

Formalization of recognition, affordances and learning in isolated or interacting animats

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Abstract

In this paper, we summarize the main properties of an algebra useful to describe architectures devoted to the control of autonomous and embodied “intelligent” systems. First, we use this formalism to propose a definition of perception as a potential function built from the integration of the sensori-motor signals. Next, we demonstrate the capability of a very simple architecture to learn to recognize and reproduce facial expressions without the innate capability to recognize the facial expressions of others. The solution relies on the importance of the interactions with another system/agent knowing already a set of emotional expressions. A condition for the learning stability of the proposed architecture is derived. The teacher agent must act as a mirror of the baby agent (and not as a classical teacher). As a result, the proposed architecture is able to learn the task. Finally, we discuss the limitations of the proposed formalism.

1. Introduction

Nowadays hardware and software technologies allow to build more and more complex artifacts. Unfortunately, we are almost unable to compare two control architectures proposed to solve one given problem. Of course, one can try an experimental comparison on a given benchmark but the results focus on the optimality regarding the benchmark (how to deal with unknown or unpredictable events?). We should be able to analyze, compare and predict the behaviors of different control architectures. For instance, we must be able to decide if two

architectures belong or not to the same family and can be reduced to a single architecture. On another level, new design principles are proposed to create more “intelligent” systems (Pfeifer and Scheier, 1999) but there is no real formalization of these principles. The only way to correctly understand and use them is to have a long explanation build on examples showing cases of success stories (examples of good robotic architectures). Our situation can be compared to the period before Galileo when people knew objects fall but were unable to relate that to the concept of mass and acceleration in order to predict what will happen in new experiments. We urgently need tools to analyze both natural and artificial intelligent systems. Previous works have focused on mathematical tools to formalize pure behaviorist or reactive systems (Steels, 1994). People have also tried with no real success to measure the complexity (in terms of fractal dimension for instance) of very simple behaviors like an obstacle avoidance (Smithers, 1995). The most interesting tools are dedicated to specific part of our global problem such as learning (see NN literature), dynamical systems (Schöner et al., 1995) or some game theory aspects (Ikegami, 1993). Yet, it remains difficult to overstep the old frame of the cybernetics (Wiener, 1961, Ashby, 1960). Finding the fundamental variables and parameters regarding some particular cognitive capabilities will be a long and difficult work but we believe we have to try to start it. After a short summary of our formalism, we will use it for the learning of attraction basins that characterize place or object recognition. A new formal definition of the perception will be derived. Next, several

formal simplification rules based on the optimization of our perception criteria will be proposed. They will be illustrated on a simple theoretical model of the development of the capability to express and recognize more and more complex facial expressions. We will try to discuss, which are the basic mechanisms necessary to allow a naive agent to acquire the capability to understand/read the facial emotions of a teacher agent and to mimic them (so as to become a teacher and to allow turn taking in an emotion expression game).

2. Basic formalism of a CS

We summarize here the basis of our mathematical formalism. Figure 1 shows a typical control architecture for what we will call a cognitive¹ system (CS). The input and output of a CS are represented by vectors in the “bracket” notation². An input or output vector x (column vector of size m) is noted $|x\rangle$ with $|x\rangle \in R^{+m}$ ³ while its transposed vector is noted $\langle x|$. Hence $\langle x|x\rangle$ is a scalar representing the square of $|x\rangle$ norm. The multiplication of a vector $|x\rangle$ by a matrix A is $|y\rangle = A|x\rangle$ with $|y\rangle \in R^n$ for a matrix A of size $n \times m$. A CS is supposed to be

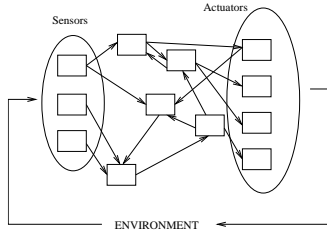


Figure 1: Typical architecture that can be manipulated by our formalism.

made of several elements or nodes or boxes associated with input information, intermediate processes and output (command of actions). We can consider that any element of a CS filters an input vector according to a

¹The term cognitive must be understood here in the sense of the study of particular cognitive capabilities (cogitare - to think) and not as a positive a priori for any kind of cognitivist approach.

²The formalism is inspired from Hilbert space used in quantum mechanics. Nevertheless, in our case it is not an Hilbert space since the operator is not linear...

³We consider the components of the different input/output vectors can only be positive/activated or null/inactivated. Negative activities are banned to avoid positive effects when combined with a negative weight matrix.

matrix of weights W and a non linear operator \mathbf{k} . This operator represents the way to use the W matrix and the pattern of interactions between the elements of the same block. It can be a simple scalar product (or distance measure) or even a more complex operator such as an “If...then...else...” treatment (hard decision making), a pattern of lateral interactions in the case of a competitive structure, a recurrent feedback in the case of a dynamical system, a shifting mechanism, a mechanism to control a focus of the attention... Hence, we can consider these elements as “neurons” even if they can be more complex algorithmic elements in other programming languages. For instance, in the case of a simple WTA⁴ box, we can write the WTA output $|y\rangle$ is $wta(A|x\rangle)$ with $|y\rangle = (0, \dots, y_j, \dots, 0)$ and $j = ArgMax(q_i)$ and $q_i = \langle A_i|x\rangle$. In the case of a Kohonen map, $|y\rangle = koh(A|x\rangle)$, the main difference is the way the output is computed: $q_i = \sum_j |A_{ij} - x_j|$. To be more precise, we should write $|y\rangle = koh(A, |x\rangle)$. Because, in the general case, an operator can have an arbitrary number of input groups, we will consider the recognition of an input is performed according to the type of its associated weight matrix. For instance, “one to one” input/output connections represented by the general identity weight matrix I is considered as the signature of a reflex pathway (because there is almost no interest to consider “one to one” learnable links). Basically, we distinguish 2 main types of connectivity according to their learning capabilities (learning possible or not): the “one to one” links (see fig. 2a) and the “one to many” connections (see fig. 2b) which are used for pattern matching processes, categorization... or all the other possible filtering. “One to many” connections will be represented in general by a A . In the case of a complex competitive and conditioning structure with 1 unconditional (US) and 2 conditional (CS) inputs, we should write for instance $|y\rangle = c(A_1, |CS_1\rangle, A_2, |CS_2\rangle, I, |US\rangle)$. To avoid too many commas in the operator expression, we simply write $|y\rangle = c(A_1|CS_1\rangle, A_2|CS_2\rangle, I|US\rangle)$ ⁵. This allows

⁴Winner Takes All.

⁵In previous papers, it was possible to write $|y\rangle = c(A_1|CS_1\rangle + A_2|CS_2\rangle + I|US\rangle)$ but many reviewers complained about the risk of misunderstanding the meaning of the operator +.

to be sure a particular matrix is always associated to the correct input vector but it does not mean the matrix has to be multiplied by the vector (this computation choice is defined by the operator itself). The main

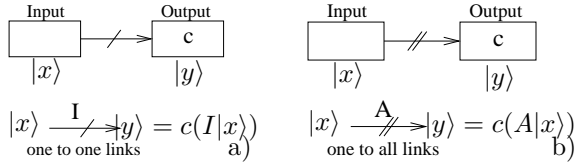


Figure 2: Arrows with one stroke represent “one to one” reflex connections (one input connected to one output in an injective manner). Arrows with labels and 2 parallel strokes represent “one to many” modifiable connections between input and output nodes. a) Unconditional “one to one” connections (used as a reflex link) between two groups. Upper image is the graphical representation and lower image is the formal notation. b) “One to many” connections with a competitive group representing the categorization of the input stimulus at the level of the output group.

difference with classical automata networks is that most of our operators are supposed to adapt or learn online new input/output associations according to their associated learning rule. For instance, in the case of a classical Kohonen rule, we should write $\frac{dA_{ij}}{dt} = koh_learning(|y\rangle, |x\rangle)$. Hence, 2 equations have to be written for each elementary box: one for the computation of the system output and another one for the weight adaptation (modification of the box memory). In this paper, we will not discuss the interest or defaults of particular learning rules. We will simply suppose the existence of learning rules able to stabilize the weight matrices in the case the system is in a particular “perception state” (this notion will be defined in the next section). So we will not need to write explicitly the learning rule but it will be crucial to remember our operators represent 2 different functions and flow of information moving in opposite directions. The first one will allow to transform sensorial information in an output code while the second one will act on the group memory in order to maintain a certain equilibrium defined by the learning rule (Gaussier, 2001).

3. Stable state of perception

In previous papers, we have shown a homing behavior can be obtained from

the competition between few sensori-motor associations learned around a goal location (see PerAc architecture proposed in (Gaussier and Zrehen, 1995, Gaussier et al., 2000)). For one position P in a given environment (or state space), we suppose 2 sensation vectors $|S_r\rangle$ and $|S_g\rangle$ can be defined. First, $|S_r\rangle = f(P)$ represents a coarse information about the motor system “proprioception” (a feedback information from the execution of the motor command) or the direction of the goal (if the goal is in the immediate neighborhood). It can be considered as a reflex or regulatory pathway linking a proprioceptive sensor to the motor command $|Ac\rangle$. Second, $|S_g\rangle = g(P)$ represents a more global information on the environment allowing to build a local but robust distance measure (metric). This measure is learned and performed by a competitive recognition group R ($|R\rangle$ representing its activity). This sensori-motor architecture for homing behavior can be defined by the following equations:

$$\begin{aligned} |R\rangle &= c(A_1|S_g\rangle) \\ |Ac\rangle &= c(A_2|R\rangle, I|S_r\rangle) \end{aligned} \quad (1)$$

which can be represented by the diagram fig. 3. The operator c represents a competitive structure (soft-WTA) able to self-organize itself according to one sensorial data flow and/or to condition one input data flow according to an unconditional flow (both learning and output computation are mixed in the single c notation). To illus-

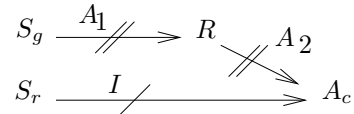


Figure 3: Diagram representing eq. 1: a simple network that can be used to learn how to return to a given place or to focus on a given object in a visual scene.

trate the system functioning and generalize it to object recognition, we simulate a very simple visual system that must learn to recognize a cross (see fig. 5b). We consider our system is recognizing an object if it is able to maintain the object in the center of its fovea or to stabilize its focus on this object. In our example, the system need to learn how to return to the center of the cross when it comes from the right

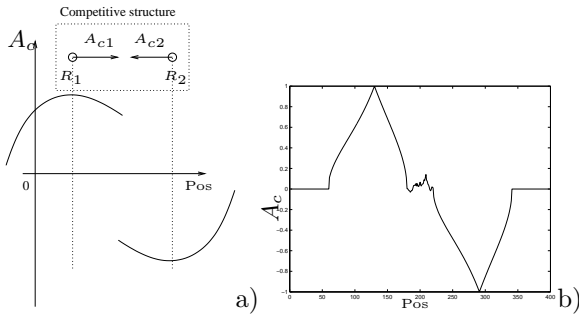


Figure 4: a) Theoretical system actions after learning of 2 sensation/actions associations and their competition according to the system position on the x axis. b) experimental value of the action level in the 1D case of fig. 5. Both max. and min. peaks are associated with the learned locations (perfect correlation between learned and tested views).

or from the left. Hence the system has to learn at least two positions located symmetrically around the goal. In our simulation, the learned locations were centered at the cross extremities (see fig. 5b). The recognition $|R\rangle$ of both learned positions is performed by a simple point to point cross-correlation between the learned local views (centered around the learned positions) and the current view centered on the gaze of the artificial eye. After the competition, the component R_1 or R_2 of $|R\rangle$ is activated according to the level of the local view recognition. The real decision is only taken at the motor level ($|Ac\rangle$ vector ⁶) and must be understood according to the global temporal dynamic of the system. Let's notice, the system behavior does not directly depend on the absolute level of recognition of the learned views or places. Only the rank in the competition process matters. Because most of the visual perturbations have the same effect on each elementary recognition, the system will continue to behave correctly until the noise has an effect on the rank in the competition for the view recognition (while classical systems fail when the noise/perturbation oversteps an absolute recognition threshold). Fig. 5 shows few robot trajectories of the gaze di-

⁶In the 1 dimension case, we suppose the robot eye can only move on a horizontal line $|Ac\rangle$ vector need 2 components: A_{c1} associated to a movement from the left to the right and A_{c2} for a movement in the opposite direction. The simulated robot actions are represented by the intensity of the speed vector on the 1D axis (the sign representing the direction of the vector - see fig. 4).

rection according to a random initial gaze direction. We can see the system always converges to the center of the object whatever its starting position is. Fig. 5 b) presents a typical trajectory and the vector field in the 2D case (the system has only learned the 4 cross extremities and the associated actions to move in the direction of the center of the cross). Learning more places allows to produce a smoother vectorial field but the global behavior remains the same. Interestingly, in the proposed architecture the goal location is not learned in the N.N. Only the strategy to reach that place is learned. We claim that when our robot is going in the direction of the goal location it is truly "recognizing" that place. It is important to note that in

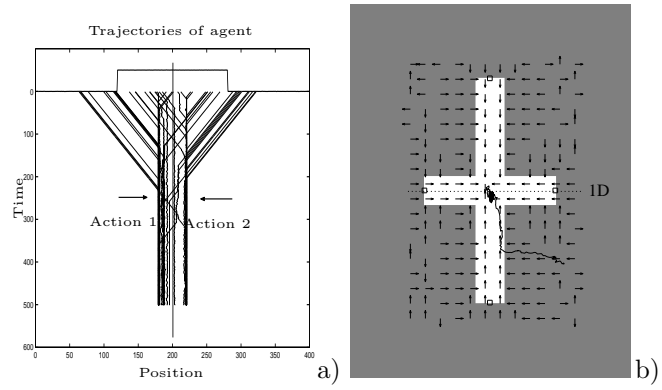


Figure 5: a) Examples of trajectories in the 1D case. The vertical line at position 200 represent the desired final position. b) Image used for the simulations (300x400 pixels, 256 gray-scale). Each small square is the position of the learned local views (101x101 pixels). The arrows indicate the orientation of the movement done at those locations. The larger square is the desired final position (goal). The line shows a sample of trajectory. In this figure only 4 views are used by the agent (one for each extremity of the cross).

the dynamical systems theory, the action is defined as the derivative of a potential field (Kelso, 1995, Schönner et al., 1995). If the field is defined according to a given position \vec{p} in the environment, we will define⁷:

$$|Ac\rangle = -\overrightarrow{\text{grad}} \text{Per} \quad (2)$$

The perception Per can be seen as a scalar function ψ representing an invariant of the

⁷We could define : $m|Ac\rangle = -\overrightarrow{\text{grad}} \text{Per}$ with m the "mass" (real or virtual) of the considered system. We suppose the Perception Per takes into account a "mass" linked to the physical body.

system (a kind of energy measure). Hence, the perception can only be defined for an active system and is dependent of the system dynamical capabilities (kind of body, sensors and actuators). Of course, we can also write: $Per(\vec{p}) = -\langle Ac|\vec{p}\rangle = -\int_{\vec{p}+\delta\vec{p}} Ac d\vec{r}$. This corresponds to our intuition of the recognition as an attraction basin. The basin shown fig. 6 results from the mathematical integration of the curves proposed fig. 4 to represent the learned sensori-motor associations and their effect according to the system location. The obtained potential field defines an attraction basin with a single minima guiding the agent towards the goal location. The only important constraint is to guaranty that the recognition of the sensori information decreases monotonously over a given neighborhood when moving away from the learned positions. To sum up, the important change

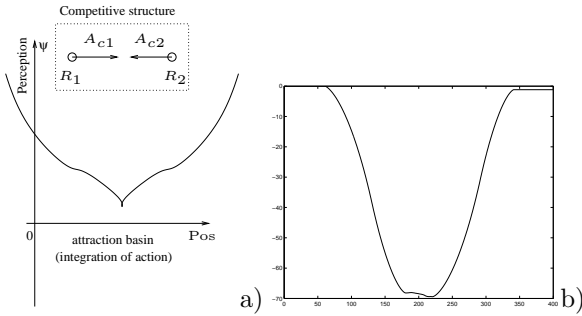


Figure 6: a) Theoretical perception and attraction basin obtained after integration of the action. b) experimental integration (after competition) of the 2 recognition levels obtained from fig. 4.

from our previous works is to consider that in the general case the sensations are not the perception and that the perception is a potential function defined by the conjunction of sensations and actions. Learning to recognize an object or a spatial location can be seen as building an attraction basin or learning some particular affordances (for instance on-line learning of few sensori-motor associations). In this case, we will say a system is in a **stable state of perception** if it is able to maintain itself in the associated attraction basin. Hence, recognizing an object (from visual, tactile, auditory... informations) can be seen as maintaining the system in a particular dynamical attraction basin (Gibson, 1979).

4. Formal simplification rules

Now, the problem is to be able to simplify a CS architecture in another one (presumably simpler to analyze and to understand). Two architectures will be considered as equivalent if they have the same behavioral attractors. This means we cannot study a control architecture alone. The interactions with the environment must be taken into account. After the learning of a first behavior, the dynamics of the interactions with the environment (the perception state) is supposed to be stabilized. In the present formalism, two types of diagram simplifications will be considered. Simplifications of the first type can be performed at any time and leave the fundamental properties of the system completely unchanged (these are very restrictive simplification rules). Those of the second type only apply after learning stabilization (if learning is possible!). They allow strong simplifications but the resulting system is no more completely equivalent to the departure system. We now present a first example of a simplification rule based on the existence of unconditional and reflex links. If we consider a linear chain of unconditional links between competitive structures such as WTA, the intermediate competitive boxes are useless since they replicate on their output their input information. Hence we can write for instance that if we have: $|b\rangle = c(I|a\rangle)$ and $|d\rangle = c(I|b\rangle)$ then $|d\rangle = c(I|c(I|a\rangle))$ which should be equal to $|d\rangle = c(I|a\rangle)$ because a cascade of competitions leads to an isomorphism between the different output vectors which become equivalent to each other after the self organization of the different groups. So we can deduce the following rule $\mathbf{c}(\mathbf{I}|c(\cdot)) = \mathbf{c}(\cdot)$. Other static simplification rules can be build in the same way (Gaussier, 2001). Other simplifications can be used to represent the effect of learning. Except for robustness, these simplifications can be introduced to compare different control architectures (or to build more complex controllers). We will suppose that the system is in a stable state of perception or interaction with its environment. That is to say, it exists a time period where the system remains almost unchanged (internal modification must not have an effect on the system behavior). Fig. 7 shows an intuitive representation of the evolution of a system

behavior through time. The system behav-

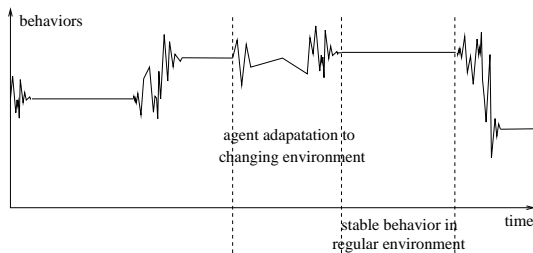


Figure 7: Intuitive representation of what is a stable behavior allowing formal simplifications of the system.

ior can evolve to adapt itself to an environment variation (or to the variation of an internal signal). In this case, it moves from a stable state to an unstable state or transition phase. It is only during the stable phases that the following simplifications can be considered as valid. Hence, we have to highlight a “before learning state” and an “after learning state” since some of the simplifications can be made at any time while some others must necessarily be made in the “after learning state”. A very simple exam-

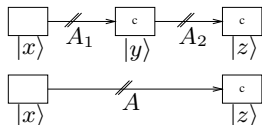


Figure 8: A cascade of competitive or unsupervised classification structures can be simplified in a single competitive or classification box with a possible loss of performance but without a change in the main properties of the architecture.

ple of such a simplification is the case of strict self organized learning group or competitive boxes (c operator) push-pully connected, fig. 8. We have $|y\rangle = c(A_1|x\rangle)$ and $|z\rangle = c(A_2|y\rangle)$ with A_1 and A_2 the matrices to learn the relevant input configurations. So $|z\rangle = \mathbf{c}(\mathbf{A}_2|\mathbf{c}(\mathbf{A}_1|\mathbf{x})) = \mathbf{c}(\mathbf{A}|\mathbf{x})$ since it is always possible to create a bijection between the activation of a given neuron in a first group and the activation of another neuron in a second group. Both sets of neurons can be considered as equivalents. A more interesting case corresponds to the conditioning learning. The conditioning network (fig. 9 a) should be equivalent “after learning” to the simple network shown fig. 9 b and can be translated by the following equation: $c(I|US), A|CS) \approx c(A|CS)$ where $|US\rangle$ represents the unconditional stimulus and $|CS\rangle$ the conditional stimulus. The

simplification “before learning” considers only the reflex pathway: $c(I|US), A|CS) \approx c(I|US)$ (functioning is equivalent in a short time delay but there is no possible adaptation) whereas the other simplification represents the equivalent NN in the “after learning” situation: not equivalent if the environment changes too much and leads the agent to be inadapted. We have shown

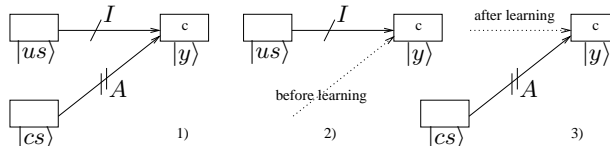


Figure 9: Image 1 is the graphical representation of a conditioning learning $|y\rangle = c(I|US), A|CS)$. Image 2 is the graphical representation of the equivalent network before learning and Image 3 after learning $|y\rangle = c(A|CS)$.

in (Gaussier, 2001) that maximizing the dimensionality (rank) of the perception matrix $\sum_P |Ac\rangle\langle S|$ can be equivalent to the mean square error minimization performed when trying to optimize the conditioning learning between the action proposed by the conditional link and the action proposed by the unconditional link. Hence, learning can be seen as an optimization of the tensor representing the perception. In other words, we can say the proposed simplification rules are relevant if the system is adapted to its environment or if the system perceives its environment correctly according to the capabilities of its own control architecture (learning capabilities). We can notice that $Per = \sum_P \langle Ac|S\rangle = tr(\sum_P |Ac\rangle\langle S|)$ while the “complexity” of the system behavior can be estimated from $rank((\sum_P |Ac\rangle\langle S|)$.

5. Application to social interactions learning

In this section, our goal is to show how our formalism can be applied to analyze a very simple control architecture and justify some psychological models (see (Canamero, 2001) for a discussion on the importance of an emotional system in autonomous agents). At the opposite to the classical pattern recognition approach, we will show that an online dynamical action/perception approach between two interacting systems has very important properties. The system we will consider is composed of two identical agents (same archi-

ture) interacting in a neutral environment (see fig. 10). One agent is supposed

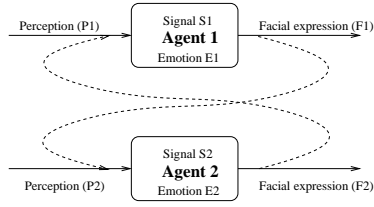


Figure 10: The bidirectional dynamical system we are studying. Both agents face each other. Agent 1 is considered as a newborn and agent 2 as an adult mimicking the newborn facial expressions. Both agents are driven by internal signals which can induce the feeling of particular emotions.

to be an adult with perfect emotion recognition capabilities and also the perfect capability to express an intentional emotion. The second agent will be considered as a newborn without any previous learning on the social role of emotions⁸. First, we will determine the conditions for a stable interaction and show that in this case learning to associate the recognition of a given facial expression with the agent own “emotions” is a behavioral attractor of the global system. We suppose our agents receive some visual signals (P_i perception of agent i). They can learn and recognize them ($|R_i\rangle$ activity). Hence, the perception of a face displaying a particular expression should trigger the activation of a corresponding node in R_i .

$$|R_i\rangle = c(A_{i1}|P_i\rangle) \quad (3)$$

c represents a competitive mechanism allowing to select a winner among all the vector components (see section 3). A_{i1} represents the weights of the neurons in the recognition group of the agent i allowing a direct pattern matching. Our agents are also affected by the perception of their internal milieu (hunger, fear etc.). We will call S_i the internal signals linked to physiological inputs such as fear, hunger... “Emotion” recognition E_i depends on the internal milieu. The recognition of a particular internal state will be called an emotional state E_i . We suppose also E_i depends on

⁸We will have to explain how our agent can recognize and reproduce gestures it cannot see itself perform and by what mechanism it connects the felt but unseen movements of self with the seen but unfelt movements of the other (Meltzoff and Moore, 1997).

the visual recognition R_i of the visual signal P_i . At last, the agents can express a motor command F_i corresponding to a facial expression. If one agent can act as an adult, it must have the ability to “feel” the emotion recognized on someone else’s face (empathy). At least, one connection between the visual recognition and the group of neuron representing its emotional state must exist. In order to display emotional state, we must also suppose there is a connection from the internal signals to the control of the facial expression. The connection can be direct or through another group devoted to the representation of emotions. For sake of homogeneity, we will suppose that the internal signal activates through an unconditional link the emotion recognition group which activates through an unconditional connection the display of a facial expression (hence it is equivalent to a direct activation of F_i by S_i - see (Gaussier, 2001) for a formal analysis of this kind of properties). Hence, the sum of both flows of informations can be formalized as follow:

$$|E_i\rangle = c(I|S_i\rangle, A_{13}|R_i\rangle) \quad (4)$$

At last, we can also suppose the teacher agent can display a facial expression without “feeling” it (just by a mimicking behavior obtain form the recognition of the other facial expression). The motor output of the teacher facial expression then depends on both facial expression recognition and the will to express a particular emotion:

$$|F_i\rangle = c(I|E_i\rangle, A_{12}|R_i\rangle) \quad (5)$$

Fig. 11 represents the network associated to the 3 previous equations describing our candidate architecture. In a more realistic architecture, some intermediate links allowing the inhibition of one or another pathway could be added but it is out of the scope of the present paper, which aims at illustrating what can be done with our formalism on a very simple example.

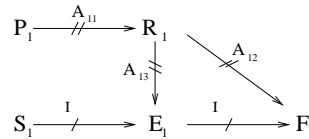


Figure 11: Schematic representation of an agent that can display and recognize “emotions” (notations see fig. 2).

5.1 Condition for learning stability

First, we can study the minimal conditions allowing the building of a global behavioral attractor (learning to imitate and to understand facial expression). Fig. 12 represents the complete system with both agents in interaction. It is considered as a virtual net that can be studied in the same way than an isolated architecture thus allowing to deal at the same time with the agent “intelligence” and with the effects of the embodiment and/or the dynamics of the action/perception loops. The following sim-

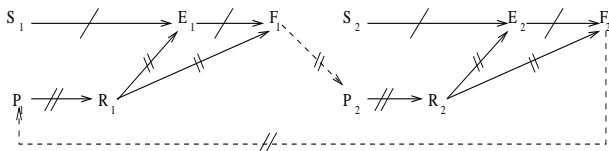


Figure 12: Schematic representation of the global network representing the interaction between 2 identical emotional agents. The dashed links represent the connections from the display of a facial expression to the other agent perception system (effect of the environment).

plications apply before learning and concern only the unconditional links (see in the previous section the simplification of a conditioning structure before learning). We simply consider the activation of S can induce a reflex activation of a stereotyped facial expression F before (and after) the learning of the correct set of conditioning. The resulting network is shown fig. 13. Next, the linear chains of “one to many”

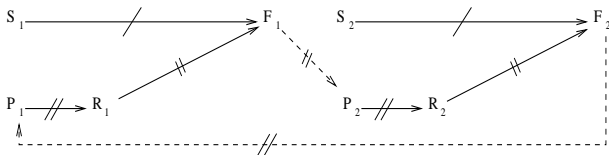


Figure 13: Schematic representation of the simplified network representing the interaction between 2 identical emotional agents (modification of fig. 12)

modifiable connections and their associated competitive learning structures can also be simplified since $\mathbf{c}(\mathbf{A}|\mathbf{c}(\cdot) \equiv \mathbf{c}(\cdot)$. We finally obtain the network shown fig. 14 a). It is much simpler on fig. 14 to see the condition of the learning stability. Since, the chosen simplifications allow to obtain a virtual network with learnable bidirectional connections between F_1 and F_2 , a condition for

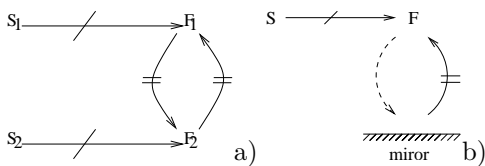


Figure 14: a) Final simplification of the network representing the interaction between 2 identical emotional agents (modification of fig. 13). b) Minimal architecture allowing the agent to learn “internal state”-“facial expression” associations.

the learning stability is that these connection weights remain stable. If S_1 and S_2 are independent, learning cannot be stable since S_1 and S_2 are connected through unconditional links to F_1 and F_2 respectively. The only way to stabilize learning is to suppose S_1 and S_2 are similar enough. Otherwise a lot of “energy” is lost to adapt continuously the connections between F_1 and F_2 (see (Gaussier, 2001) for more details). Because, the agent representing the baby must not be explicitly supervised, a simple solution is to suppose the agent representing the parent is nothing more than a mirror. We obtain the network fig. 14 b) where the architecture allows the system to learn the “internal state”-“facial expression” associations. Hence, we show that from our departure control architecture, learning is only possible if the parent agent (supposed to be the teacher) imitates the baby agent. The roles are switched according to the classical point of view of AI and learning theory. This shows how taking account the dynamics of interactions between two agents can change our way of thinking learning and more generally cognition problems.

5.2 Learning the emotional value of facial expressions

The first simplifications bring us to the conclusion that learning stabilization is possible if the teacher/parent agent acts as an imitator of the baby agent. Now, we will suppose these conditions are respected. From the initial equations of the system, we will derive another set of simplifications in order to prove the beginner (or naive) agent can learn to associate the visual facial expression displayed by the teacher agent to the correct emotional state. We suppose the agent 1 perceptive input P_1 is the result of

a linear projection of the facial expression (output) of the agent 2 and vice versa. We will write $|P_1\rangle = B_1|F_2\rangle$ and $P_2 = B_2|F_1\rangle$. Hence, $|R_1\rangle = c(A_{11}|P_1\rangle) = c(A_{11}.B_1|F_2\rangle) = c(A'_{11}|F_2\rangle)$ (with $A'_{11} = A_{11}.B_1$). We can then replace in this new expression of R_1 , $|F_2\rangle$ by the result of the computation of the second agent (using eq. 5). We obtain:

$$\begin{aligned} |R_1\rangle &= c(A'_{11}|c(I|E_2), A_{23}|R_2\rangle)) \\ &= c(A'_{11}|c(I|E_2), A_{23}|c(A_{21}|P_2\rangle))) \end{aligned}$$

On the other side, we have $|P_2\rangle = B_2|F_1\rangle$ so:

$$\begin{aligned} |R_1\rangle &= c(A'_{11}|c(I|E_2), A_{23}|c(A_{21}.B_2|F_1\rangle))) \\ &= c(A'_{11}|c(I|E_2), A_{23}|c(A'_{21}|F_1\rangle))) \quad (6) \end{aligned}$$

A'_{21} is defined as the matrix resulting from $A_{21}.B_2$.

All the preceding simplifications could be made at any time (here, it is before learning). The following simplification can be done only after learning (and need the learning stability condition ie the second agent is a mirror of the first one). If the obtention of learning is possible (the error between F_1 and E_2 can be minimized in the means square sense), conditioning learning in eq. 6 should result in: $I|E_2\rangle \approx A_{23}.c(A'_{21}|F_1\rangle)$. if both architectures are identical, since there is no influence of learning on this simplification, we obtain by symmetry: $|E_1\rangle \approx A_{13}.c(A'_{11}|F_2\rangle)$. Then, we can simplify eq. 6.

$$\begin{aligned} |R_1\rangle &\approx c(A'_{11}|c(A_{23}|c(A'_{21}|F_1\rangle))) \\ &\approx c(A'_{123}|F_1\rangle) \quad (7) \end{aligned}$$

(we also have $|R_1\rangle \approx c(A'_{12}|E_2\rangle)$ but we won't use it.) Eq. 7 can be interpreted as the fact the activity of agent 1 visual face recognition is a function of its own facial expression. If we replace the value of F_1 obtained from eq. 5 in eq. 7, we obtain:

$$|R_1\rangle \approx c(A'_{123}|c(I|E_1), A_{13}|R_1\rangle)) \quad (8)$$

Here again $I|E_1\rangle$ is the reflex link and $A_{13}|R_1\rangle$ the conditional information. The conditional link can learn to provide the same results as the reflex link. If E_1 can be associated to R_1 then we obtain:

$$\begin{aligned} |R_1\rangle &\approx c(A'_{123}|c(I|E_1)) \\ \text{and } |R_1\rangle &\approx c(A'_{123}|E_1) \quad (9) \end{aligned}$$

This result shows the activity of the face recognition system is a direct function of the agent emotional state (R_1 can be deduce from E_1). In conjunction with the relation linking E_1 to R_1 (eq. 4) we can deduce the agent 1 (baby) has learned to associate the visual recognition of the tested facial expressions to its own internal feeling (E_1). The agent has learned how to connect the felt but unseen movements of self with the seen but unfelt movements of the other. It could be generalized to other movements since we showed in (Gaussier et al., 1998, Andry et al., 2001, Andry et al., 2002) that a simple sensori-motor system is sufficient to trigger low level imitations.

6. Conclusion and discussion

In this paper, we have improved a formalism proposed in (Gaussier, 2001) to define more correctly what perception can be in a situated and embodied agent. The formalism has been used to simplify an "intelligent" system and to analyze some of its properties. We have shown a very simple architecture can learn the bidirectional association between an internal "emotion" and its associated facial expression. To demonstrate this feature, we have first proved that learning is only possible if one of the agents acts as a mirror of another. We have proposed a theoretical model that can be used as a tool not only to understand artificial emotional brains but also natural emotional brains. Let us consider a newborn. She expresses internal states of pleasure, discomfort, disgust, etc, but she is not aware of what she expresses. Within our theoretical framework, we can expect that she will learn main associations between what she expresses and what she experiences through her partners' mirroring of her own expressions. Seeing what she feels will allow the infant to associate her internal state with an external signal (i.e. her facial expression mirrored by someone else). Empirical studies of mother-infant communication support this view. For instance, two-month-old infants facing a non contingent televised mother who mirrors their facial expressions with a delay become wary, show discomfort and stop imitating the mother's facial expressions (Nadel et al., 2004). The primary need of mirroring is also demonstrated by the progressive disappearance of facial ex-

pressions in infants born blind. Another prospective benefit of the model is to give a simple developmental explanation of how facial expressions come to inform the growing infant about external events through the facial reading of what those events trigger in others (Feinman, 1992). Finally the model leads to suggest a main distinction between two processes of emotional matching: matching a facial emotion without sharing the emotion expressed: in this case there is a decoupling (Scherer, 1984) between what is felt and what is shown, thus it is pure imitation, and matching a facial emotion with emotional sharing, that is to say feeling what the other expresses through the process of mirroring, a definition of empathy (Decety and Chaminade, 2002).

In our team, we also use this formalism as a programming language to describe different architectures for visual object recognition, visual navigation, planning, visuomotor control of an arm, affordance learning, imitation games... Future works will have to focus on how to manage different learning time constants and how to represent the body/controller co-development. What are the minimal structures that cannot be simplified? What kind of really different operators have to be considered? What kind of invariant has to be added to take into account all the ideas of the animat approach and the embodied cognition? Computational models avoiding the passive aspect of the architectures studied in this paper should be the next step of our work especially to study when internal recurrences or loops in the system architecture can be simplified or not.

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