settings.

Fig. 3 is an illustration of a cell's response under various configurations. In the left chronogram (from time 0 to time 80), the delay (from 1 to 3 time units in this case) in response to a stimulus can be adjusted by tuning the firing threshold T. After firing, sharp drops in internal potential can be noted. It results in a cell firing only once even after mutliple excitations, i.e. slow dynamics. Such property is obtained with a high value of p (subtraction constant at spike firing). In the right part of the chronogram, the opposite setting is used: small loss of potential after spike firing threshold enables the cell to generate train of spike firing after even a single stimulation.

3.1.2. Temporal learning rule

At each time step, the weights $W_{ij}(t)$ are updated according to the temporal learning rule introduced by Shigematsu et al. (1996).

The temporal learning rule (detailed below) is a revised Hebbian rule with synaptic history. The classical Hebbian Rule reinforces connections if responses of both input and output cells are simultaneously active, independently of the history of the input signals, as formulated by Eq. (4),

$$\Delta W_{ij} = C_{ij}.X_j(t).Y_i(t) \tag{4}$$

The temporal learning rule (1) strengthens connections when an input pulse train is an intense burst signal or a one shot signal stimulated simultaneously with another input signal, and (2) weakens them when the input signal has a very low frequency or is out of phase with other input signals.

Mathematically, the synaptic history is an accumulated value of the input signal received by the ith cell, from the jth cell, at a synaptic site of the dendritic portion of the ith cell.[2] It is computed by:

$$H_{ij}(t) = X_j(t) + q.H_{ij}(t-1) \tag{5}$$

where q is a decay coefficient ($0 < q < 1$). After one input pulse, this input history will decrease exponentially to zero.

When the ith cell is fired, a new connection efficacy (from each synapse j) is calculated according to the following equations:

If $H_{ij}(t) \geq H_1$ then

$$\Delta W_{ij} = c_1.(W_{\max} - W_{ij}).Y_i(t)$$

If $H_{ij}(t) < H_1$ and $H_{ij}(t) > H_2$ then

$$\Delta W_{ij} = c_2.(W_{\min} - W_{ij}).Y_i(t)$$

where c_1, c_2 are parameters fixing the learning speed, $W_{\max}$ and $W_{\min}$ are respectively maximum and minimum values of the connection efficacy and H_1 and H_2 are two thresholds, respectively, set for enhancement and depression. When the after-effect of an input signal is nearly zero and the history is smaller than H_2, the efficacy is not changed, i.e. the memory in the efficacy is not erased by noncorrelated signals. This learning calculation is applied to firing cells only.

3.2. The input/output interface

3.2.1. Delta–sigma modulation

As an interface between the perceptual inputs to the spiking neuron net, we use the delta–sigma modulation. This transforms continuous signals into pulse trains, which can be handled by the SAM neurons. We follow the procedure reported by Panter (1965). Briefly stated, the trains of pulses are generated so as to minimize the difference between the temporal integration of the generated pulses and the input signal, as illustrated in Fig. 4.

3.2.2. Adaptive output filter

The interface between the spike trains and the motor system is a IIR low pass filter. Since the range of output

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[2] Shigematsu et al. (1996) relates it to an after-effect such as an intra-cellular calcium ion concentration that can be observed in biological systems.
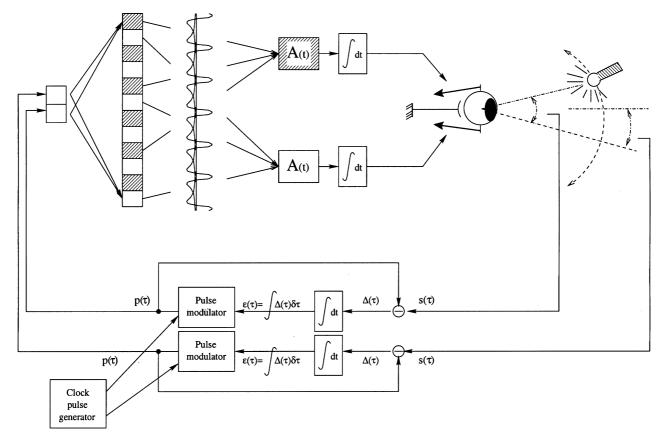
Fig. 4. The experimental system.

value can change greatly, we attached a long time constant filter in parallel with the above filter and compare the outputs to generate normalized output.

3.3. Experimental system

The experimental system (Fig. 4) consists of two main parts: the simulated mechanical system (right) and the neural system (left).

The mechanical system is a simulation of a simplified version of ESCHeR. It is a one-DOF eye, controlled in rotational position. The target-to-image projection follows the ESCHeR's foveated projection curve. The eye interacts with an independent target. The image position of the target is limited within the field of view (60° from the center). When the target goes beyond this limit, its image position is encoded as 60° off the center of the fovea.

Both proprioceptive (joint rotation angle) and extero-ceptive (target position in the field of view) are modulated through delta–sigma modulation into two pulse trains. The unit time of the modulation is currently set to 10 ms.

The neural architecture consists of two layers. The input layer receives the sensorimotor patterns (the motion of the target image on retina and the proprioceptive data) encoded as pulse trains. They are generated by the interaction between the eye and the target.

The input layer is fully connected to the second layer.

The second layer consists of 12 'spiking neurons'. The temporal learning rule is applied to them at each time step. Each cell spontaneously generates spikes occasionally. Currently a spontaneous spike is generated with probability of 0.2.

All cells of the second layer are laterally connected by a Mexican-hat-shaped inhibition function (Fig. 5). In effect, each cell has excitatory connections to its close neighbors (two on both sides of each cell, in the current experiment), and inhibitory connections to further cells. This connection is the source of various internal dynamics such as selective activation, coupled oscillators, etc.

Output connections are made to two output nodes from the intermediate layer in a interleaved manner (some connections are omitted in Fig. 4 to avoid over-loading the drawing). The connections have uniform weights. At each time step, the population activities $A(t)$ (spatial integration of the spikes) of the two sets of cells are fed to each low pass filter and to generate an antagonistic pair of commands (one in the left direction and the other in the right direction). The commands are fed to the motor system.

The initial connection efficacies in the neural system are randomly distributed within an interval of [0.4:0.6]. During learning, the weights are limited to the range of [−1.0:2.0]. The lateral inhibition connection weights are fixed.
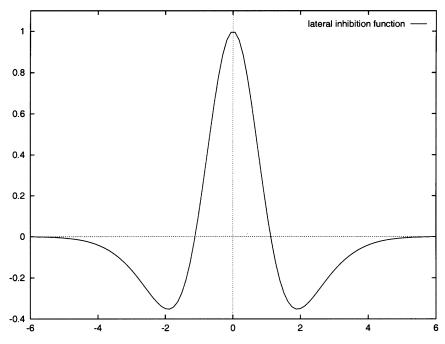
Fig. 5. Lateral inhibition among cells in the intermediate layer.

3.4. Experiment

The external target stimulus was fixed throughout the first experiment. Initially, the stimulus is aligned with the optical axis of the camera such that there is no neural activaton due to the presence of this stimulus (because the input to the network basically encodes the motion of the target image).

The neural network is uniform and symmetric, and no initial bias was imposed on the synaptic connection weights; their initial values are random.

The resulting behavior is shown in Fig. 6. The behavior (motor response to retinal motion) in the initial period (up to 1 s, or 100 time steps) looks somewhat random, whereas the behavior in the final period (after 1.5 min) clearly shows an almost regular repetitive pattern. An observer may attribute 'circular reaction' behavior to this pattern.

In the initial period (Fig. 6), small motor commands are emitted. Although there is no external stimulus, the cells in the intermediate layer spontaneously fire. This spontaneous firing is stochastically distributed over time and space but its population activity integrated over time (via the output filter) occasionally creates ocular motion.

If the network is disembodied, the uncorrelated spontaneous firing only acts as a small noise to the network activity, and the system may stay in a stable but trivial state, the null activation (on average) state. However, because we have an embodied system, exteroceptive information becomes non-null due to the occasional motor output. Moreover, due to the foveal vision, the retina is strongly sensitive to small motion in the fovea. These lead to self exploratory motions as an emergent dynamics.

During exploratory motion, the network constantly learns about correlation in space (between the image position and the proprioception) and time. This immediately affects the motor output, which affects the image motion through the ocular motion and image projection process. And the network experiences a novel pattern. This is the cause for the constant variation of the overall behavior.

Fig. 6 (bottom row) shows the connection weight maps from the initial (left, random) and the final (right) period. The adaptation of the connection weight distribution has the following circular causality: (1) the learning changes the connection weight distribution; (2) the connection weight distribution changes the spatiotemporal input patterns; and (3) the input patterns affect learning process (of course).

Thus, the connection weights acts as a kind of a selective input filter for the learning algorithm. And the learning changes this filter's characteristics. This is one example of the attentional dynamics discussed in Section 2. In this sense, the connection weight distribution is acting as an internal observer discussed in Section 2.1.

After about 1.5 min the emerging dynamics reaches a quasistable state (Fig. 6). The average frequency of the oscillation may derive from the time delay constants throughout the interaction loop. Thus the apparent behavior may be somewhat trivial.

However, the interesting point is that this quasistable state did not explicitly exist initially. It was explored by the emergent dynamics discussed above, and then the system got entrained there. Moreover, the network was uniform and symmetric with random initial weights. It had no a priori constrains or a mechanism in the neural network to bias the evolution of the dynamics.

Another interesting point is that the final behavior is not completely stable. We can observe small fluctuations
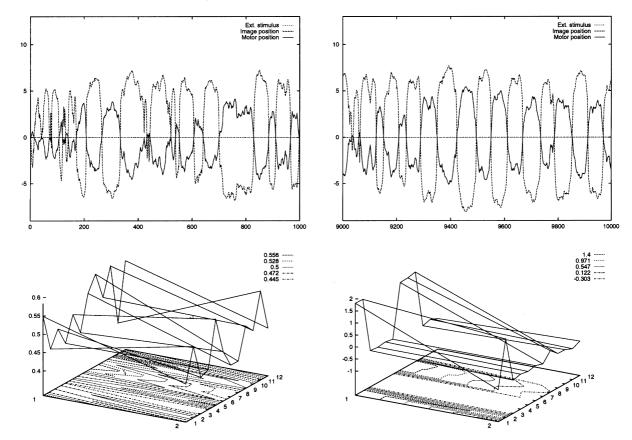
Fig. 6. Experiment with a static target. Top row: time series of target position in the environment (external stimulus), target position on the retina (image position), and the motor output. The horizontal axes denote the time steps in each period (one step is 10 ms). The target position in the environment is fixed to its origin, so it is constantly zero. The image position and the motor output always have an exact relationship (reversed and through the projection curve), because the target is stationary. Left plot is from the initial period (0–10 s) and the right plot is from the final period (90–100 s). Bottom row: connection weights at the initial (left) and the final (right) period. The vertical axis denotes connection weight value, the right horizontal axis denotes cell numbers in the intermediate layer, and the left axis denotes two input neurons (number 1 is image exteroception, number 2 is motor proprioception).

throughout the period. The system is not in a 'dead' stable state. This means two things: (1) the dynamics is actually entrained in this particular pattern because the perturbation did not make it stray away from it; and (2) the system is still exploring around the current entrainment dynamics.

4. Case Study II: on-line adaptation and emergence of coordination

So far we have seen an example element for self exploration and entrainment to a single self interaction dynamics (circular reaction).

In this section, we introduce an example for the emergent coordination issue (Berthouze and Kuniyoshi, 1998). This experiment was done on a real ESCHeR system.

4.1. Coordination of redundant DOFs: emergent VOR

The problem investigated in this example is the redundancy of mobility between overlapping rotational degrees of freedom (DOFs) (see Section 1.1) under the

effect of the nontrivial nonlinear visual oculomotor control due to the nonlinear projection of the lens.[3]

In biological systems, this is solved by the prewired but adaptive (Itoh, 1984) VOR (vestibulo-ocular reflex), which stabilizes the retinal image during a neck movement by generating a compensatory eye movement. For a target at infinite distance, it is achieved by causing the motion of the eyes to be equal and opposite to the motion of the head. It can be seen as a transformation from head velocity to eye velocity (Jordan, 1990). When the target is not at infinite distance, a real time adaptation is achieved, for which Kawato (1990), Kawato and Gomi (1992) and Gomi and Kawato (1992) proposed and verified a computational model called Feedback Error Learning (FEL).

In the present experiment (Berthouze and Kuniyoshi, 1998) in this section, we have investigated the following point: is it possible that the coordination of redundant DOF motion emerges from a set of distributed controllers,

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[3] In terms of control theory, the visuomotor control on ESCHeR is relevant to the control of a four-DOF nonlinear redundant manipulator: it has a nonlinear image-to-joint Jacobian because of the optics' nonlinearities and it has redundancy in horizontal rotations of vergence and pan.

without any internal neural connections for explicit coordination, by interacting with the world through its body? This is different from the above biological model because the biological model has such internal connections. Our experiment is not meant as a model for the biological mechanism. Rather, we used this particular setup to explore the idea of emergent coordination through embodiment.

4.2. The experimental system

Fig. 7 shows our experimental architecture (Berthouze and Kuniyoshi, 1998). We used the real ESCHeR system as the experimental platform. The motion control system is a collection of independent FEL based adaptive controllers, each connected to one motor joint and receiving common image data (target position) input.

Each adaptive controller independently implements the FEL model with the following organization:

1. a reflexive component: a conventional feedback controller with a very low gain which models a very rough innate knowledge about the coupling of the actuator with the environment. The tuning of these controllers (the value of their gain ranging from 1×10^{-4} and 3×10^{-4} rad/s in our implementation) results from a tradeoff between (1) the convergence of each controller (the linear controller guides the learning of the adaptive component of each controller) and (2) the overall stability of the architecture (higher gain values result in higher sensitivity to delays);

2. an adaptive component: a three-layer feed-forward neural network which issues motor commands based on the perceptual inputs. Both input and output layers

are linear and dedicated to normalization. The hidden layer uses nonlinear activation functions (arctangent sigmoids). Synaptic modification is achieved using a back-propagation with momentum (Rumelhart et al., 1986). While any Newton-like method (such as in multilayer perceptron, Cerebellar Model Articulator Controller or Radial Basis Function) would be acceptable, the use of back-propagation made a real time implementation possible (reduced computational load). The weight decay technique (Chow and Teeter, 1994) is used to prevent a degeneration of the synaptic weights in order to promote a continuous adaptation; and

3. component integration: the motor commands issued by both components are summed and fed to the output (one joint motor). The motor command issued by the reflexive component is backpropagated through the adaptive network to modify its connection weights. Thus, reflexive motor command serves as an error signal for the learning of the adaptive component; the network learns to minimize the interventions of the reflexive component. This is the FEL model (Kawato and Gomi, 1992; Gomi and Kawato, 1992).

The reason behind choosing FEL is that it is a self consistent 'on-line' method, which can learn very efficiently during the normal operation of the system; it does not require a separate off-line 'training' phase [as in the related approach by Jordan (1992)] or any external reinforcements. Another reason is its use of a 'reflexive' component; it needs to implement only quite a rough qualitative (and linear) model of the target system, but nevertheless plays a crucial role in assuring the convergence of the learning. This gives us important insights about the role of innate reflexes in shaping the emergent dynamics and learning (Pfeifer, 1995).

The important point in our experiment is that the FEL method is used only for individual joint control and not for the global coordination. Actually, for our purpose, it does not have to be the FEL model, as long as each component is an adaptive and predictive controller.

4.3. Experiment

The visual stimulus is given in the form of a swinging pendulum. Fig. 8 shows the motor behavior of the two DOFs (the vergence and the pan) during learning.

Before the system engages in the interaction with the environment, there is no a priori knowledge on how each controller relates to another. They interact with each other through the sensorimotor loop between actuators and perceptual apparatus.

Applying unconstrained motor learning techniques to nonlinear redundant manipulator is generally avoided because the risk of getting trapped in stable but inconsistent minima increases with the dimension of the learning space.
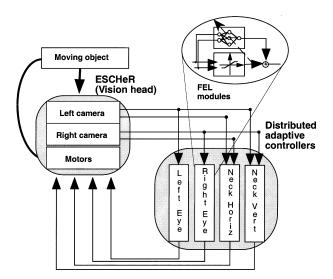

Fig. 7. Overview of the architecture of the experimental system. ESCHeR system is used as a real robotic testbed. It has four DOFs; the eye vergence joint and the neck pan joint are redundant. Moreover, the foveated lens introduces nonlinear, nontrivial image-to-motion mapping. The distributed FEL (Feedback Error Learning) controllers independently learn the sensorimotor loop between ESCHeR and the environment. The control system has no internal connections between the modules for explicit coordination.
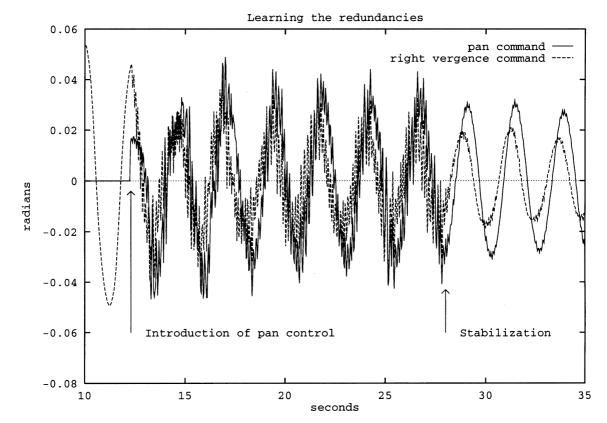
Fig. 8. Learning to deal with redundancy. Motor commands for the pan and the vergence joints from each corresponding controller are plotted for the period of 10–35 s in the experiment. The visual stimulus is given by a light at the end of a swinging pendulum. The pan control is enabled with delay, at 12.5 s. High frequency vibrations are observed until a VOR-like control law is learned.

In our experiment, we adopted an analog of a biological notion of 'freezing of degrees of freedom', i.e. in some motor behavior during early developmental periods, the motor DOFs are reduced as if they are frozen: at first, only the vergences are controlled, until a stable control is learned (qualitative estimation). Then the control of the redundant joint (pan joint) is enabled.

As shown by Fig. 8, when the redundancy is introduced at 12.5 s the system becomes unstable and exhibits strong vibrations. After this transient unstable period (about 15 s), a stable coordination (conjugate vergence and pan motion) has emerged. In effect, the system acquired a good target tracking performance as well as saccading at speed comparable to humans. For other results and further details, refer to Berthouze and Kuniyoshi (1998).

The above experiment suggests that coordinated behavior can emerge from a set of distributed adaptive controllers which are independently interacting with the environment through the shared body. Because the body imposes consistent constraints on the interaction, the coordination can be achieved even when there is no explicit internal connections among the controllers. Each adaptive controller has crude innate knowledge (reflex) which adds a useful constraint for stabilizing and guiding the unsupervised learning.

As clarified earlier, our experiment is not meant as a model for the biological mechanism. However, it suggests an interesting possibility: the neural connections for coordination, such as VOR, may be automatically created by the following step: (1) let the distributed controlllers take over and wait for the emergence of coordination as an embodied dynamics structure (as in the above experiment); (2) then assume a neural mechanism which 'senses' this dynamics structure, which creates appropriate explicit connections to stabilize the coordination. A first step towards this hypothesis would be the mechanism which can 'sense' the coordination pattern, which will be investigated in the next section.

5. Case Study III: categorization of interaction dynamics

In this section, we investigate the issue of a neural mechanism for observing and categorizing the self interaction dynamics, based on our recent work (Berthouze et al., 1998). As discussed in the previous section, this issue is a step towards building a neural mechanism which 'senses' the emergent higher-order dynamics structure (an example given in the previous section) and then creates an internal structure (activation patterns, connections, etc.) which directly participates in it (i.e. stabilizes, actively controls, remembers, combines, etc.). Since the interaction dynamics has a spatiotemporal pattern, we naturally adopted the SAM model (Section 3.1) to carry out our first experiment presented below.
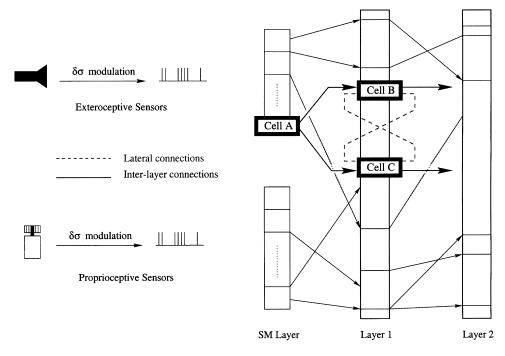
Fig. 9. Spatiotemporal associative memory: data from exteroceptive/proprioceptive sensors are modulated into pulse train by $\delta-\sigma$ modulation. Each layer is fully connected to the next one (from left to right) with initially random weights. Lateral connections exist within both layer 1 and layer 2. The highlighted subsystem (cell A, cell B, cell C) can be assimilated to a coupled oscillator and confers to the overall architecture very high dynamic properties.

In the emergent coordination experiment in the previous section, it was observed that when we made experiments over long learning periods, rapidly changing interaction patterns sometimes lead to an overall reconfiguration (chaotic-like dynamics) of the control network. This is due to the continuous fast adaptation process. Although such reset could be perceived as an interesting property (it contributes to the exploration of new sensorimotor spaces by the same principles discussed in Section 3), it eventually endangers the integrity of the system over its interaction with the environment.

It is thus desirable that only stable sensorimotor configurations emerge from the robot's environmental interaction.[4]

The hypothesis investigated in this section is that if it is possible to have the system categorize[5] its sensorimotor couplings during explorative behaviors, then appropriate use of this categorization could guide the adaptive interaction between the controllers, in a similar way as the conventional feedback controller guides the adaptive component in FEL. Conceptually, this is a higher-order replication of the reflex versus adaptivity paradigm on which our work in the previous section was based. Naturally, such categorization must not be explicitly designed but should emerge from the system's interaction with the environment. In the following sections, we present the dynamical system approach that we undertook to address this issue.

5.1. The architecture for dynamics categorization

As shown in Fig. 9, our architecture is an extension of the one presented in Section 3. It consists of two main components:

1. sensorimotor layer (left, SM layer): the flow of sensorimotor patterns, as generated by both the exteroceptive and proprioceptive sensors (in this paper, two cameras, two signals each, and the camera drive motor encoders, six joints), is transformed in trains of pulses through the delta–sigma modulation described in Section 3.2.1; and
2. associative layers (right, layer 1–2): from one to two layers were used in the experiments reported in this paper. Layers of increasing index model higher-order association. The number of layers reflect a qualitative estimation of the complexity of the sensorimotor couplings present in the system.

5.2. Experiments

Explorative behaviors are modeled as a stochastic distribution of several visuomotor behaviors, each of them involving various sensorimotor couplings:

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[4] In must be understood here that the stability discussed here is not related to stabilizing the dynamics of the system in its environment but rather stabilizing the internal configuration of the system so that it can interact with its environment without loss of its integrity.

[5] In this paper, we will define categorization in a way very similar to Thelen and Smith (1994), also mentioned by Pfeifer and Scheier (1996a): global functions of categorization are memory, learning and performance which arise dynamically from reentrant mapping of motor activity along with sensory information from many modalities… Both signals are completely coupled and act together to form the global maps that are the basis of further development… (p. 160).

1. random head motion: head and eye joints are randomly actuated, visual stimuli are random as well. This atypical visuomotor behavior is included so that the sensitivity of the architecture to uncorrelated sensorimotor patterns can be evaluated;
2. head motion: head joints (pan and tilt) are actuated without intervention of the VOR reflex described below, i.e. eyes are not coordinated. The interest of this behavior is twofold: (1) the eyes being mounted on a common tilt, tilt actuation generates similar perceptual patterns in each eye; and (2) horizontal neck motion will generate optical flow patterns compatible to horizontal eye motions;
3. eye motion: only eye joints (vergences) are activated. Optical flow patterns should be similar to the flow patterns generated by the above behavior. Correlation of both behaviors would ground the understanding of the redundancy between the joints as well as knowledge about body structure;
4. vestibulo-ocular reflex: as in animal VOR, this reflex stabilizes the retinal images during a neck movement by compensatory eye movements. For a target at infinite distance (approximation made in this experiment), it is achieved by causing the motion of the eyes to be equal and opposite to the motion of the head. It can be seen as a continuous transformation from head velocity to eye velocity; and
5. nystagmus reflex: when the eyes reach an extreme position (i.e. an object of attention reaches the periphery of the field of view with an outward direction), they are rapidly flicked back to a new starting position. Unlike VOR, it is a one-shot simultaneously coordinated control of all joints.

The above listed visuomotor behaviors drive the ocular system, generating sensorimotor patterns which are observed by the neural architecture through exteroceptive/propriorceptive data. The neural network is initialized as indicated in Table 1. Because layer 2 must learn higher-order couplings, it is tuned to have a slow dynamics; p is

set high so that internal potential drops sharply after firing. The lateral inhibition curve is set so as to activate connections with cells located at most three cells apart. Further cells are inhibited according to the inhibition function shown in Fig. 5. A typical experiment consists of up to 10,000 behavior switching (those switching are controlled externally). Fig. 10 displays the result of the spike firing monitor we developed for this experiment. The upper part of the monitor displays the activity of the cells [visual input (cells 0–3), motor command (cells 4–9), layer 1 (cell 10–24)] over about 500 time units (an average 100 switching of behaviors).

At each time unit, the value of the highest connection efficacy over the whole network is calculated and serves as an index of the learning stability. After stabilization, each input is intensively fired (burst firing) in order to measure the state of the network and the pathways associated with that burst firing are recorded.

As shown in the lower display of Fig. 10, well-defined clusters appear. Each of them correspond to a spatio-temporal correlation between this sensorimotor component and one/many of the other components. A different view on this categorization is provided by Fig. 11 where the distribution of peak connection efficacies between input layer and layer 1 is projected on a 2D plane. With this representation, back-projecting the clusters on the input layer makes the reading of existing first-order correlations between inputs straightforward.

In Fig. 12, we analyze the operating factors (i.e. accumulated potential, internal potential and synaptic history) of a cell that belongs to one of the clusters shown above. This analysis consists of alternative sequences of uncorrelated and (temporally or spatially) correlated excitations. In Fig. 12, we distinguish two areas (Area 1 and Area 2) of particular interest: in Area 1, the absence of cell firing indicates a good robustness to uncorrelated inputs. Meanwhile, high sensitivity and stability to correlated inputs is observed in Area 2. After two consecutive correlated excitations, the cell generates a pulse train. Uncorrelated

Table 1
Initialization of the neural architecture for a typical experiment

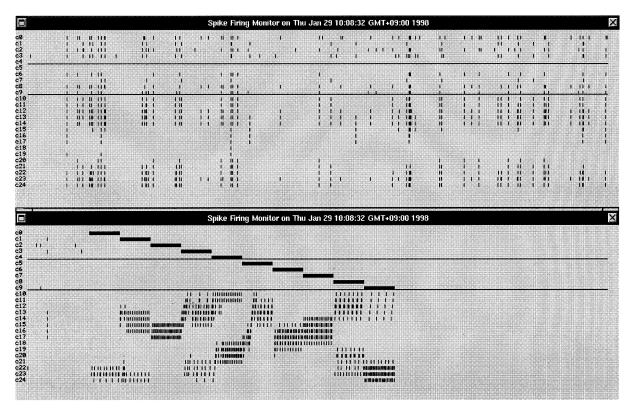|	Input layer	Layer 1	Layer 2	
n	4 + 6	15	20	Number of cells at each level
a	0.5	0.5	0.5	Decay constant for internal potential
q	0.6	0.6	0.6	Decay constant for synaptic history
p	0.6	0.6	0.9	Subtraction constant (strong loss of int. potential at spike firing)
T	0.4	0.4	0.5	Firing threshold
W_{ij}		0.35	0.07	Connection efficiency initialization (slow dynamics in layer 2)
H_1		0.8	1.6	Threshold for connection efficacy enhancement
H_2		0.3	0.2	Threshold for connection efficacy depression
c_1		0.04	0.04	Learning speed for connection enhancement
c_2		0.01	0.01	Learning speed for connection depression
W_{max}		2.0	2.0	Maximum connection efficacy
W_{min}		−1.0	−1.0	Minimum connection efficacy

Fig. 10. Diagram of the spiking pattern of each cell during a typical experiment. Horizontal axis denotes time. Each row corresponds to a cell. Upper display shows the spiking pattern during learning. Lower display shows the result of a connectivity test by supplying burst inputs to each of the input cells (c_0-c_9).

excitations input during the pulse train, while not directly affecting the cell firing, result in a sharp drop of accumulated potential which eventually stops the train pulse.

6. Discussions and future directions

In Section 2, we have proposed the elements of embodied interaction dynamics based on the speculations about imitation abilities. Those are: entrainment dynamics, spontaneous dynamics and spatiotemporal patterns, emergent coordination and quick adaptation, sense of self as spatiotemporal patterns, and attentional dynamics.

Through the three case studies, we have presented basic models, experiments, and interpretations which are related to the above elements. They are not complete, definitive

results, as our research program is in its early stage. However, they provide us with some insights and indicate a plausible direction of research towards scaling up our understanding of adaptive interactive systems.

Case Study I was on self exploration and self entrainment. The experiment suggested that it can start from a spontaneous dynamics (e.g. spontaneous spiking of neurons, in our model) through the intrinsic embodied dynamics. And the dynamics emerges through a process in which the system adapts to the dynamics and thereby changing the dynamics itself, to which the system adapts, until it reaches a quasistable dynamics (e.g. which partly relies on the intrinsic dynamics, in our case).

The important point is the following: if we introduce a mechanism which adapts to the dynamics while participating in it, and if both the adaptation and the dynamics
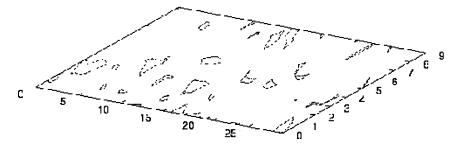

Fig. 11. Emergence of clusters in the first intermediate layer. Right-hand axis corresponds to the input layer (sensorimotor pattern), while left-hand axis corresponds to cells in layer 1.
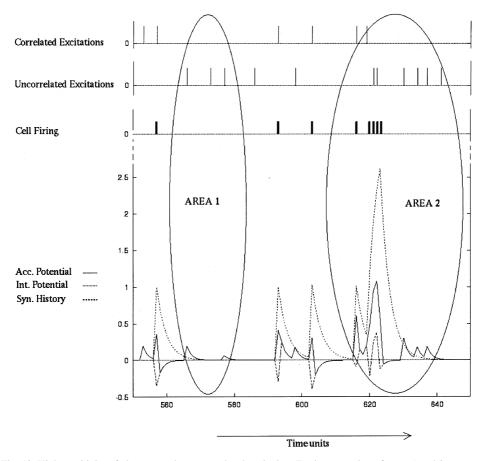
Fig. 12. High sensitivity of cluster member to correlated excitation. For interpretation of areas 1 and 2, see text.

itself have similar time scales, then the overall behavior becomes nontrivial and emergent. Because as the network learns, it results in changes of the whole dynamics, which in turn is learned by the network. In such cases, the network may be acting as an internal observer.

We proposed a 'filter hypothesis' which attributes the notion of internal observer to the adaptive connection weights in our spiking neural net model: the connection weights acts as a kind of a selective input filter for the learning algorithm, and the learning changes this filter's characteristics, so they move on. One aspect of this 'attentional dynamics' may appear as the steep peaks running around on the intermediate layer (with lateral inhibition) of our network.

The experimental result given in this case study is very preliminary. It needs much further investigation. Especially, due to the simplified simulation of the physical body and the lack of any built-in reflexes, it is difficult to interpret the meaning of the apparent behavior. Experiments with much more complex body, innate mechanisms and the realistic environment are strongly urged.

Case Study II gave an example in which the coordination of a redundant sensorimotor system can emerge from a group of interacting adaptive controllers. They have no explicit internal connections to each other. By interacting through the shared body and the environment, the coordination has emerged.

The neural model used in this experiment is different from the other two case studies. However, we believe that it can be replaced by the spiking neural net model with the temporal learning rule, as it has the essential required property such as on-line adaptation. A concrete model remains an open research issue.

The above case studies revealed another key issue: quick on-line adaptation to emergent spatiotemporal patterns and creating a higher structure (neural pathways) which explicitly participates in the corresponding dynamics. This is important as the emergent dynamics in exploration or coordination is often transient. And with such a mechanism, the problem of scaling up the system without destroying existing dynamics may be solved.

Case Study III was a first step towards an emergent categorization of acquired coordinated behavior, which will lead to categorical (selective and prototypical, or entrainment) responses to novel sensorimotor patterns. The current experiment was done for a set of different a priori behavior patterns which are externally switched from one to another. The network created clusters corresponding to the underlying behavior types by observing the sensorimotor patterns. This experiment shows that the network has some potential to categorize the interaction dynamics. Of course, in the future study, the external switching must be avoided, and true emergent patterns must be dealt with.

The above architecture should be extended so that as soon as the network categorizes a dynamics, it participates in it. Then the bootstrapping cycle will be complete. Actually, Case Study I showed that the same network can actually control the body.

We envisage an integration of all the elements examined in the above case studies; it will have quick on-line adaptivity embedded in embodied interaction dynamics, emergent coordination patterns acquired through embodied interactions among the adaptive components, and boot-strapping ability which creates higher-order neural activities that participate in the emergent dynamics, all in a unified architecture. With this architecture, the agent can grow more and more complex while maintaining its integrity, the higher-order patterns are stabilized and 'remembered' (becomes a persistent dynamics). When the system perceives another agent's behavior, it quickly correlates the perceived spatiotemporal pattern with the remembered sensorimotor patterns in a supramodal (Meltzoff and Moore, 1997) manner, generating a complex sensorimotor pattern which is 'similar' to the observed behavior.

This way, we may be able to achieve a unity of embodied dynamics and various imitation abilities (Gaussier et al., 1994), not in a separate stages or components, but as inter-twining dynamical processes. And by imitation, the agent can participate in rich interagent interaction, which will be essential for true achievement of communication, cooperation, and mutual understanding.

Acknowledgements

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