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Toward an Integrative Dynamic Recurrent Neural Network for Sensorimotor Coordination Dynamics.

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1. Introduction

The utilization of dynamic recurrent neural networks (DRNN) for the interpretation of biological signals coming from human brain and body has acquired a significant growth in the field of brain-machine interface. DRNN approaches may offer an ideal tool for the identification of input-output relationships in numerous types of neural-based signals, such as intracellular synaptic potentials, local field potentials, EEG and EMG which integrate multiple sources of activity distributed across large neuronal assemblies. In the field of motor control, the output signals of the DRNN mapping concern movement-related kinematics signals such as position, velocity or acceleration of the different body segments involved. The most direct input signals consist in the electromyographic signals (EMG) recorded over the different superficial muscles implicated in movement generation. It is generally recognized that the non-invasive recording of the EMG envelope signal represents a reasonable reflection of the firing rate of the motoneuronal pools including both central and afferent influences (Cheron and Godaux, 1986). In addition, the combination of the multiple EMG signals may reveal the basic motor coordination dynamics of the gesture (Scholz and Kelso, 1990; Kelso, 1995). A major interest of the EMGs to kinematics mapping by a DRNN is that it may represent a new indirect way for a better understanding of motor organization elaborated by the central nervous system. After the learning phase and whatever the type of movement, the identification performed by the DRNN offers a dynamic memory which is able to recognize the preferential direction of the physiological action of the studied muscles (Cheron et al. 1996, 2003, 2006, 2007). In this chapter, we present the DRNN structure and the training procedure applied in case of noisy biological signals. Different DRNN applications are here reviewed in order to illustrate their

usefulness in the field of motor control as diagnostic tools and potential prosthetic controllers.

2. Multiple EMG signals as a final output controller

The behavior of cortical neurons has been well related to movement segmentation, velocity profiles and EMG patterns (Schwartz and Moran, 1999) confirming the hypothesis that the timing of muscle activation is generated by the central neural structures. For instance, the agonist–antagonist organization of the muscles and the reciprocal mode of command are represented by the activity of a subset of cortical neurons correlated inside of cortical maps, with activation of one group of muscles linked to a simultaneous decrease in the activity of the opposing set of muscles (Cheney et al. 1985; Jackson et al. 2003, 2007; Capaday, 2004). The organization of the EMG burst is, in some instances, the peripheral reflection of the central rhythmical activity of the brain during the movement genesis (Bengoetxea et al. 2010). This rhythmical organization could be viewed as resulting from a motor binding process (Sanes and Truccolo, 2003) supported by the synchronization of cortical neurons forming functional assemblies in the premotor and primary motor cortex (Jackson et al. 2003; Hatsopoulos et al. 2003, 2007; Rubino et al. 2006). Moreover, the timing of the antagonist EMG burst is pre-programmed by the cerebellum and our DRNN has been able to learn and reproduce such aspect of motor control (Cheron et al. 2007). This will permit to use the antagonist EMG burst to stop adequately a prosthetic movement. We have also demonstrated that the DRNN is able to reproduce the major parameters of human limb kinematics such as: (1) fast drawing of complex figure by the upper limb (Cheron et al. 1996, Draye et al. 1997), (2) whole-body straightening (Draye et al. 2002), (3) lower limb movement in human locomotion (Cheron et al. 2003; Cheron et al. 2006) and (4) pointing ballistic movement (Cheron et al. 2007). In all of these experimental situations we have found that the attractor states reached through DRNN learning correspond to biologically interpretable solutions (Cheron et al. 2007). It was recently demonstrated that neural network with continuous attractors might symbolically represent context-dependent retrieval of short-term memory from long-term memory in the brain (Tsuboshita and Okamoto, 2007). Indeed, as recurrent neural networks take context and historical information into account they are recognized as universal approximators of dynamical systems (Hornik et al. 1989; Doya, 1993). This means that the DRNN mapping between EMG to kinematics may give rise to a dynamical controller of human movement.

3. The DRNN structure

Our DRNN is governed by the following equations:

$$T_i \frac{dy_i}{dt} = -y_i + F(x_i) + I_i \tag{1}$$

where $F(a)$ is the squashing function $F(a) = (1+e^{-a})^{-1}$, y_i is the state or activation level of unit i, I_t is an external input (or bias), and x_i is given by:

$$x_i = \sum_j w_{ij} y_j \tag{2}$$

which is the propagation equation of the network (x_i is called the total or effective input of the neuron, W_{ij} is the synaptic weight between units i and j). The time constants T_i will act like a relaxation process. It allows a more complex dynamical behaviour and improves the non-linearity effect of the sigmoid function (Draye et al. 1996, 1997). In order to make the temporal behaviour of the network explicit, an error function is defined as:

$$E = \int_{t_0}^{t_1} q(y(t),t) \, dt \tag{3}$$

where t_0 and t_1 give the time interval during which the correction process occurs. The function $q(y(t), t)$ is the cost function at time t which depends on the vector of the neuron activations y and on time. We then introduce new variables p_i (called adjoint variables) that will be determined by the following system of differential equations:

$$\frac{dp_i}{dt} = \frac{1}{T_i} \, p_i - e_i - \sum_j \frac{1}{T_i} \, w_{ij} \, F'(x_j) \, p_j \tag{4}$$

with boundary conditions $p_i (t_1)=0$. After the introduction of these new variables, we can derive the learning equations:

$$\frac{\delta E}{\delta w_{ij}} = \frac{1}{T_i} \int_{t_0}^{t_1} y_i \, F'(x_j) \, p_j \, dt \tag{5}$$

$$\frac{\delta E}{\delta T_i} = \frac{1}{T_i} \int_{t_0}^{t_1} p_i \frac{dy_i}{dt} \tag{6}$$

The training is supervised, involving learning rule adaptations of synaptic weights and time constant of each unit (for more details, see Draye et al. 1996). This algorithm is called 'backpropagation through time' and tries to minimize the error value defined as the differential area between the experimental and simulated output kinematics signals.

3.1 Improved DRNN training in case of noisy signals

We found that for certain noisy biological signals, the results obtained using the procedure described above were not satisfying. In some cases the convergence to a minimum error value was very slow or the learning process could lead to some bifurcations, as shown in Figure 1. In order to solve those problems, we brought two improvements to the DRNN training procedure: firstly, by using a convergence acceleration technique, and secondly by developing a technique to optimize the DRNN topology (i.e. the number of hidden neurons) to use.

The convergence acceleration technique we used is inspired from Silva and Almeida (1990). In their method, they defined an adaptive learning rate ε_{ij} different for each inter-neuron connection w_{ij}, namely for each synaptic weight and time constant. The acceleration consists in modifying the learning rate depending on the error function gradient sign. If the sign changes after iterating, it indicates that the learning went too far and so that the learning
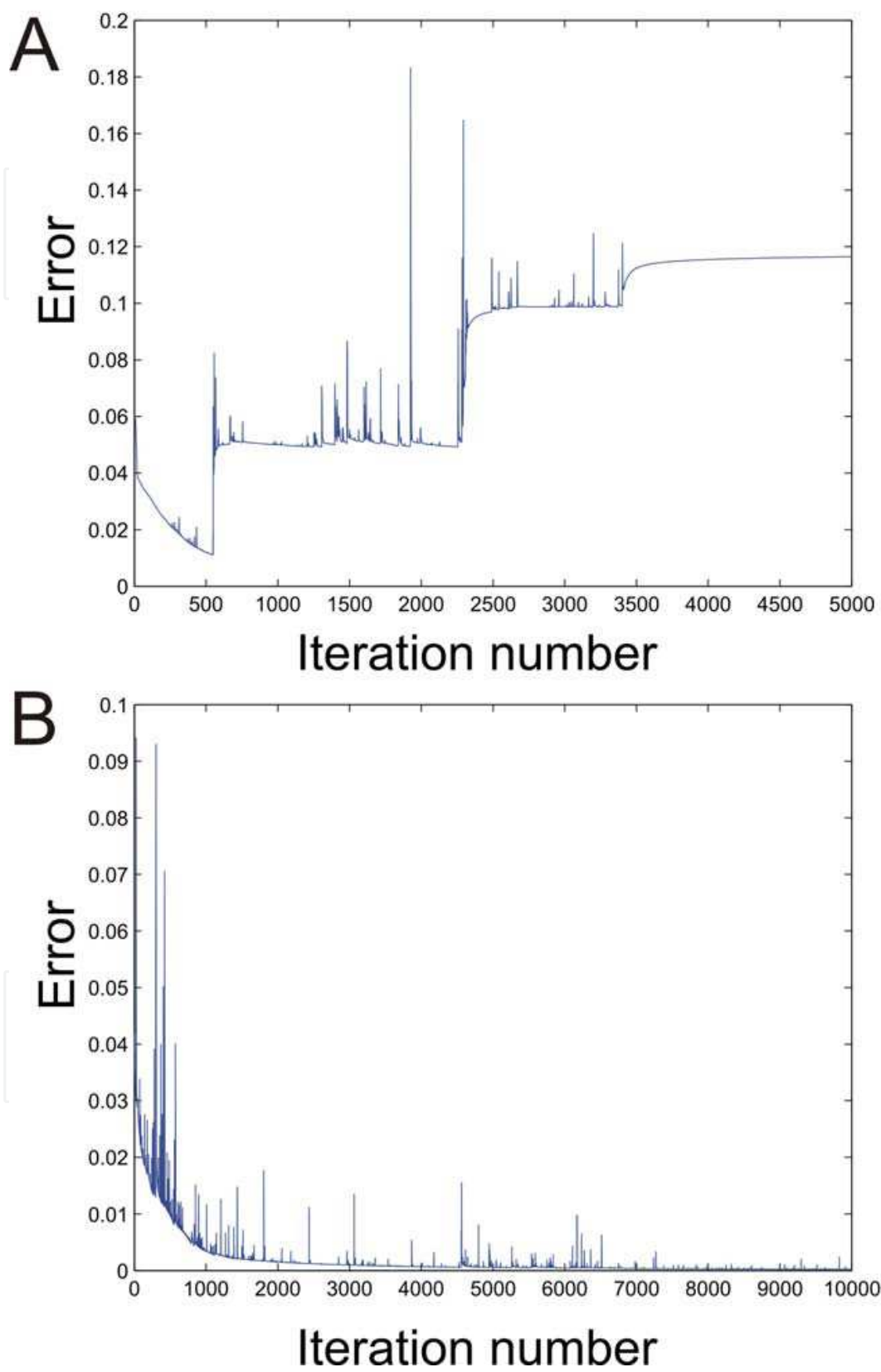
Fig. 1. In A, typical example of a training procedure where the error function increases with the number of iterations before enhancements. In B, same illustration after enhancements.

step is too big. In this case, the learning rate is multiplied by d (by default, d=0.7). If there is no sign change after iterating, it means that the learning rate is too small. It is then multiplied by u (by default, u=1.3) in order to increase the step length and thus accelerate the search for the minimum error value. Formally, the algorithm is the following:

- Small values are chosen for each ε_{ij}
- At the step n, the learning rate is defined as:

If

$$\frac{\partial E}{\partial w_{ij}}(n) \cdot \frac{\partial E}{\partial w_{ij}}(n-1) \geq 0$$

Then

$$\varepsilon_{ij}(n) = \varepsilon_{ij}(n\text{-}1) \cdot u$$

Else

$$\varepsilon_{ij}(n) = \varepsilon_{ij}(n\text{-}1) \cdot d$$

- The connections w_{ij} are incremented:

$$\Delta w_{ij}(n) = -\varepsilon_{ij}(n) \cdot \frac{\partial E}{\partial w_{ij}}(n)$$

We observed that this method effectively accelerates the learning convergence, but can also lead to an abnormal behavior such as a monotonous increase of the error function along the number of learning steps as shown in Figure 1 B. Therefore, a new procedure was developed checking at each learning step if the new learning rate ε_{ij} will not lead to an increase of the error function. In that case, learning rates are halved. For each step n, the mathematic formalism is the following:

If $E(\text{n} + 1) > E(n)$
Then $\varepsilon_{ij}(n) = \varepsilon_{ij}(n)/2$

Thanks to this procedure, the error function exhibits now a much better behavior, as depicted in Figure 2A. Finally, in order to obtain the best results as possible, the parameters that lead to the lowest error are stored along the learning. Thanks to those enhancements, the DRNN has a higher probability to converge in the training phase.

Because the initial values of the parameters are random, a global optimization of the topology is valuable. It consists in training a certain amount of different neural networks with a certain topology and then, the same procedure has to be done again with another topology. Finally, the total amount of DRNNs is tested on another dataset and the best DRNN is chosen based on an error criterion. This criterion can be the sum of training and testing errors, the testing error, or any other combination. Figure 2A and B show respectively the impact of this approach on the link between a noisy and complex signal and the curve of walking kinematics before and after enhancements,

4. DRNN identification of EMG-kinematic relationships during maturation of toddlers' locomotion

The emergence of the very first steps in toddler's locomotion is considered as a milestone in developmental motor physiology because it represents the first basic skill implicating whole body movement in vertical posture upon which goal directed repertoires are built (Cheron
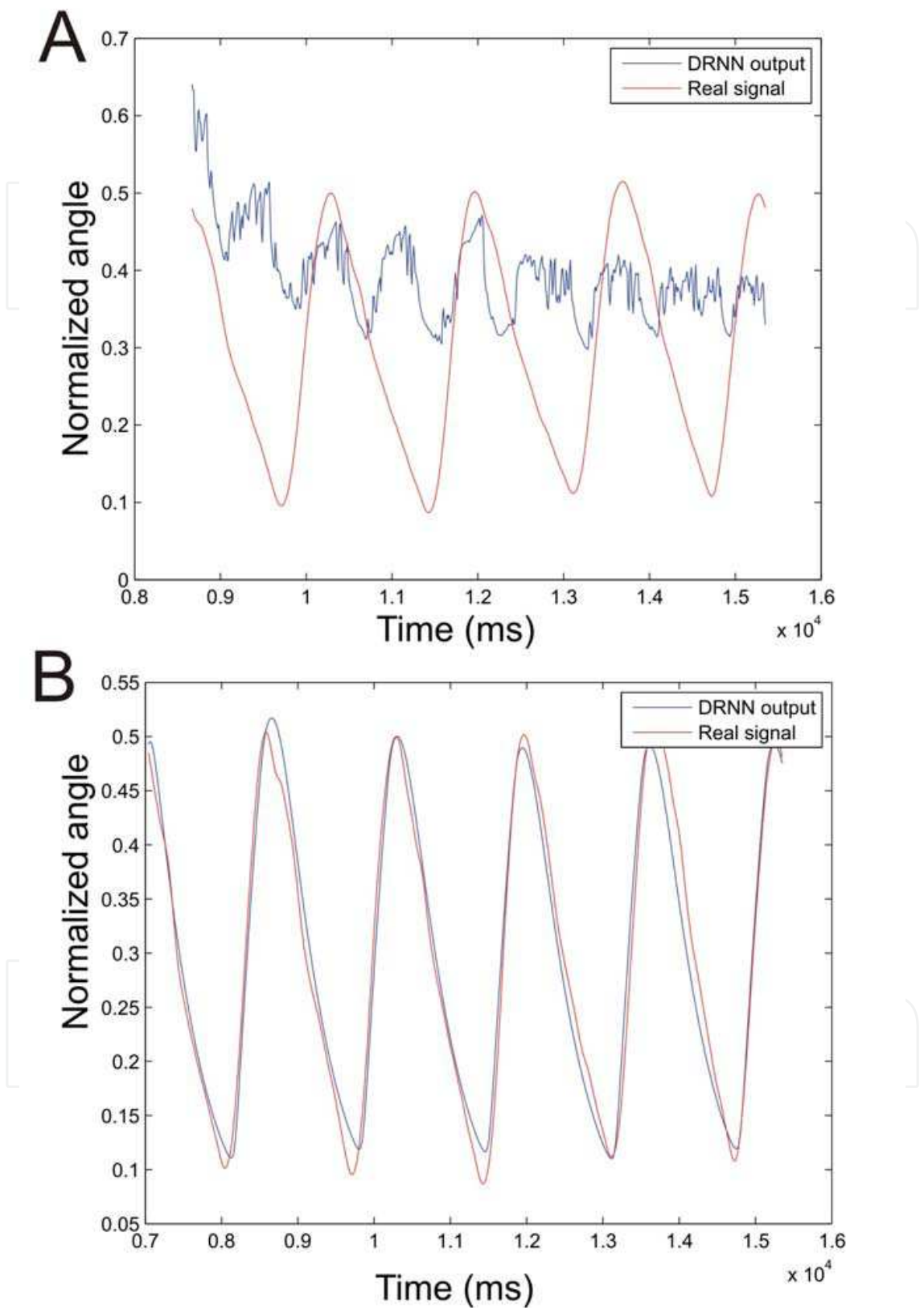
Fig. 2. In A, illustration of a bad result of the DRNN output due to a bifurcation in the training procedure. In B, example of successful results obtained thanks to the acceleration method applied during the training procedure and optimization of the DRNN topology

et al. 2001a,b, 2006; Ivanenko et al. 2004). The generation of the first steps is performed on the basis of highly variable and complex EMG patterns including erratic bursts and co-contractions (Cheron et al. 2006; Okamoto and Goto. 1985, Okamoto and Okamoto, 2001, Okamoto et al. 2003). Such behavioural emergence may be analyzed in the context of neural group selection theory for which final or more stable solutions are selected upon numerous variable and unstable patterns (Edelman, 1987; Sporns and Edelman, 1993; Thelen and Corbetta, 1994; Turvey and Fitzpatrick, 1993). However, classical analytic tools failed to extract such relationships during the first three months of gait maturation. We apply our DRNN methodology previously developed in adult gait (Cheron et al. 2003) here for studying the functional relationships between multiple EMG signals and the elevation angles of the three main segments of the lower limb in toddlers'gait. The first derivative of elevation angles of the thigh, shank and foot were chosen because they represent robust parameters of human locomotion (Borghese et al. 1996; Lacquaniti et al. 1999) including in children (Cheron et al. 2001a).

Despite the recent development of artificial neural networks using multiple EMG time course as input for providing joint torque (Koike and Kawato, 1995; Savelberg and Herzog, 1997), joint angular acceleration (Koike and Kawato, 1994; Draye et al. 2002) or position (Cheron et al. 1996) of the upper limb, this type of mapping has sparsely been used in the field of human locomotion (Sepulveda et al. 1993). Conceptual and technical problems could explain why the neural network approach has been limited in the field of locomotion studies. Walking movement, although seemingly stereotyped, is highly complex as it integrates equilibrium constraints and forward propulsion in a multi-joint system. Therefore separate feedforward neural models could be developed, one for postural control and one for propulsion movement implicating some gating or selecting devices for an appropriate switch between these different networks. Although this type of approach has proved successful for arm movement control (Koike and Kawato, 1994), it is problematic for the control of task with simultaneous postural and movement requirements such as locomotion where distinction between the two modes of control is difficult on the basis of EMG signals. Moreover, in walking the great number of joints and body segments involved pose the problem of choice of the kinematic parameter to be used as the output of the neural mapping. Technically, the majority of neural networks used for EMG-to-kinematics mapping have been of the feedforward type (Sepulveda et al. 1993; Koike and Kawato, 1994). In these networks, information flows from the input neurons to the output neurons without any feedback connections. This excludes context and historical information, which are thought to be crucial in motor control (Kelso, 1995).allowing to take into account time history and re-entrance of information flux into the controller.

As explained above, the DRNN attractor states reached through artificial learning may correspond to biologically interpretable solutions and provide a new way to understand the development of the functional relationship between multiple EMG profiles and the resulting movement. Here, we followed the evolution of these attractor states during the early maturation of gait. As the coupling of neural oscillators between each other and with limb mechanical oscillators is progressively integrated with growing walking experience, we hypothesized that the EMG to kinematics mapping by the DRNN will become an easier task during the maturation of gait. For this, 8 surface EMG and kinematics of the lower limb have been acquired in 9 toddlers, (5 girls and 4 boys) by the motion analysis system ELITE (BTS Italy), during their very first unsupported steps (Fig. 3A). Four toddlers have been acquired on different days preceding and following the onset of independent walking.
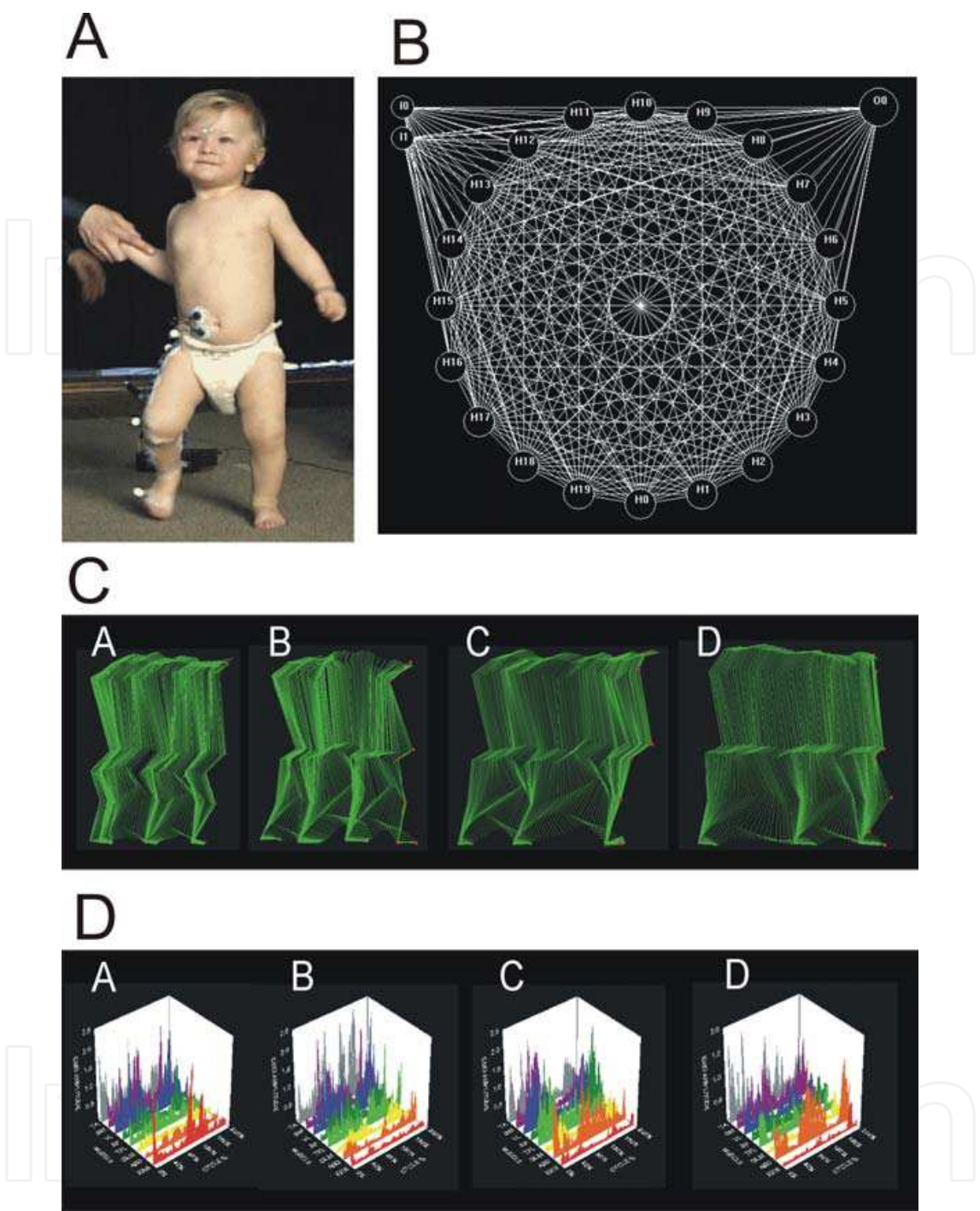
Fig. 3. In A, illustration of one toddler during the acquisition of gait data (A). The kinematics was recorded by the optoelectronic ELITE system (BTS, Italy) and retro-reflective markers fixed on the skin over the following bony landmarks: Fifth Metatarsal Head (5M), Lateral Malleolus (LM), Lateral Condylus (LC), Greater Trochanter (GT), Anterior Iliac Crest (IL), Acromium (AC), Ear (EAR), Nose (NOS). The EMGs were recorded by surface electrodes fixed over the following muscles: Tibialis Anterior (TA), Gastrocnemius Medialis (GM), Vastus Lateralis (VL), Biceps Femoris (BF), Tensor Fascia Lata (TFL), Gluteus Maximus (GLM), Rectus abdominis (ABD) and Erector Spinae (ERS). In B, architecture of the Dynamic Recurrent Neural Network (DRNN), illustrating 20 fully connected Hidden Units

(H0-H19), two Input Units on the left (I0 and I1), and one Output Unit (O0). Note that in this experiment we used 8 Inputs, 3 Outputs and 35 Hidden Units. In C, stick diagrams of one representative toddler on four acquisition days: A: two weeks before the very first unsupported steps. A parent holds one hand of the toddler. B: very first unsupported steps. C: after one week of independent walking experience. D: after 1.5 month of independent walking experience. In D, EMG signals corresponding to the acquisitions of the stick diagrams shown in C. These signals are filtered, rectified and integrated. For each day, at least 3 training sets of two successive walking cycles, starting with "Toe Off" are used in this study.

Informed consent has been given by their parents and the procedures were conformed to the Declaration of Helsinki.

The smoothed and rectified EMG signals of one representative subject are illustrated in Figure 3, C. These signals are sent to all 35 hidden units of the DRNN (Fig. 3B), whose synaptic weights and time constants are adjusted during the supervised learning procedure. In order to quantify the likeness of the simulated output signals with respect to the original one, we calculated a similarity index (SI) using the following equation:

$$SI = \frac{\int f_1(t)f_2(t)dt}{\left[\left(\int f_1(t)^2 dt\right)\left(\int f_2(t)^2 dt\right)\right]^{\frac{1}{2}}}$$

If $f_1(t) = f_2(t)$, then SI = 1.

Then the DRNN output (f_2) is compared to the experimental kinematics' data (f_1) (this correspondence is expressed by SI). If an SI > 0.99 is reached within 10000 iterations, we consider that the training has been successful and its generalization capacities will be tested. The Figure 4A illustrates the artificial learning success rate (ALSR) considered as the ratio of "successful network trainings" (reaching a SI > 0.99 between the acquired kinematics and the simulated ones within 10000 iterations), compared to the total learning trials, for each acquisition day. There is no significant difference in the ALSR (F=2.17; p=0.17) between different days. This means that artificial learning success rates are not significantly related to the degree of early maturation in gait and that the DRNN reach their attractor states whatever the maturation of the input-output signals. The natural variability of the toddler's gait kinematics was assessed by the analysis of the different steps performed during the same day by calculating the same SI used before to qualify the ALSR. In this case, a SI=1 means that there is no variability between the different steps. We found that it is only after 44 days of unsupported walking experience that the pattern is more stabilized. The generalization ability was assessed by the comparison of the kinematics calculated from unlearned EMG of the same acquisition day by a successfully trained DRNN with the kinematics corresponding to this unlearned EMG (Fig. 4C). The recognition index (RI) uses the same formula as the previously calculated SI but in this case the comparison is made between simulation obtained when an unlearned pattern is used as input and the real one. Interestingly, in contrast to the evolution of the SI, the RI presented a regular improvement from the first unsupported steps on to the 44th day (F=7.25; p=0.0003).

We may conclude from these results that while the ALSR is not significantly related to the degree of early maturation in gait, there is a clear improvement of the identification process for the more experienced walking patterns (day 4), which are also more reproducible.
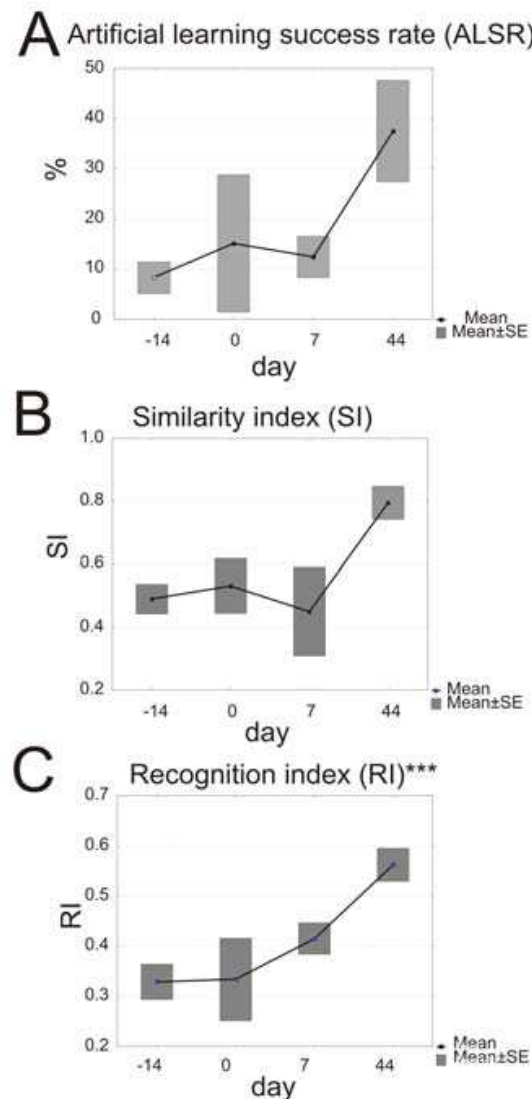
Fig. 4. Histograms of the evolution of the artificial learning success rate (ALSR) (A), the similarity index (SI) (B) and the recognition index (RI).

Correct recognition of unlearned EMG patterns by a trained DRNN is significantly related to the walking experience of the toddler. In this context, the DRNN could be used to follow and quantify the maturation of a toddler's and/or child's gait. The increase in the RI during gait maturation could be interpreted as a better coupling between neural oscillators and limb mechanical oscillators, which could be progressively integrated by toddlers. By this way, the relationship of multiple muscle EMGs and resulting kinematics can slowly be generalized. This fits relatively well with Gibson's concept (1988) suggesting that dynamic patterns emerge through exploration of available solutions before subsequent selection of preferred patterns. (Gibson, 1988). The initial solutions acquired through self-organized principle are often unstable and become more stable with practice. In this initial state, the DRNN can learn but its generalization ability is weak. It is only when behaviours have been practiced sufficiently and when the task and the context are unchanging that stable patterns emerge facilitating the generalization ability of the DRNN. Neurophysiological data are in favour of the existence of a central pattern generator (CPG) involving the spinal and supra spinal levels acting as a dynamic network generating rhythmic leg patterns (Hadders-Algra,

2002; Hadders-Algra et al. 1996). The dynamics of this innate complex progressively emerges through the process of repeated cycles of action and perception (Edelman, 1987; Sporns and Edelman, 1993). Our DRNN approach of EMG to kinematics mapping of toddler's locomotion offers a new investigation tool of such complex processing.
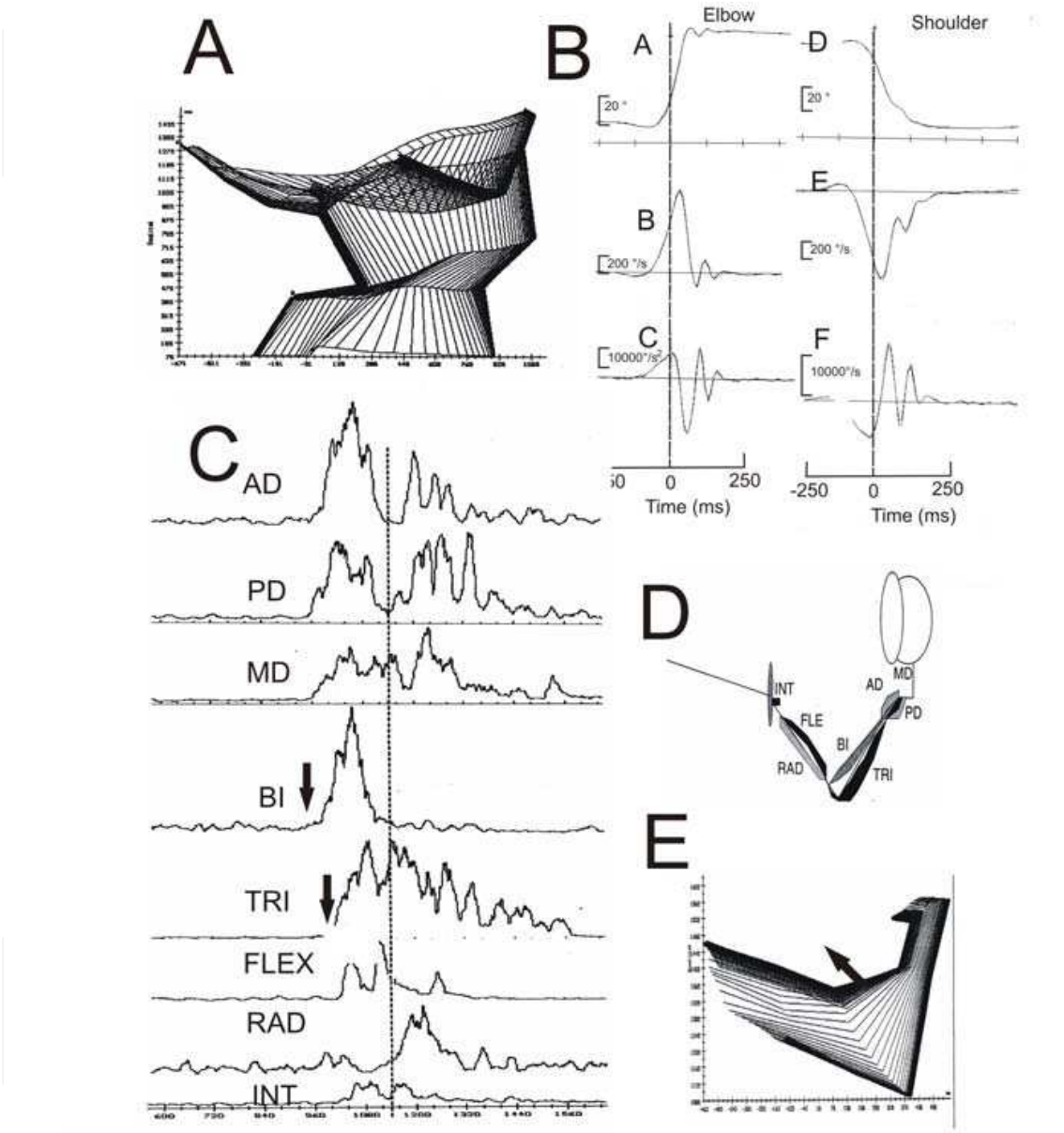

Fig.5. Lunging movement realized by an elite fencer. In A, kinogram of the whole body movement. In B, angular position (A, D), angular velocity (B,E) and angular acceleration of the elbow and the shoulder, respectively. In C, rectified EMG bursts of the anterior deltoïd (AD), posterior deltoïd (PD), medial deltoïd (MD), biceps (BI), triceps (TRI), flexor common (FLEX), radialis (RAD) and interroseus (INT) muscles. In D, simplified sketch of muscles anatomy. In E, kinogram of the upper limb extension movement. The vertical lines correspond to the time of the touch. The black arrows pointed to the onset of the BI and TRI muscles.

5. DRNN approach reveals interaction torque in sport movements

EMG to kinematics mapping was applied to lunging movement performed by elite fencers. This stereotypical movement (Fig. 5A) is a whole body movement, but our mapping was only concerned with the upper limb movement (Fig. 5C) and related muscles (Fig. 5D). The angular acceleration of the shoulder and the elbow (Fig. 5E) were used as output signals and the rectified EMG of 8 superficial muscles (Fig. 5B) as input signals of a DRNN composed in this case of 20 neurons.

The thrusting movement of the upper limb consists of a very rapid extension of the elbow joint (Fig 5B). Logically, this elbow extension should be accomplished by the prime mover action of the triceps (TRI)(Fig. 5C). However, the inspection of the time onset of the EMG burst of the TRI muscles shows that it is not the first event and that the EMG of the biceps muscle (BI) arrives earlier (Fig. 5C and 6C). Quite surprisingly, this muscular strategy only occurred in elite fencers and not in amateur fencers and may be explained by using a peculiar mechanical law implicating the interaction torque between the shoulder and the elbow. Indeed, the EMG recording demonstrated that the BI muscle is the prime mover of the extension. How this can be done?
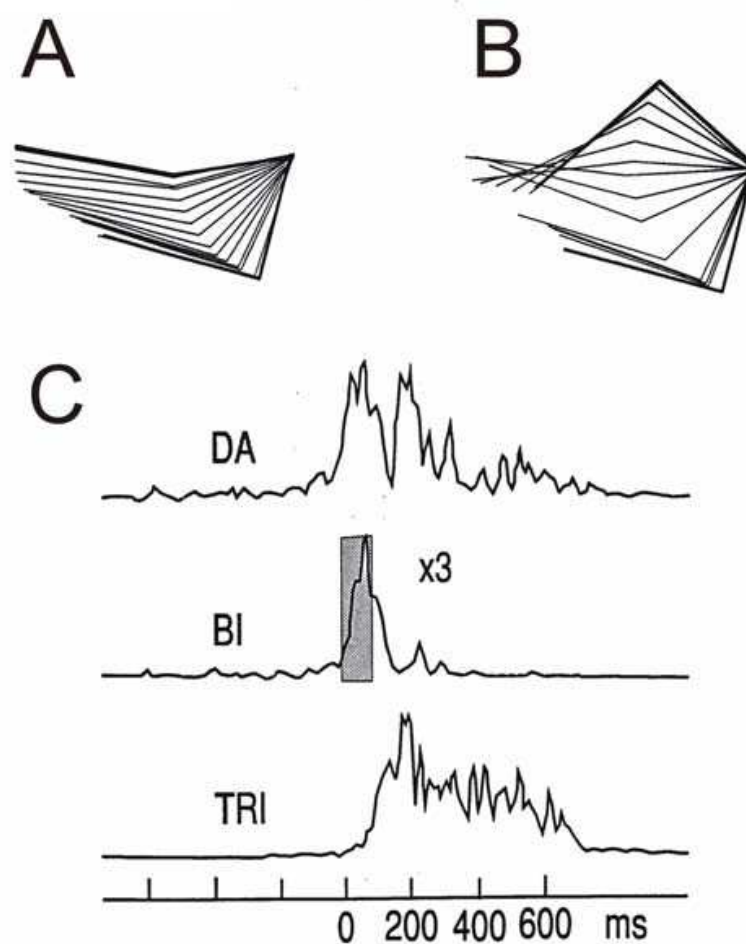
Fig. 6. DRNN simulation of the thrusting movement before (stick diagram in A) and after the artificial increase (X3) of the EMG burst of the BI muscle (stick diagram in B) (rectangular grey area in C). Note the hyperextension of the elbow induced by the BI increase.

As a biarticular muscle, the BI is able to produce an elevation of the arm. If this movement is explosive it can induce a passive but very fast extension of the forearm like in a flying effect. After the learning phase the DRNN is able to reproduce the lunging movement (Fig. 6A) and it is thus possible to use it as a simulator for testing the hypothesis that this extension movement is due to the effect of a dynamic interaction torque. The net torque is defined as the sum of all of the torques acting on a joint. In the lunging movement of the arm, the net torque acting at the elbow is equal to the sum of the gravitational, interaction, and muscle torques. In our case, the EMG bursts may be considered as a representation of the muscle torques acting on the different implicated joints and used as DRNN inputs. Bastian et al. (1996) elegantly established the inverse dynamics equations for the extension movement of the arm during a reaching task. The calculation of the net torque as the product of the moment of inertia of the involved segments and the angular acceleration around a given joint, determines the time series of joint angles and resultant limb trajectory. The angular acceleration of the shoulder and the elbow (Fig. 6B,C,F) are given here as output signals for the DRNN mapping. If the gravitational torque for the same movement remains the same regardless how fast the movement is made, in contrast the dynamic interaction torque, the passive mechanical torque generated when two or more linked segments move one another, depends greatly on joint velocity and acceleration. Like in the very fast lunging movement performed by the elite fencers, the interaction torques increase in magnitude. Thus in order to test our hypothesis that the DRNN has identified the dynamic interaction torque acting on the elbow, we have artificially increased the amplitude of the BI burst acting as the prime mover of the lunging movement (Fig. 6). When this increased BI burst (3X) was used in conjunction with the other unmodified EMG burst as input for a learned DRNN, it produced a strong reinforcement of the extension movement of the elbow. This demonstrates that the DRNN has identified the BI burst as inducing an interaction torque at the elbow joint by the production of the elevation movement of the arm. The final proof of this interaction effect should be obtained by performing inverse dynamics analysis in parallel to the DRNN simulation, but this demonstration is out of the scope of the present chapter.

6. Acknowledgements

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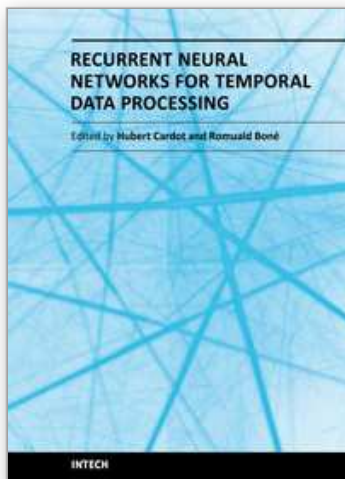
Recurrent Neural Networks for Temporal Data Processing

Edited by Prof. Hubert Cardot

The RNNs (Recurrent Neural Networks) are a general case of artificial neural networks where the connections are not feed-forward ones only. In RNNs, connections between units form directed cycles, providing an implicit internal memory. Those RNNs are adapted to problems dealing with signals evolving through time. Their internal memory gives them the ability to naturally take time into account. Valuable approximation results have been obtained for dynamical systems.

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