A Dynamic Neural Network Identification of Electromyography and Arm Trajectory Relationship during Complex Movements

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Abstract—**We propose a new approach based on dynamic recurrent neural networks (DRNN) to identify, in human, the relationship between the muscle electromyographic (EMG) activity and the arm kinematics during the drawing of the figure eight using an extended arm. After learning, the DRNN simulations showed the efficiency of the model. We demonstrated its generalization ability to draw unlearned movements. We developed a test of its physiological plausibility by computing the error velocity vectors when small artificial lesions in the EMG signals were created. These lesion experiments demonstrated that the DRNN has identified the preferential direction of the physiological action of the studied muscles. The network also identified neural constraints such as the covariation between geometrical and kinematics parameters of the movement. This suggests that the information of raw EMG signals is largely representative of the kinematics stored in the central motor pattern. Moreover, the DRNN approach will allow one to dissociate the feedforward command (central motor pattern) and the feedback effects from muscles, skin and joints.**

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I. Introduction

The recording of the electromyographic (EMG) activity accompanying fast voluntary movement offers an interesting insight into the control of movement [1]–[5]. However, the current EMG analysis suffers from different technical limitations in modeling the relationship between the EMG signal and the related movement [6], [7]. For example, in almost all the studies, EMG signals are approximated by simple geometrical shapes (such as rectangles or triangles). Although, this type of model has been used to investigate the relationship between the triphasic EMG signals and limb dynamics during unidirectional fast movements [1], [8], its application to more complex movements (as those implicated in the fast drawing of a figure eight) is more hazardous. In this situation, the muscle activation pattern is far more complex than the triphasic pattern of fast unidirectional movements for which the physical action of each EMG burst was determined. In particular, the kinematic analysis of this type of complex and continuous movements into distinct segments [9] was not easy to apply in the analysis of the EMG activity [10].

The objectives of this study were to: 1) develop an alternative approach based on artificial dynamic recurrent neural networks (DRNN) to map the raw EMG data of the figure eight movement onto the corresponding kinematics of the arm and 2) prove that this DRNN identification is biomechanically plausible. The neural network consists of fully interconnected neuron-like units with two types of adaptative parameters: classical weights between the units and the time constants associated with each neuron. Specifically, this network identifies some of the complex relationships between the muscle activity (EMG) and the upper-limb kinematics during complex movements.

II. Methods

Four male right-handed subjects between 21 and 25 years (mean weight: 73 kg and mean height: 179 cm) were asked to draw as fast as possible four figures eight with the right extended arm in free-space (the initial directions of the movements were up-right, up-left, down-left, down-right, respectively). The movements of the arm were recorded and analyzed using the optoelectronic ELITE system (including two TV cameras working at a sampling rate of 100 Hz) [11].

Surface EMG patterns of seven muscles were measured using telemetry. Muscle activity was recorded using pairs of silver-silver chloride surface electrodes on the following muscles: posterior deltoid external and internal (PDE and PDI), anterior deltoid (AD), median deltoid (MD), pectoralis major superior and inferior (PMS and PMI), and latissimus dorsi (LD). Surface electrodes were positioned at the approximated geometrical center of the muscle belly with an interelectrode distance of 2.5 cm. From previous experiences with the analyzes of fast unidirectional movements of the arm which revealed quite large differences in shoulder muscle activation patterns (with respect to amplitude and to relative timing), it can be concluded that crosstalk between these muscles is small. Raw EMG signals (differential detection) were amplified (1000 times) and bandpass filtered (10–2000 Hz). After this, the EMG's were digitized at 2 kHz, full-wave rectified and smoothed by means of a third-order averaging filter with a time constant of 20 ms [12].

Four infrared reflecting markers were attached to the arm (on the shoulder, elbow, wrist, and index finger), the three-dimensional (3-D) spatial position of these markers were computed by the ELITE system. As the movements were performed with the extended limb, the information from the four markers is partly redundant. The reconstruction of the movement of the arm by the ELITE system using the trajectories of the four markers confirmed the visual inspection that the upper arm, forearm, hand, and index finger acted as a rigid link. Thus, we used the data with the best definition related to the representation of the figure eight: the position of the index marker.

The artificial neural network is a fully connected 20-neuron network. It is governed by the following equations [13]

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

where y_i is the state or activation level of unit i, $F(\alpha)$ is the squashing function $F(\alpha) = (1 + e^{-\alpha})^{-1}$, and x_i is given by

$$x_i = \sum_j w_{ji}\, y_j. \tag{2}$$

This latter equation is *the propagation equation of the network*. The time constants T_i will act like a relaxation process. The correction of the time constants will be included in the learning process in order to increase the dynamics of the model. The correction of the weights and the time constants is done by the algorithm of "backpropagation through time" also known as the algorithm of "time-dependent recurrent backpropagation" [14]. In order to avoid confusion, we differentiate the algorithm of backpropagation through time proposed by Rumelhart *et al.* [15] and the algorithm, also named backpropagation through time, presented in this paper. In the algorithm of Rumelhart, the behavior of a recurrent network is achieved in a feedforward network at cost of duplicating the structure many times (the recurrent network is unfolded into a multilayer feedforward networks that grows by one layer on each time step). Unfortunately, this simple solution is suffering from its growing memory requirement in considerably long training sequences. We use an algorithm that does not unfold the recurrent network but computes the learning equations using a forward and a backward step through time (time appears explicitly in the equations). Since we want our network to exhibit some particular temporal behavior, the error function will be a functional defined as

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

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

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

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

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

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

These equations were first proposed in [13] using ordered derivatives but can be derived either using a finite difference approximation, the calculus of variation, the Lagrange multiplier, or even from the theory of optimal control in dynamic programming using the Pontryagin maximum principle. The integration of the learning equations gives the corrections to apply to the weights and time constants in order that the network reproduces the arm trajectory performed by the subject. The training of the neural network is supervised: the input patterns consist in the EMG signals of the seven muscles, the output patterns the spatial coordinates of the position of the index figure marker provided by the ELITE system (Fig. 1). Each training was associated

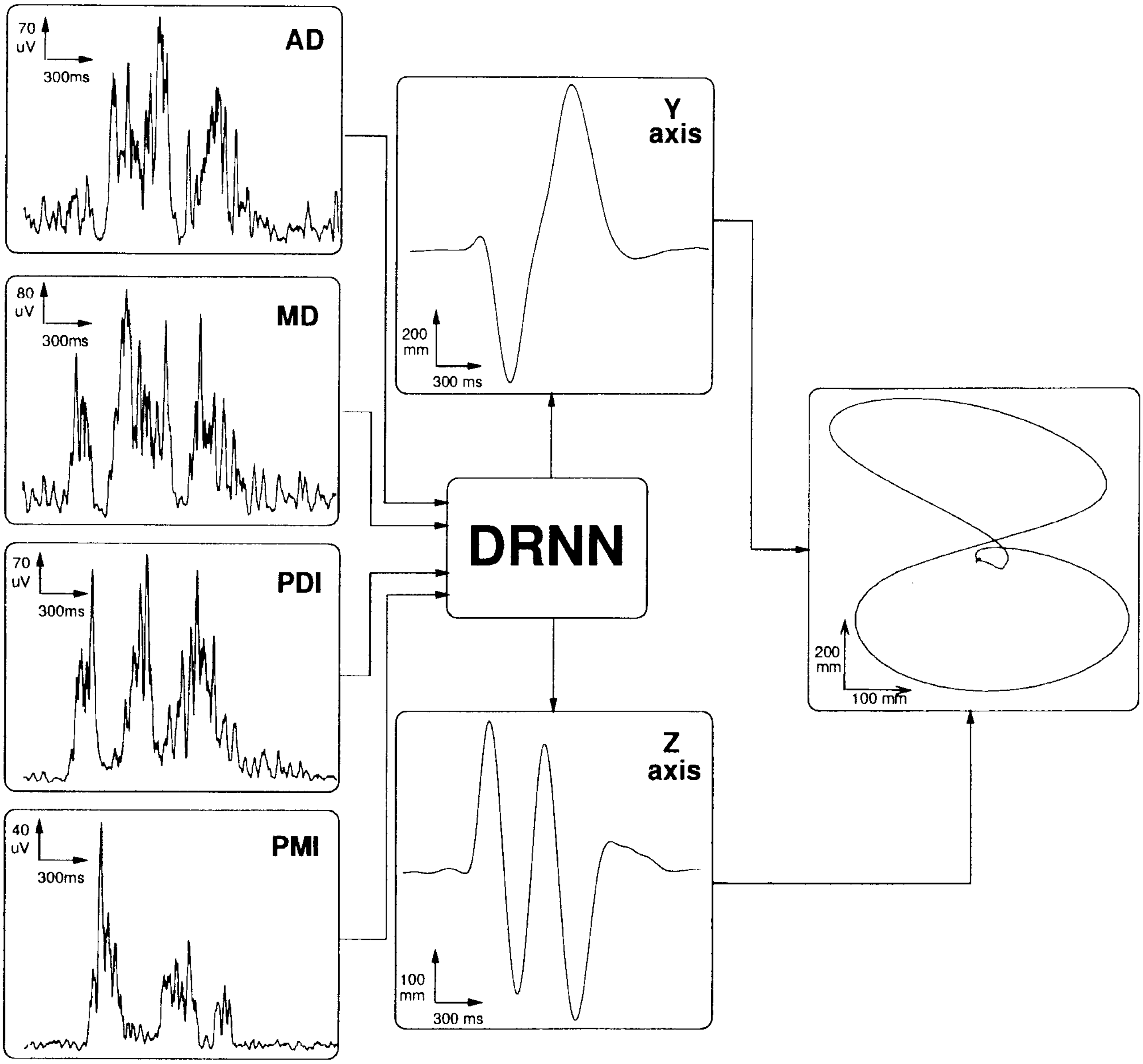

Fig. 1. Input–output organization of the DRNN. The inputs consist of seven full-wave rectified EMG signals (four of them are depicted). The outputs are the Y and Z coordinates of the index marker during the drawing of the figure eight (shown on the right) with the extended arm. This movement is characterized by two main components in the vertical direction (Y axis—down and up) and by four main components in the horizontal direction (Z axis—right, left, right, and left) (see Fig. 2).

to only one subject and for only one type of electrode location. The training of the network took an average of 24 hours of continuous running on a SUN 670MP machine (typically 10 000–12 500 epochs). The error is given by the measured area between the experimental and the simulated trajectories [computed using a discretized two-dimensional (2-D) integral derived from (3)]. We chose that area instead of the squared sum of the differences between the two curves to take into account the length of the time step (and thus the number of points to draw one trajectory) The training is stopped when the error reaches an asymptotic lower bound [16].

After having trained the network, a test of its generalization ability must be performed. For that purpose, we recorded the activity of the same seven muscles and index finger position when the subjects were asked to draw a circular trajectory instead of figure eight. We presented to the trained network these EMG signals and compared the experimental and simulated trajectories.

In order to test the biomechanical plausibility of the DRNN simulation, we must first determine, in the present experimental conditions, the mechanical pulling direction of each muscle. For this purpose, the subjects were asked to perform a series of self-terminated ballistic movements of 60 cm of amplitude around the initial position from which the figure eight was realized (the directions of the fast movements were indicated by a series of lines drawn every 22.5° on a panel localized in front of the subject). During this task, EMG patterns of agonist-antagonist muscles controlling the primary shoulder movements demonstrated the commonly observed triphasic EMG response [17]. The classical triphasic EMG pattern is unmistakable in agonist and antagonist EMG's. It consists of three main bursts of EMG activity corresponding to the starting (initial burst of the agonist), stopping (burst of the antagonist), and clamping (second burst of agonist) phases of the movement. For movements performed as fast as possible, the estimation of

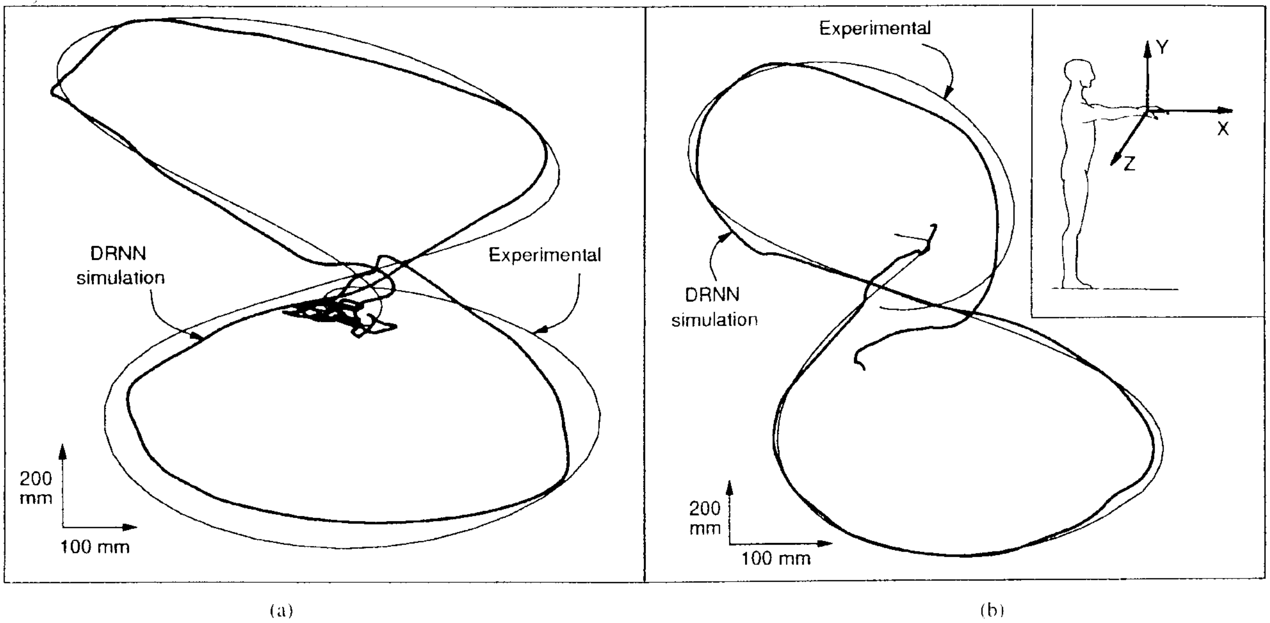

Fig. 2. (a) and (b) show the comparison between an experimental trajectory recorded with the ELITE system (thin lines) and the simulated curve generated by the DRNN (thick lines) for two different subjects. (inset) Reference axis associated with the arm movement.

the mechanical pulling direction was close to the direction of the largest peak of the initial agonist EMG activity. The beginning and the end of the first agonist EMG burst were defined by visual inspection of single trials. The integral of the EMG signal between these two instants were used to determine on a polar diagram the field of agonist activation of the muscle (the *preferential field*). This type of diagram provides the directional tuning of muscle activity [18].

Finally, the testing of the biomechanical plausibility of the DRNN simulation was realized by performing artificial lesions of the EMG signal (small cut-off of 50 ms in duration) in a well identified EMG burst of one muscle. This modified signal associated to all the other unmodified EMG signals were provided to the DRNN (previously trained with all the normal EMG signals). The resulting altered trajectory was compared to the normal one. We computed the error vector of the arm velocity between the normal and altered trajectories. The direction of the error vector would indicate which directional tuning the DRNN has attributed to the lesioned muscle. This information was then compared with the real directional tuning recorded on the same subject.

We chose to validate the model using artificial lesions because an analytical validation is, at the present time, impossible due to inherent problems of biomechanical analysis (redundancy of muscle activations, different strategies across subjects...). The only way to retrieve information concerning the quality of the DRNN identification dedicated to only one movement for one subject is to modify the only available parameters (EMG input signals) in order to analyze the effects on the output signals (altered trajectories).

III. Results

A. *Characterization of the Recorded Movements*

The mean duration of the figure eight movement was 1.3 ± 0.6 s, the mean vertical and horizontal amplitudes were 878.6 ± 165.6 mm and 486.6 ± 166.7 mm, respectively ($n = 16$, i.e., four trials for each of the four subjects, the variability within each subject is of the same order). The sequence of sampled data given by the ELITE system for one movement was about 3000 points per variable (comprising seven EMG signals and two arm coordinates).

B. *Characterization of the EMG Signals*

The full-wave rectified EMG of four of the seven shoulder muscles, recorded in one representative subject are shown in Fig. 1. For each muscle, we were able to dissociate the EMG activity into several bursts. Two of these muscles (MD and PDI) act like prime movers for this movement started toward the extension-abduction direction [Fig. 2(a)]. Let us point out that this prime movers combination of a flexion-abduction actuator (MD) and of a extension-abduction actuator (PDI) is explained by the small initial curve trajectory oriented toward the flexion-abduction direction. All the experimental trajectories present this initial inverted curvature.

The two other illustrated muscles (PMI and AD) clearly act as antagonist during the first part of the movement. Unfortunately, this reciprocal (agonist-antagonist) pattern will not remain constant for the duration of the movement and thus, no analytical identification is possible. For example, the AD burst activation overlaps both a silent phase and an activation phase of the PDI in the mid-part of the movement.

C. *DRNN Performance*

Among the 20 fully connected neurons of the DRNN, 18 receive the inputs (all the different EMG signals) and two give the output [the coordinates Y and Z, [see Fig. 2(inset)]. We only train the network with these two latter coordinates because they define the action plane. The amplitude of the movement according to the rostro-caudal axis (X axis) is very weak and is mainly due to the skeletal constraint. In this case, this passive movement could not have been identified by the DRNN on the basis of the EMG signals (mainly related to the voluntary movement).

Fig. 2(a) and (b) shows a comparison between the experimental trajectory (recorded by the ELITE system) and the simulated one (produced by the DRNN) for two different subjects. The DRNN performance is good and the simulated curve reproduces all the

TABLE I
MEAN ABSOLUTE DIFFERENCES AND STANDARD DEVIATIONS BETWEEN THE ACTUAL AND THE OUTPUT PREDICTED BY THE MODEL FOR RANDOM PERTURBATIONS ON ALL THE MUSCLE EMG. THESE VALUES ARE COMPUTED OVER 50 DRAWINGS OF THE TRAJECTORY OF FIG. 2(a)

Perturbations	Position Y (mm)		Position Z (mm)	
	Mean	Std Dev.	Mean	Std Dev.
Random noise (in the range $\pm$ 20%)	22.9	17.4	26.3	17.1
Random increase (in the range +20%)	11.3	9.1	10.1	7.3
Random decrease (in the range −20%)	15.2	11.5	10.9	8.6
Total range of the movement	836		422	

particularities of the human complex movements, whatever the initial direction of the movement.

Moreover, once the network was trained, we subjected it to perturbations on all the input muscle EMG [see Table I, reported to the trajectory of Fig. 2(a)].

We alter the signal with random perturbations in the range $\pm$20% on all the input signals. The network exhibited its robustness: the positions varied no more than $\pm$26.3 mm for the Z position. If we express that value as a proportion of the total range for the particular Z position (i.e., 422 mm), this difference is less than 6%. These results highlight the biologically plausible features of the model: one knows that while EMG data tend to be quite variable, positions are far more consistent. The perturbation experiments reported in Table I provide some more evidence that the model is valid.

Moreover, after the training phase, the DRNN is able to reproduce unlearned trajectories (e.g., circle, ellipse...) on the basis of their corresponding EMG signals. These experiments highlight the generalization ability of the network.

D. Test of the Physiological Plausibility of the DRNN Simulation

Fig. 3 illustrates the result obtained after an artificial lesion (AL) selectively performed on the first burst of the EMG of the PMI muscle. In this case, the late part of this burst [Fig. 3(a)] has been cut off during 50 ms (during this interval, the EMG was set to 0.0 μV). This altered EMG signal, and the six other unaltered EMG signals are fed to the DRNN previously trained with the normal EMG patterns. The resulting trajectory is compared to the normal one [Fig. 3(b)]. It is clear that the arm is not able to reach the lower part of the normal figure eight. This altered movement is compatible with the physiological action of the PMI (extensor-flexor actuator).

To quantify the effects of the AL, we computed the error vector (EV) of the arm velocity between the normal and the altered trajectories [Fig. 3(c)]. As we could expect it, the EV is directed toward the top.

In this case, the mean amplitude of the EV recorded during the time of the AL was 2.11 $\pm$ 0.82 m/s. The peak amplitude of 3.81 m/s was reached 15 ms after the onset of the lesion. Afterwards, the amplitude of the EV decreases continuously until 70 ms after the end of the AL. After this point, the EV is directed toward the bottom with small values and never vanishes until the end of the movement.

A total of 64 AL experiments were performed in different EMG bursts of all the muscles.

Fig. 4 summarizes some of the AL experiments for which the mean EV is compared to the preferential field of the corresponding muscles. For example, for the AD muscle, eight AL's were performed, and the mean EV's are illustrated on a polar diagram. Most of the mean EV's were directed toward the flexion-adduction direction. It is the same direction that the preferential field of the agonist activation of this muscle. The concordance between the mean direction of the

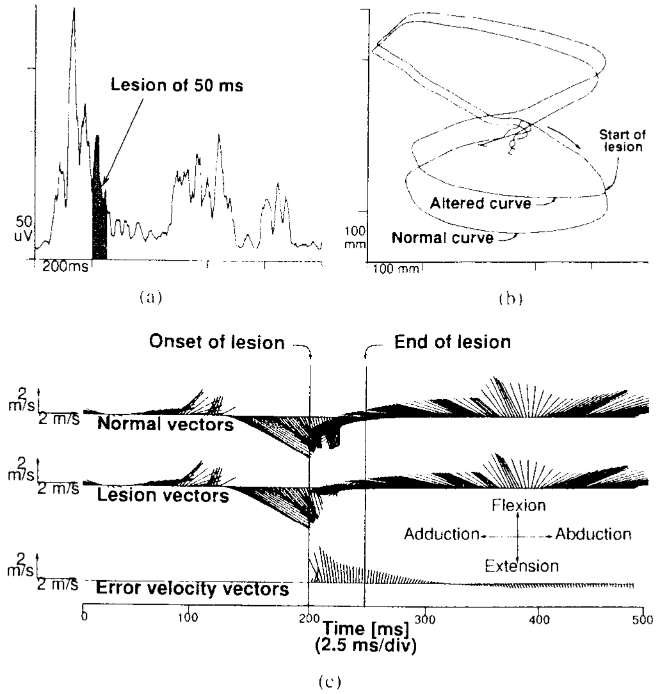

Fig. 3. (a) Small lesion of 50 ms of duration on the EMG signal of the PMI muscle. (b) Comparison between the normal and the altered trajectories (produced by the DRNN). (c) Illustration of the velocity vectors of the normal and altered trajectories. The error velocity vectors are obtained by the difference between the preceding ones. Velocity vectors are depicted each 22.5 ms.

EV's (computed from the results of the DRNN simulation) and the preferential field of the three other muscles action (recorded on human subjects) is also demonstrated.

IV. DISCUSSION

The main feature of the proposed DRNN is that its simulated movements are the result of the interaction between raw EMG signals without any theoretical assumptions concerning the type of control.

It is well known that the temporal evolution of the EMG of the individual shoulder muscles are broadly tuned with respect to the direction of movement [17], [19]. Our model is particularly suitable for the identification of the temporal relationship between all the muscles involved in the drawing of the figure eight which is known to be a highly learned trajectory [9], [10]. In order to control a movement, the central nervous system uses internal representation (IR) or mental image [20]. In the case of the figure eight, this IR is constructed from sensory-motor information acquired during the learning of general writing. The recorded EMG represents a combination of the IR (open-loop control) and a closed-loop control (reflex) based on muscle spindle information. In its present form, our DRNN simulation is not able to dissociate the different components resulting from IR or reflex modulation but further developments would include this type of information.

The suitability of the DRNN is mainly due to the adaptative time constants associated to each neuron-like unit. These ones greatly increase the dynamical features of the model [13], [21]–[23]. Moreover, in our network, the time constants are part of the learning process and remain within an interval of values compatible with biology. The DRNN's are much more adapted to temporal treatments than the classical feedforward networks which are more dedicated to classification tasks. Our network identifies efficiently all the temporal

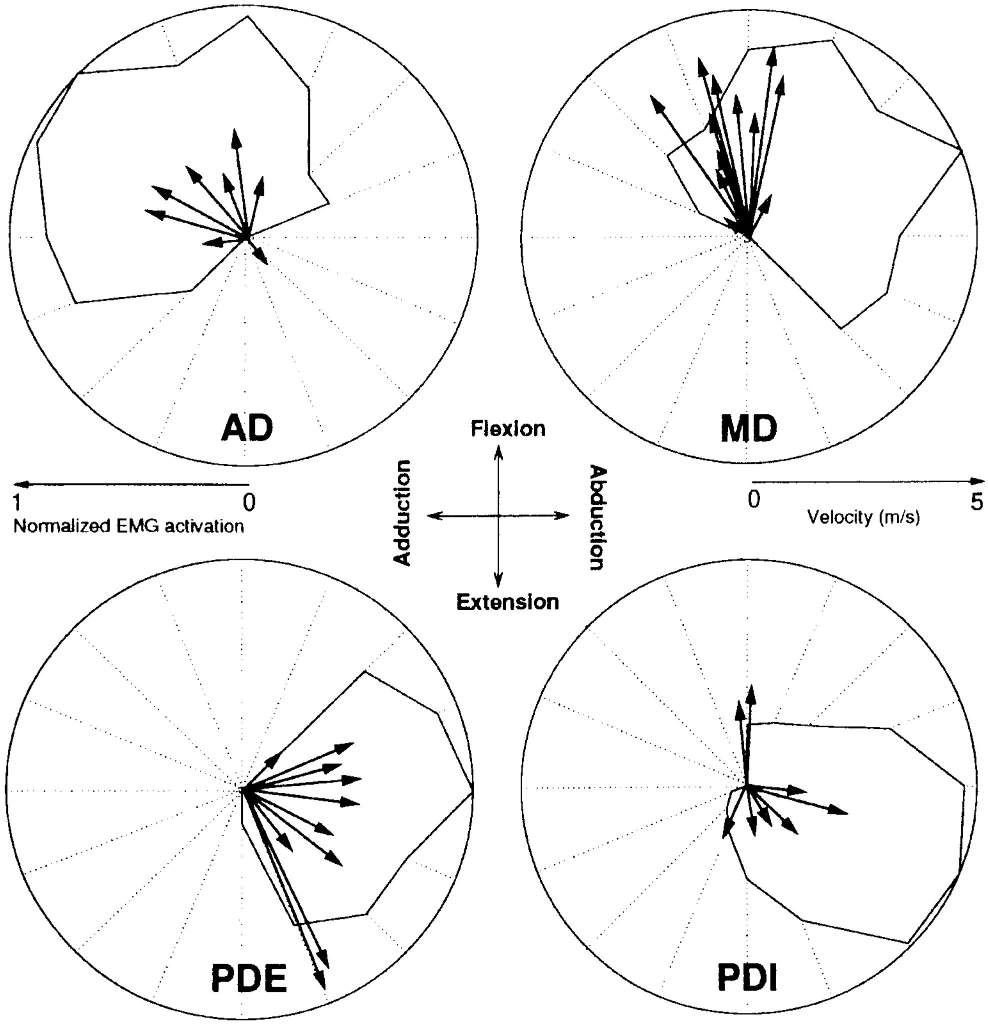

Fig. 4. Polar diagrams for the comparison between the preferential field of the normalized agonist activation of the muscle recorded on human subjects performing self-terminated ballistic movements (white areas) and the mean EV's computed from the AL's performed on the corresponding muscle (vectors). The outer circle of the polar diagrams corresponds to a value of one for the normalized EMG activation and to a value of 5 m/s for the velocity.

relationships and thus circumvent one of the main weaknesses of feedforward neural networks [24].

The cause-and-effect sequence of events necessary for the drawing of a figure eight movement includes: 1) retrieval and activation of a prelearned figure eight central command, 2) transmission of the command to the motoneurons, 3) muscle activation and development of the concomitant EMG signals, 4) generation of forces at joints regulated by anthropometric parameters of the skeleton, and 5) movement of the arm in free-space. Although the DRNN realizes the EMG [step 3)] to kinematics [step 5)], the step 3) concerning the generation of forces is missing. The main problem is that the muscles are not ideal actuators: muscle force does not depend solely and linearly on its activation (neural input) but depends in a nontrivial way on its length and its contraction velocity [25], [26]. The lack of this information in the DRNN may partly explain the reverse identification of some muscle actions (Fig. 4). In fact, some muscle actions were identified as eccentric (negative work) instead of physiological concentric (positive work). Nevertheless, while certainly not conclusive, we believe that the AL's reported in Figs. 3 and 4 provide some evidence that the DRNN is biomechanically plausible. The fact that the direction of the EV coincide with the preferential field of activation of the corresponding muscle proves that the DRNN has at least identified the directional action of the different muscles. Moreover, as the present DRNN is able to reproduce unlearned trajectories when it is previously trained with the figure eight means that the information content in the combination of the seven EMG signals is, in the case of the figure eight, sufficiently relevant to reach the generalization ability. This also means that the figure eight is an ideal movement for the learning process of the DRNN. The particular curve implicates throughout the movement a permanent change of its direction combining clockwise and counterclockwise rotation.

Future experiments will include the extension of the DRNN to other types of complex movements using multijoint control and the utilization of different types of input signals derived from the EMG data. For example, the treatment of the EMG inputs by means of different biological filters (Hill-type muscle model) including tension-length and force-velocity relationships of muscle-tendon actuators can provided a good approximation of muscle force [12]. The training of the DRNN will be made with this type of force signal. The comparison of the DRNN simulation signals would probably gain further insight regarding the validity of the DRNN approach.

There are number of research avenues that have potential in future applications of the DRNN approach. This type of simulation studies can be of great importance in the fields of basic motion research, preventive health care, pre-surgery simulation, physical rehabilitation and sport performance. For example, the network could be trained on pathological EMG and movement data on one patient prior to orthopedic surgery. Then, it could be possible to simulate, by changing some of the EMG inputs of the previous learned network, the effects expected by surgery. In the same way, the DRNN would be particularly helpful in physical rehabilitation where it could be used to realize a rehabilitation training program including an appropriate selection of muscle activations as well as the adequate temporal and spatial combination of antagonist muscles.

V. Conclusion

The present results show that DRNN's are successful in identifying the complex mapping between full-wave rectified EMG signals and upper-limb trajectory.

The performance of this identification reinforce the idea that the study of the relationship between EMG signals and kinematics will lead to insight into the formation of the central motor pattern.

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