

Random recurrent neural networks for autonomous system design

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Abstract

In this article, we stress the need for using dynamical systems properties in autonomous architecture design. Particularly interesting is the ability to always remain on an attractor, thus achieving *stable dynamical behaviors*. A change in the behavior corresponds to the switch from one attractor to another one through a bifurcation. We use and study a random recurrent neural network (RRNN) model exhibiting these properties when various inputs are presented. We propose a local Hebbian learning rule which stabilizes the response of the system for given inputs. After training, the system is able to perform *recognition*, i.e to produce a specific regular cyclic attractor while the learned input is present. After training, our system can also make *associations* between two different inputs, i.e to produce the same cyclic behavior when one of the two associated inputs is missing. Our RRNN is then implemented on a robotic system, under visual and sensori-motor influences. After learning periodic motor sequences in association with visual inputs, our system can now discriminate between matching and unknown visual sequences. When a visual sequence matches an inner sequence, the system produces regular periodic movements. On the contrary, when there is a conflict between visual inputs and inner dynamics, the system tends to produce chaotic aperiodic movements. Our work finally illustrates more general considerations on the act of perception: the ability to recognize an item could be intrinsically linked to the ability to produce associated behaviors.

1. Introduction

Autonomous systems have to adapt and react to a rapidly changing environment. Moreover the environment may be unknown and unpredictable. So the design of such systems may not stand alone on prewired reac-

tions. However, some regular patterns may be found in the environment dynamics. These patterns may be the basis for sensory-motor learning and temporal sequence learning. So an autonomous system dealing with such an environment has to achieve the following properties:

- stable behaviors, though the inputs are changing
- if necessary, rapid change in behaviors
- learning new appropriate behaviors

Animals are particularly well adapted autonomous systems. So, one of our source of inspiration is to capture the relevant necessary informations that make animals behave autonomously. Neurobiological research can become a source of inspiration for people who work in the conception of intelligent and autonomous systems ("animat" approach (Meyer and Wilson, 1991)). In particular:

- In animals, the observed behaviors are mainly the superimposed results of low level and high level processes that compete or cooperate.
- Our conception of autonomous systems is also driven by a constructivist approach. This enables to ground our representations on real data (Varela et al., 1993, Kuniyoshi and Berthouze, 1998). Hence, the attractors of our system have a matching correspondence in terms of image seen, movement performed or expected.
- The question of learning is central in the design of such systems (Verschure and Pfeifer, 1992, Millan, 1994, Thrun and Mitchell, 1995, Donnat and Meyer, 1996, Gaussier et al., 2000). In particular, the constraints of brain architecture allow to learn correlations between particular kinds of data but not others. These restrictions in the learning capability seem to be mainly linked with the ecological constraints of the animal survival.

In this article, we first present the main arguments for a dynamical systems approach of perception (section

2). In section 3, we present the RRNN model we use, in particular, the various dynamical regimes it may exhibit, and how they may be related to the inputs. Then we propose in section 4 a local Hebbian learning rule stabilizing stimulus-associated dynamical patterns. This learning rule is able to correlate either informations coming from the same sensory channel (sequence learning), or from different ones (vision and movement matching). Finally, we apply our model to a simple control task on a mobile robot (section 5), and we show that one can observe sharp transitions in the behavior of the system which depend on the matching between the visual scene and the movements produced.

2. Dynamical systems and perception

2.1 Neurobiological approach

Our first source of biological inspiration comes from the pioneer “dynamical” approach to cognition performed by Freeman on the olfactory bulb of the rabbit (Skarda and Freeman, 1987, Yao and Freeman, 1990). He has shown that natural attentive waiting states correspond to chaotic dynamics, and that presentation of a known odor leads through a bifurcation to almost cyclic dynamics. Even local and specific to the olfactory bulb, these results prove to be relevant for taking inspiration from dynamical systems theory for the analysis of brain processing. Indeed, recently, important progress has been made in the precision of brain signal capture, and new phenomenons are observed which stress the role of global distant correlations in brain computation. As the subject or animal carries out a cognitive act (recognition, action selection ...), one can observe global spatio-temporal patterns of activation emerging from background activity. Such patterns have a very short life (of the order of tenths of milliseconds) and their extinction leads to the emergence of new patterns (MacLeod and Laurent, 1996, Neuenschwander et al., 1996, Jirsa et al., 1998, Rodriguez et al., 1999). These transitions from one stable behavior to another can be seen as bifurcations, which can either occur through interactions with the environment or through inner dynamical constraints.

2.2 Dynamics in artificial systems design

We use artificial neural networks in order to design our control architectures. The main stream of connectionist methods, derived from Hopfield networks, feed-forward networks and Kohonen maps, produce static signals as their input values remain constant. Such static behaviors never occur in real brain activity. A more “biologically inspired” approach taking into account a more precise modeling of a neuron (latencies of discharge and discrete pulses for instance) may leads to more complex dynam-

ics. We do not claim such a local biological precision. Indeed, we are mainly concerned with simplifying the biological complexity in order to exhibit the simple control variables of the system. The idea here is to show that a neural system that spontaneously exhibit several dynamical regimes when interacting with its environment can help to produce autonomous agents whose behavior has more common points with real animals. Under this paradigm, the system that has to be taken into account is the inner dynamics *plus* the environment inputs. Hence the emerging attractor does not only correspond to the inner state of the system, but is a combination of the inner dynamics and the inputs. In such a system, action should both depend on the input (command) and on inner dynamical constraints.

Spontaneous dynamical behaviors occur under certain conditions in recurrent neural networks (RNN). Lots of recurrent models exhibit cyclic sequential behaviors when properly set (Hertz and Prugel-Bennett, 1996) and can learn from observation some characteristics of a given dynamical system (Williams and Zipser, 1989, Tani and Fukumura, 1995). Some works have yet applied RNN to robotic control. Tani (Tani and Nolfi, 1998) used a hierarchy of RNN for categorizing different sensory-motor situation. With a different approach, Schöner (Schöner et al., 1995, Bicho and Schöner, 1997) uses the Neural Field formalism (Amari, 1977) for controlling a mobile robot. In its system, the attractor is always a fixed point. The system goes continuously from one attractor to the other through bifurcations depending on input variations.

3. Basic properties of the model

3.1 A random recurrent model

Our dynamical system (1) is defined as a pool of N interacting units, whose state is described with an activation vector $\mathbf{x}(t)$. The external world is represented by the input vector signal $\mathbf{I}(t)$. This system is a discrete-time neural network with random recurrent connections and analog neurons. Random neural networks have been introduced by Amari (Amari, 1972) in a study of their large size properties. Our model keeps the global recurrent architecture of Hopfield networks (Hopfield, 1982); the main difference stands on the fact that the initial weights are randomly chosen.

$$x_i(t) = f_g \left(-\theta + I_i(t) + \sum_{j=1}^N J_{ij} x_j(t-1) \right) \quad (1)$$

The J_{ij} ’s are the synaptic weights, and θ is the activation threshold. The J_{ij} ’s values are initially randomly chosen with Gaussian law $\mathcal{N}(0, 1/N)$. This means in particular

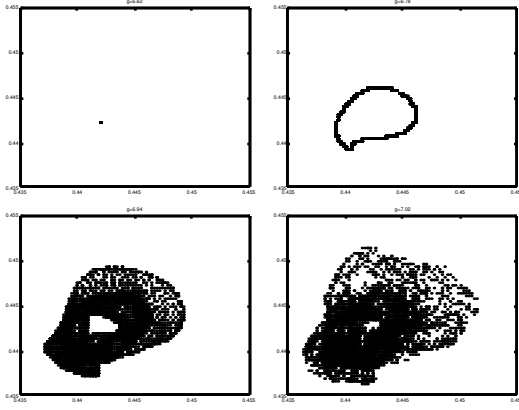


Figure 1: **Quasi-periodicity route to chaos.** Four return maps are represented, on the basis of mean signal $m_N(t)$, for increasing values of the gain parameter g (i.e $g = 6.62$ – fixed point –, $g = 6.78$ – limit cycle –, $g = 6.94$ – T2-torus – and $g = 7.02$ – chaos –). Principle of return map : $m_N(t)$ is on the x-axis, $m_N(t+1)$ is on the y-axis. Transients have been discarded. Other parameters are $N = 200$, $\theta = 0.1$.

that our connection pattern is *not symmetric*, which is a necessary condition for developing complex dynamics. We take a monotonic non-linear sigmoidal transfer function $f_g(u) = (1 + \tanh(gu))/2$, whose gain is $g/2$. This function takes its values in $]0, 1[$. Notice that our system is deterministic as soon as the input signal does not include noise.

The dynamics can be characterized by the observable $m_N(t)$ defined as the mean signal of $\mathbf{x}(t)$:

$$m_N(t) = \frac{1}{N} \sum_{i=1}^N x_i(t) \quad (2)$$

3.2 Autonomous dynamics and attractors

If the external signal $\mathbf{I}(t)$ is static (does not change with time), the system dynamical activity only stands on inner interactions. Our system is dissipative, so that any trajectory tends to converge towards a small invariant structure whose volume is null: the *attractor* of the system. The characteristics of this attractor determine the *dynamical regime* of the system. In one given system (defined by its weights and thresholds values), the transitions from one dynamical regime to the other occurs through bifurcations while continuously increasing the gain parameter g . We typically find four different dynamical regimes: fixed point, limit cycle, T2-torus and chaos (fig. 1) (Doyon et al., 1993, Cessac et al., 1994). This generic process of the dynamics becoming more complex is called a quasi-periodicity route to chaos (Bergé et al., 1992).

3.3 Cluster formation

In this paragraph, we take $\mathbf{I}(t) = 0$, in order to characterize the spontaneous dynamical organization that takes place in our system. As soon as the gain parameter g is high enough, every random network tends to produce a complex spatio-temporal pattern of activation. We will see here that the non-linear transfer function f_g has a very important structuring role.

Theoretical results on the statistical repartition of activation in our model when the size tends towards infinity (thermodynamic limit) have been previously studied (Cessac, 1995). There are two possible regimes at the thermodynamic limit: fixed point and chaos. Considering potential signals $u_i(t) = -\theta + \sum_{j=1}^N J_{ij}x_j(t-1)$, the chaotic regime is analog to a Gaussian process at the thermodynamic limit:

$$\mathbf{u}(t) = \mathbf{u}^* + \mathbf{b}(t)$$

Where \mathbf{u}^* is a Gaussian static vector and $\mathbf{b}(t)$ a white noise.

This limit behavior can help to analyze the dynamics of finite-size systems, which present a greater variety of dynamical regimes. Here we consider a finite-size system in a cyclic regime, near destabilization, with a *real*¹ positive period τ . Even if such cyclic regimes are not described at the thermodynamic limit, they however imitate the characteristics of a Gaussian process, in particular:

1. Mean potentials u_i^* repartition tends to obey to a Gaussian law.
2. Individual potential signals tend to be desynchronized. This means that individual phases are uniformly distributed in $[0, \tau[$.

We now consider activation signals $x_i(t) = f_g(u_i(t))$. Due to the nonlinearity of f_g , we see that:

1. Neurons whose mean potential u_i^* is strongly positive or negative have almost constant output signals. Such neurons are called inactive or quiescent. Only neurons whose potentials oscillate around zero have their signal amplified by the transfer function. Such neurons are called *active* neurons. They are responsible for the propagation of the inner signal (coming from the interactions within the RRNN) throughout the system. For usual parameter values, active neurons represent about 30% of the whole population.
2. Activation signal $x_i(t)$ tends to be sharpened, with peaks (or gaps) of activation corresponding to maxima (minima) of the potential signal $u_i(t)$. This leads

¹Even if our system is discrete time, the value of τ depends on the spectrum of the linearized system near the fixed point at destabilization value g_c . This implies that τ takes its value in $[2, +\infty[$.

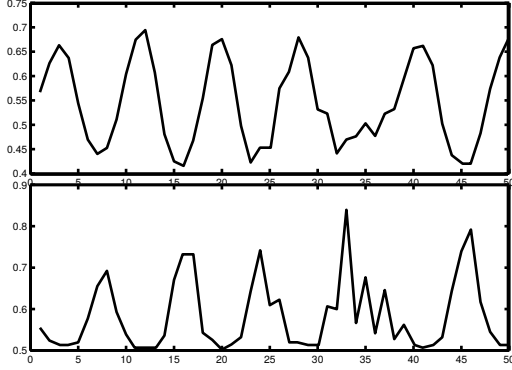


Figure 2: Mean signals from two phase-opposite clusters in chaotic regime. Parameters : $g = 5.5$, $N = 100$, $\theta = 0.1$.

to increase the correlation between neurons whose potential signals have neighbor phases. Such neurons have their activation signal almost phased-locked on discrete instants. We thus have the emergence of clusters of neurons which produce closely correlated activation signals. If we consider two clusters whose phase shift is 1, it seems that the first cluster propagates its signal towards the second cluster. From one cluster to another, we finally have a circular dynamical organization. This organization, which strongly depends on the value of τ , can not be deduced from the synaptic weights, but emerges from global interactions.

These two points help us figure out the dynamical organization of our networks. We have a majority of inactive neurons, and a minority of active neurons which tend to clusterize and propagate the inner signal in an *activation loop*. Moreover, for one given system, this circular dynamical organization remains stable in different regimes. Figure 2 shows that two neural clusters whose phase is opposite in cyclic regime keep this phase opposition in a chaotic regime.

3.4 Constraint dynamics

We now consider that the input signal $\mathbf{I}(t)$ is non-constant with time, so that there is a competition between inner influences and outer influences (the signal coming from the external world). The important point is that any change in spatial or temporal input characteristics modifies the nature of the dynamical system itself.

In simulations, input signals can be static or dynamic. A static input is a Gaussian random vector (of law $\mathcal{N}(0, \sigma_I^2)$) which is maintained during a period of time T (T is of the order of 100 time steps). A dynamic periodic input is a looping sequence of k random vectors so that the period of input signal is $\tau_I = k$.

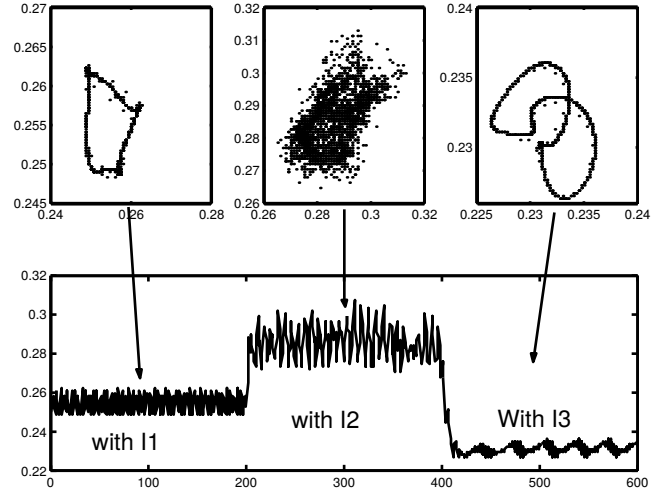


Figure 3: Evolution of the dynamics while the system is successively submitted to 3 strongly correlated random static inputs. Mean signal $m_N(t)$ and return maps are represented. We find two cyclic regimes and one chaotic regime. Parameters $g = 5$, $N = 200$, $\theta = 0.4$, $\sigma_I = 0.3$.

Static inputs When a static input is presented during a period of time T , strong changes occur in the dynamical organization. There is a change in the level of activity of neurons, a change in periodicity, etc... The important point is that two very close static inputs can produce very different patterns of activation. Figure 3 shows the evolution of the mean signal $m_N(t)$ when the system is submitted to 3 different static inputs \mathbf{I}_1 , \mathbf{I}_2 and \mathbf{I}_3 , for periods of 200 time steps. The three random vectors are strongly correlated (mean correlation: 0.95). However, dynamical regimes, periodicity and repartition of activity are very different in the three cases. It finally appears that our system is extremely sensitive to small changes on inputs values. The dynamical organization is thus *unstable* relatively to the system's inputs.

Periodic inputs When the system is submitted to a periodic input $\mathbf{I}(t)$, there is a competition between inner and outer periodicity (even in a chaotic regime where one can find residual periodicity). The system reveals to be very sensitive to external periodicity. This means that once again, the system reconfigures its dynamical organization in order to adapt to the external constraint.

that the response of the system is specific to the input. Indeed, if one given static input \mathbf{I}_1 induces one given attractor, neighbor or noisy versions of \mathbf{I}_1 will not necessarily produce the same attractor. However, we want to build a system which can generalize, i.e. which can react specifically to a neighborhood of \mathbf{I}_1 . We thus need to *stabilize* the dynamical response associated with \mathbf{I}_1 . We will now implement a learning rule reinforcing dynamical regularities and activation loops in our system.

The learning rule obeys the following properties:

- **Unsupervised learning:** the dynamical response may not come from an outer command. The system determines its own response.
- **On-line learning:** there is no *a priori* knowledge on the nature of the inputs to learn.
- **Local learning rule:** the change in the synaptic weights only stands on the activity of afferent and efferent neurons.

A simple Hebbian learning rule was proposed on our model in (Daucé et al., 1998). However, this first rule induced severe limitations in terms of storage capacity.

We use in our present implementation a second rule based on an *habituation* principle. This choice relies on the idea that a neuron will favor afferent signals that often change with time, and ignore static signals. Our rule thus reinforces the *effective covariance* between afferent and efferent neurons. In particular, the constant components of afferent activation signals are subtracted. Using a sliding window, we estimate the mean activation \bar{x}_j (we only take into account the most recent values of activation). The covariance rule was first introduced by Sejnowski (Sejnowski, 1977), and has been adapted to our problem (capture of dynamical regularities) by taking into account the temporal shift induced by the transmission delay (in our case, the delay is 1). The rule is:

$$J_{ij}(t) = J_{ij}(t-1) + \frac{\alpha}{N} (x_i(t) - \bar{x}_i)(x_j(t-1) - \bar{x}_j)$$

We have seen that a majority of neurons in our system have an almost constant activation value (silent or saturated). Such neurons are not involved in the learning process. If two active neurons belong to clusters whose phase shift equals one, then the link from one to the other is systematically reinforced by the learning rule. Indeed, even when the dynamics is chaotic with a residual periodicity, the learning process tends to *simplify* it towards cyclic dynamics. It thus reinforces the activation loop structure, and increases both amplitude and periodicity of the inner dynamics.

Recognition and generalization Figure 4 shows a typical learning process on a system submitted to a static

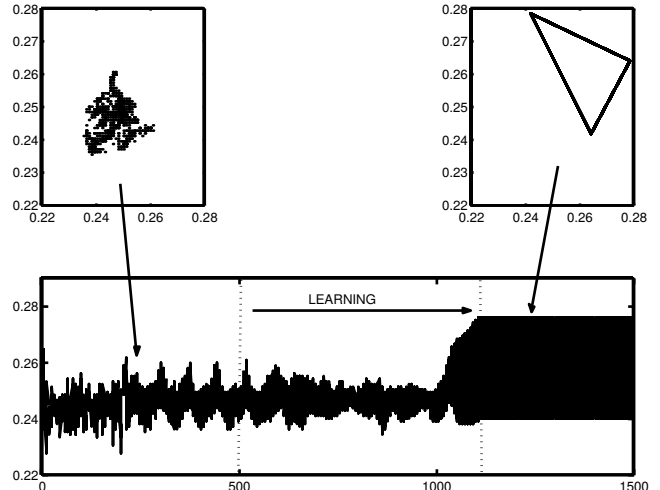


Figure 4: **A learning experiment.** Evolution of the mean signal $m_N(t)$ during the learning process, when the system is submitted to a static input \mathbf{I}_1 . Upper left: return map of $m_N(t)$ before learning. Upper right: return map of $m_N(t)$ after learning (dots linked by lines). Main signal: time evolution of $m_N(t)$ during the whole experiment. Learning process is activated for $500 < t < 1100$. Parameters: $N = 200$, $g = 6.3$, $\alpha = 0.1$, $\theta = 0.4$, $\sigma_I = 0.3$.

input \mathbf{I}_1 . Before learning, the dynamics is chaotic, with a residual periodicity close to period 3. After learning, the dynamics is strictly periodic of period 3. When the learning process is stopped, the new system is now able to *recognize* \mathbf{I}_1 , i.e. the system systematically switches its dynamics towards this specific 3-periodic dynamical organization when \mathbf{I}_1 is presented.

An important point is that after learning, the dynamical response associated with \mathbf{I}_1 is *stabilized*. This means that in the neighborhood of \mathbf{I}_1 , the system tends to produce a dynamical response which is very close to the one associated with \mathbf{I}_1 (see Figure 5).

So, learning displays two new properties in our system:

- **Recognition:** Our system is now able to discriminate between learned inputs and non-learned inputs. *Recognition occurs with a change in dynamical regime (bifurcation) leading to periodic attractors* associated with every learned input.
- **Generalization:** Our system produces almost similar dynamical organization in a neighborhood of the learned input. This relies upon the ability to produce the same actions in closely related situations.

Associativity The property of associativity can be shown when learning occurs with inputs composed of two different independent signals, i.e. $\mathbf{I}(t) = \mathbf{I}_1(t) + \mathbf{I}_2(t)$. $\mathbf{I}_1(t)$ is called the main stimulus and $\mathbf{I}_2(t)$ the associate stimulus.

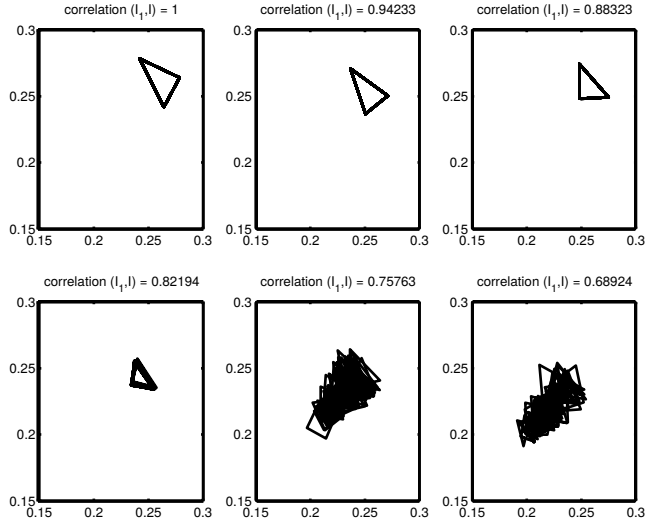


Figure 5: **stabilization of dynamical response in the neighborhood of the learned input.** Six return maps on the basis of $m_N(t)$ signal after learning input \mathbf{I}_1 . The first return map corresponds to the dynamics associated with \mathbf{I}_1 . The next 5 return maps correspond to 5 different inputs, whose correlation to \mathbf{I}_1 is decreasing from left to right. Dots are linked by lines in order to see 3-periodic attractors. Parameters: $N = 200$, $g = 6.3$, $\alpha = 0.1$, $\theta = 0.4$, $\sigma_I = 0.3$.

We will first take a simple example, which illustrates that this kind of system may associate static and periodic inputs, and learn several associations.

The learned signals are made of two components: $\mathbf{L}_k(t) = \mathbf{I}_k(t) + \mathbf{D}_k$, where $\mathbf{I}_k(t)$ is a periodic input of period τ_k , made of centered Gaussian vectors $\mathcal{N}(0, \sigma_I^2)$ and \mathbf{D}_k a static Gaussian vector issued $\mathcal{N}(0, \sigma_D^2)$. Figure 6 shows the dynamical behavior of a network which has learned five such associations. After learning, signals associated with the full input $\mathbf{L}_k(t)$ are in cyclic regime, and signals associated with static inputs \mathbf{D}_k alone remain in chaotic regime. However, the same period and a correlation around 0.4 between individual activation signals can be found in associated dynamics, while periods are different and correlations equal to zero in non-associated dynamics.

This property of associativity is very important in real world applications, as one want to see whether the system can produce a learned action in presence of an associated stimulus. The point now is to see how our system can produce a motor command on the basis of inner dynamics.

5. Robotic experiment

The recognition and associativity properties denoted in our single population model can be usefully adapted in real applications such as robot navigation. We take the example of a robotic experiment in order to confront

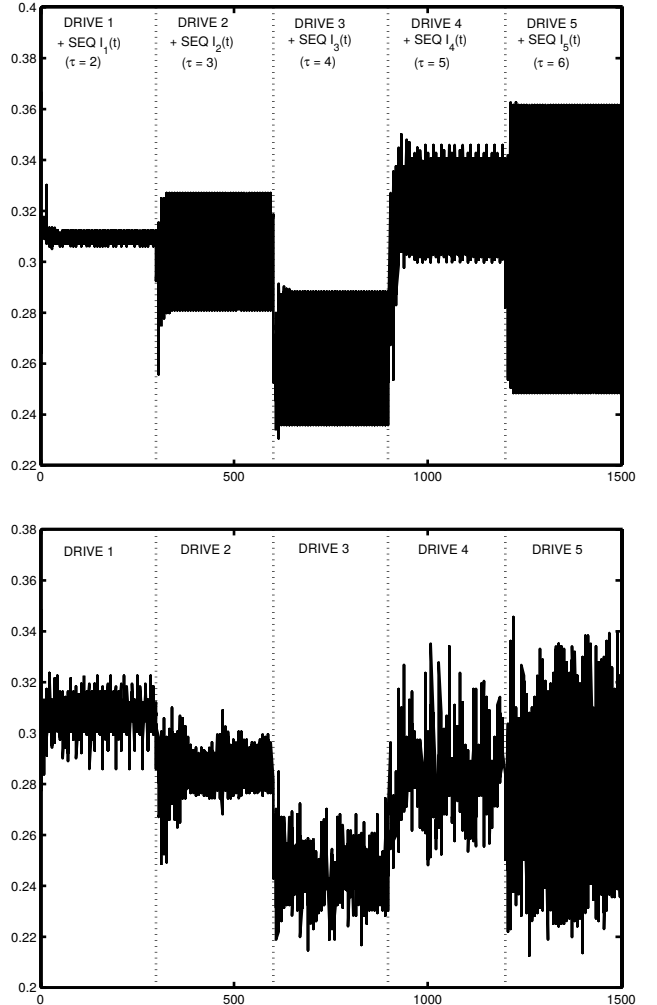


Figure 6: **Dynamical signals obtained with full stimulation (upper figure) and associative static stimulation (lower figure)** Five combined signals $\mathbf{L}_k(t) = \mathbf{I}_k(t) + \mathbf{D}_k$, for k in $1..5$, have been learned on the same system. Time is on the x-axis, mean signal $m_N(t)$ on the y-axis. Every stimulus is presented during 300 time steps. Parameters: $N = 200$, $g = 8$, $\alpha = 0.1$, $\theta = 0.4$, $\sigma_I = 0.2$, $\sigma_D = 0.3$.

our RRNN model with real world data and show some properties that can be obtained when associating visual scenes and movements.

5.1 Multi-layer model

The idea is to build interfaces which both display external signals to the RRNN and receive a signal from it, thus interpreting inner dynamical responses. A nearly similar neural architecture can be found in (Williams and Zipser, 1989), but the back-propagating learning rule used by these authors prevents them from

reaching “unstable” dynamics. Our purpose here is to start from such unstable dynamics in order to regularize it according to the input signal. The learning rule is then extended to every link between the interface and the RRNN. This means in particular that when no external signal is displayed on the interface, the links from the RRNN produce a signal which shows what *should be present* on the interface, according to what has previously been learned. Hence an interface displays the input to the RRNN, but also the output of the RRNN. In case we have two interfaces, one corresponding to visual perception and the other corresponding to motor movements, we build a system which is able to produce movements according to both visual entries and learning-induced representations.

5.2 Basic control architecture

The basis of the control architecture is the Per-Ac block developed in our team (Gaussier and Zrehen, 1995). The robotic platform is a Koala robot provided by K-Team SA (Switzerland). A CCD camera gives pictures of the environment. They are not processed as a whole, but are split into several 32x32 subimages. These subimages are taken around feature points which may vary depending on the application, but which mainly are high curvature points (corners ...) extracted from the gradient of the image. Then a log-polar transformation is applied to the subimages giving some invariance with respect to shift and distance. The subimages are afterwards learned on a Probabilistic Topological Map (PTM) (Gaussier and Zrehen, 1994). In a navigation context, the correspondence between a subimage (called now “landmark”) with its angular position (azimuth) in respect with an absolute direction (north given by a compass for instance) gives the position of that landmark in the environment. The set of (landmark, azimuth) gives the position of the robot in the environment. Merging landmark and azimuth information is performed on an associative map. These configurations are learned on an other map (fig. 7). The neurons of this map may be linked with a particular movement. Thus, in association with each position in the environment, it is possible to learn a movement. This process enables to reach a goal by successively going from one learned position to the other (Gaussier et al., 2000).

5.3 Extended control architecture

The robotic architecture previously developed may only learn the association between a location and a movement. Our RRNN has the property to learn both spatial and temporal informations. So, it may learn the association between a position and a movement, and simultaneously a sequence of movements. Hence, we have replaced the map learning the set of landmark and azimuth infor-

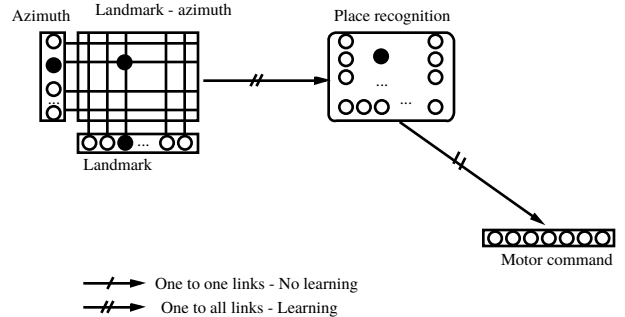


Figure 7: **Global architecture for merging landmark and azimuth informations, and learning a location.** The correspondence between a landmark and its azimuth is learned in the (landmark-azimuth) map. Each set of landmarks and azimuths (thus corresponding to one location) is learned by one neuron in the “Place Recognition” map. Then this neuron may be linked with one neuron in the “Motor Command” map. This gives the movement to perform at the learned location.

mation by a RRNN, and we have added a motor input to this RRNN in order to learn the sequence of movements (fig. 8). As stated above, by using interfaces, the complexity of the dynamics of the RRNN is not a disadvantage for giving stable motor commands. The RRNN has $N = 100$ interconnected neurons.

In the experiments, the robot is limited to movements corresponding to 7 possible rotations from -90° to 90° , with 30° steps. The choice between these actions is made according to the activation states of the motor interface. It is made of 7 neurons, each associated with one motor command, so that the neuron with maximal activation determines the movement. At each position, what is learned is the movement to perform and the set of (landmark, azimuth) taken from the robot camera. We have chosen to limit the movements to rotations because it is an easy way to produce sequences matching the same visual inputs. A loop trajectory could also have been used.

Together with the image, we force a signal on the motor interface. This signal is periodic and corresponds to the sequence $(+30^\circ, +60^\circ, +90^\circ)$, so that after one sequence the robot has made a half-turn. A different image is seen at each position. After two sequences, the robot goes back to a previously learned position. So an image is only associated with one movement, but the same movement is associated with two different images (front and back images after one sequence).

There are two stages in the training process. First, we iterate the dynamics without changing the weights until the system reaches its stationary dynamics. Second, we iterate the learning rule while the robot is moving. Due to friction between wheels and ground, the real rotation performed is different from

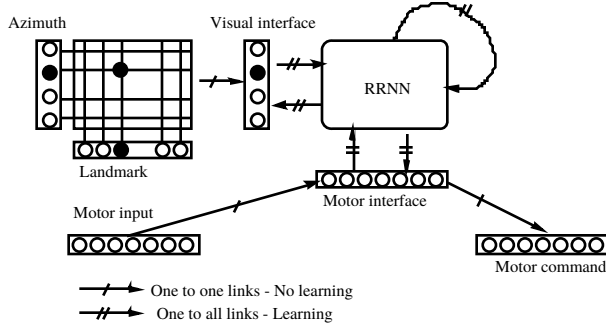


Figure 8: **Extended control architecture.** The previous “Place recognition” map has been replaced by the RRNN and two interface modules. In addition, in order to learn a motor sequence, a “Motor Input” map codes the movement to learn.

the command issued. So during the training process, the robot is moved back to a learned position when the shift is too big. The learning process is lasting 20 time steps (one time step corresponds to one movement).

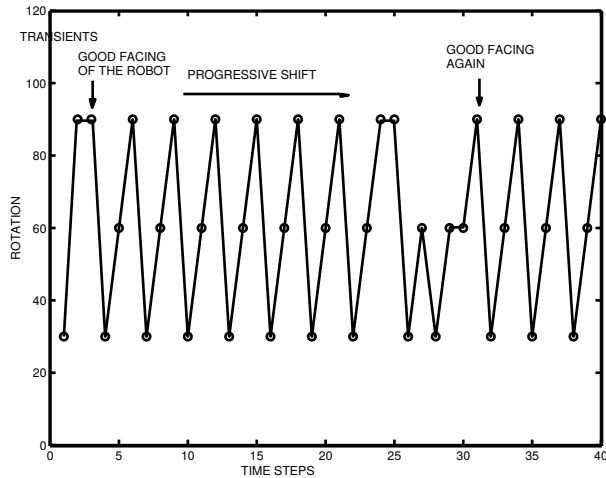


Figure 9: **Example of recalibration after a shift.** Rotation angle versus time when the robot is gradually shifting. The first two steps are transients. Then the rotations show the learned periodic sequence ($+30^\circ$, $+60^\circ$, $+90^\circ$) corresponding to the visual inputs. The real robot angle shifts and suddenly the robot loses the correspondence between the image in front of him and the associated movement. Finally the robots finds a good matching and resumes the periodic sequence.

After this learning process, the resulting system is tested. The forcing motor signal is removed, so that the robot determines its movement only from the information issued by the RRNN. After a transient time of around 10 time steps, the robot performs the succession of learned rotations. As stated before, there is a progres-

sive shift of the robot orientation so that after a while the image in front of it is associated with a movement which is different from the movement it would perform if following the sequence. So there is a *conflict* between the movement associated with the perceived image and the movement proposed by the learned sequence. What happens is not a take over of one movement over the other, which would be the case if what has been learned is either the associations or the sequence. For some time steps the movements performed are not following the sequence anymore, nor correspond to the ones associated with the image (fig. 9). But eventually, the robot goes back to a learned position, triggers the associated movement and now resumes the good sequence. So the robot is able to recalibrate its position based on a recognized image.

In order to illustrate the fact that what has been learned is not the movement sequence alone, we have conducted the following experiment. Once the robot is performing the good sequence, the camera is hidden. The movement sequence is not the good one anymore, though there are some patterns of it (fig. 10). When the robot can see again, it is able to go back to the learned sequence based on a recognized image.

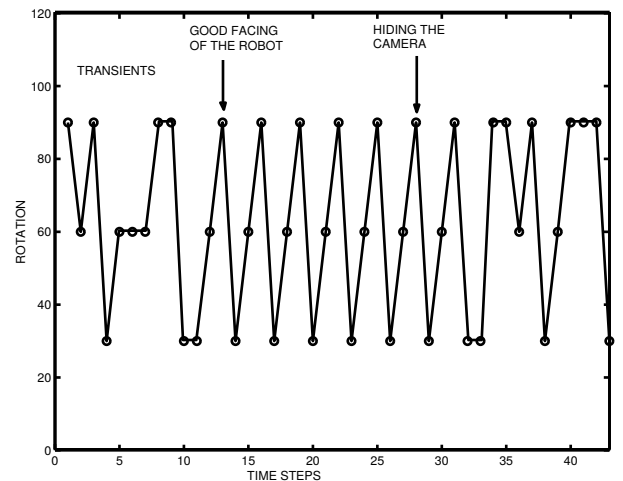


Figure 10: **Example of visual input masking.** Rotation angle versus time when the camera is suddenly masked. The first 12 steps are transients. When the camera is hidden, the robot loses the periodic sequence.

The learning rule increases the coherency between the inner chaotic dynamics of the RRNN and the evolving values of visual and motor inputs. This higher coherency corresponds to a regularization of the dynamics (it becomes less chaotic), and the possibility to use such regularity to produce a motor command. When the visual input matches the previously learned image, the dynamics remains regular and the motor commands correspond to the learned sequence. When the visual information tends

to misfit the learned image, the dynamics qualitatively changes and gets more chaotic, so that the system is able to perform an *exploration* of its visual environment in order to find the matching visual input. When there is no possible match (for instance when the scene is hidden, or when the robot is moved to another place), the dynamics remains chaotic, and the robot stands searching for a matching input in its environment.

6. Conclusion

The RRNN we have presented has both properties of learning input-output correlation (sensory-motor associations) and temporal sequences. Hence it may act as a working memory where *representations* of a combination of the external perception and the internal state are coded. The complexity of the coding is not an obstacle for using such a system in real world applications as demonstrated on the robot experiment. However, these working representations have to be transferred to another part of the system for long time storage. Moreover, this storage may not necessarily be of the same nature as the one in the working memory. In biological terms, what we have constructed plays the same role as an hippocampus, our RRNN playing the role of the CA3 structure. This architecture is linked with a planning structure enabling action selection and motor control (Quoy et al., 1999b, Quoy et al., 1999a). It remains now to be seen how the RRNN may be linked with such a planning system. It is already possible to link an image and a movement with an internal motivation (searching for a particular object, or going to the power station ...). Another kind of hippocampal model has been implemented in our group for learning temporal sequences (Gaussier et al., 1999) and sensory-motor associations (Gaussier et al., 2000).

Our system has still to be improved. For the moment, the RRNN is working with discrete time steps. But real stimuli are continuous by nature. So we first need to develop the same kind of RRNN under a continuous time formalism. Next, the main drawback is the need to tell the system when to stop learning. We have chosen to stop after a fixed number of iterations. If learning reduces the dynamics on a limit cycle, it is easy to recognize such a regular signal and stop learning. However, it is still unclear about an optimal learning stopping criterion when the system is still chaotic. Moreover, we believe there is no such optimal criterion ...

To sum up, both aspects of association and sequence learning may be found in our system, but the most interesting point stands in its ability to dynamically adapt its behavior to external changes. This adaptability is not dependent on an ad hoc parameter tuning, nor a set of specific rules, but emerges from the interactions between the robot and its environment. These interactions are taken into account by a learning rule. Not

only biologically founded, these new results emphasize the role of RRNN for designing adaptive systems.

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