# Improved Identification of the Human Shoulder Kinematics with Muscle Biological Filters

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**Abstract.** In this paper, we introduce new refinements to the approach based on dynamic recurrent neural networks (DRNN) to identify, in humans, the relationship between the muscle electromyographic (EMG) activity and the arm kinematics during the drawing of the figure eight using an extended arm. This method of identification allows to clearly interpret the role of each muscle in any particular movement.
We show here that the quality and the speed of the complex identification process can be improved by applying some treatments to the input signals (i.e. raw EMG signals). These treatments, applied on raw EMG signals, help to get signals that are better reflections of muscle forces which are the real actuators of the movements.

## 1 Introduction

Human movements are a fascinating field of research. One can only be filled with wonder in front of the accuracy, the speed and the grace of human movements. Briefly, we can describe the cause-and-effect sequence of events that takes place for a human movement to occur as [11] : *(i)* registration and activation of the movement command in the central nervous system; *(ii)* transmission of the movement signals to the peripheral nervous system; *(iii)* contraction of the muscles that develop tension with concomitant generation of electromyographic (EMG) signals; *(iv)* generation of forces at synovial joints; *(v)* regulation of these forces by the anthropometry of the skeleton; *(vi)* movement of the rigid skeletal segments in a manner that it is recognized as the functional movement desired by the central nervous system.

In this paper, we will be interested in the relationship between the electromyographic (EMG) signals (which are a reflection of the command signals sent by the central nervous system to the muscles) and the movements of the skeletal systems. If we refer to the model presented below, we are interested in understanding the relationship between steps *(iii)* and *(vi)*.

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We will then apply different treatments on raw EMG signals in order to get signals that are better reflections of the muscle forces (which are the real actuators of the movement). These improvements will lead to a better and faster identification of the relationship we are concerned about.

## 2 The considered application

We will restrict the application of the neural networks to the identification of the kinematics of the human arm during complex movements in free space. A conventional identification system to handle this task is very difficult to design. Indeed, this one would have to take all the concepts of biological motor control into account but even like that, the quality of the identification would be poor because we still ignore many of these concepts (such as the real pathway of informational signals between the muscles and the central nervous system or some movement invariances). Several techniques have been proposed to solve this complex problem using techniques such as the theory of optimization, the identification using mathematical high-order functions or statistical correlation between EMG and limb movements. Unfortunately, all these techniques require important approximations on the EMG signals and/or provide poor simulation results.

### 2.1 Related works

The identification of the EMG-kinematics relationship has been considered by several researchers essentially to solve the problem of *distribution* i.e. *how are the large number of muscle forces distributed among relatively few joints ?* (this problem is sometimes referred as redundancy, it is linked to the ill-posed problem).

There have been essentially three strategies that researchers have followed

- **Studying the relationship between EMG and muscle force.** Inman *et al* in 1952 [7] first observed changes in myoelectric signal amplitudes according to variations in the applied muscle load.
- **Estimating individual muscle forces by means of mathematical optimization theory.** One can obtain an acceptable mechanical description of individual muscle forces in human movements only by solving an indeterminate system of equations; this latter fact, along with kinematic invariances of movements, has led to the use of mathematical optimization theory [3]. As explained before, one major problem is that the cost function to be minimized (or maximized) cannot be known exactly *a priori.*
- **To correlate EMG and joint positions or moments.** Pedotti in 1977 [10] made a qualitative investigation of EMG and joint moment correlations for the lower limbs during level walking. Although his study, which included seven muscles, was inconclusive, it did illustrate the complexity of the problem.

Sepulveda *et al* estimate that despite the lack of progress the third strategy has the greatest potential; they were the first to use an artificial neural networks algorithm for correlating EMG and joint kinematics and dynamics in human gait [11]. They proposed a feedforward neural network to solve the distribution problem : it was able to converge and slight perturbation to all EMG inputs led to similar output predictions. They also noticed several limitations : their model does not include physical arrangement of muscles, force-velocity relation or sensory feedback information. The most severe drawback was that feedforward neural models did not include temporal relationships (i.e. parameters at time $t+1$ are a function of what happened at time $t$) although the learning algorithm did present the training patterns in sequential order.

Facing the interesting results of artificial neural methods in solving biomechanical tasks but, also, the drawbacks of feedforward networks, we concentrate our research on the application of recurrent dynamic networks to EMG-human arm kinematics relationship identification.

## 2.2 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 series of 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). They were asked to perform the movement repetitively (5-10 cycles) at a self-determined frequency (generally from 0.7 to 1.2 kHz).

The movements of the arm were recorded and analyzed using the optoelectronic *ELITE* system (including 2 TV cameras working at a sampling rate of 100 Hz.

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 analysis 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 cross-talk between these muscles is small. Raw EMG signals (differential detection) were amplified (1,000 times) and bandpass filtered (10-2000 Hz). After this, the EMGs 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.

Four infra-red reflecting markers were attached to the arm (on the shoulder, the elbow, the wrist and the index finger), the three-dimensional 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 which is governed by the following equations [5] :

$$T_i \frac{dy_i}{dt} = -y_i + F(x_i) \quad \text{with} \quad x_i = \sum_j w_{ji} \; y_j \tag{1}$$

where $y_i$ is the state or activation level of unit $i$, $F(\alpha)$ is the squashing function (sigmoid-like function) and $x_i$ the total input of the neuron. Immediately, we can notice that our model presents two types of adaptive parameters : the classical weights between the units and the time constants $T_i$. These ones 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. It has been proved that these adaptive time constants have a very good influence on the network frequential behaviour, on its dynamical features and on its long-term memory capacities (for more details and the complete learning algorithm, see [4]). The network was trained to reproduce the arm trajectory performed by the subject in response to the EMG signals. Each training was associated to only one subject and for only one type of electrode location.

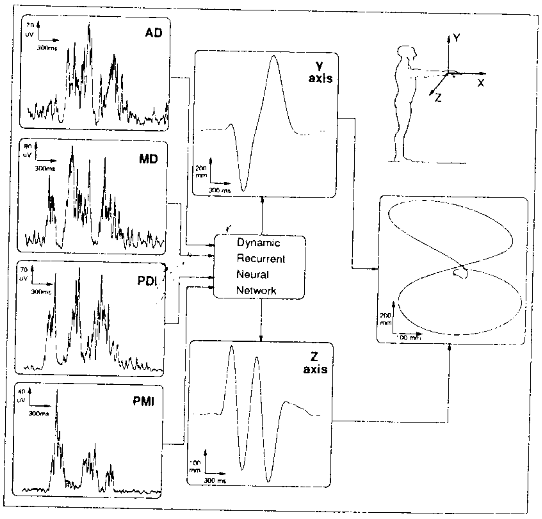


**Fig. 1.** *Input-output organization of the DRNN.*

### 2.3 Results

Among the twenty fully connected neurons of the DRNN, eighteen receive the inputs (all the different EMG signals) and two of them give the output (the coordinates $Y$ and $Z$, see Figure 1). 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).

We have already proved that DRNNs are successful in identifying the complex mapping between full-wave rectified EMG signals and upper-limb trajectory (see [2]. We have shown that the quality of the identification of the mapping allows to clearly interpret the role of each muscle in any particular movement. We have developed a method to prove the plausibility of the identification using artificial lesions and error vectors. Moreover, our neural model is able to reproduce unlearned trajectories when it is previously trained with the figure eight; that 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. This highly learned trajectory enables the DRNN to identify neural constraints [8] such as the covariation between geometrical (the curvature) and kinematics (the tangential velocity of the arm) parameters of the movement [12] (more details can be found in [2]).

## 3 Improvement of the simulation model

The application presented in the previous section consists in the identification of the relationship between the *raw* EMG signals sent to the arm muscles and the related arm kinematics. This section is devoted to the presentation of different treatments that we can apply on raw EMG signal in order to get a signal that is a better reflection of the muscle force. Indeed, forces generated by the muscles are the real actuators of the movements. As we will see, these improvements in the quality of the input signals lead to a better and faster identification of the relationship we are concerned about.

The improvements will be divided in three different categories : filtered EMG input signals, sign-adjusted EMG input signals, muscle forces using biological filters.

### 3.1 Filtered EMG input signals

Neural delays and muscle lag are essential characteristics of muscles. Although the axon velocity is quite high (50 m/s), the minimal reflex response time from a foot sensor (afferent + efferent pathways $\approx$ 2 m) is about 40 ms. Similarly, a centrally initiated command will also take about 40 ms to reach a distal muscle. This means that triggering of the first motor unit takes 40 ms with a further electromechanical delay in the start of the muscle twitch, followed by the lag due to the low-pass characteristics of the muscle twitch itself [9]. Thus, the peak tension from the very first motor unit might not be reached for a further 50 to 110 ms, followed by delays in the recruitment of further motor units. The EMG signal (recorded by the electrode which is generally located over the middle of the muscle) is always slightly delayed behind the neural pulse trains. There is thus an electromechanical delay between the time that the EMG signal is recorded and the time it takes for the electrical wave to propagate along the muscle fibers to each tendon at a velocity of about 4 m/s. Electromechanical delays can add another 20 ms to neural delays. The propagating force arrives at the tendon in the form of a twitch which has been analyzed as a critically damped, second-order, low-pass system with cut-off frequency around 5 Hz [9]. Such a transfer function of the muscle will cause a further lag in the buildup of tension.

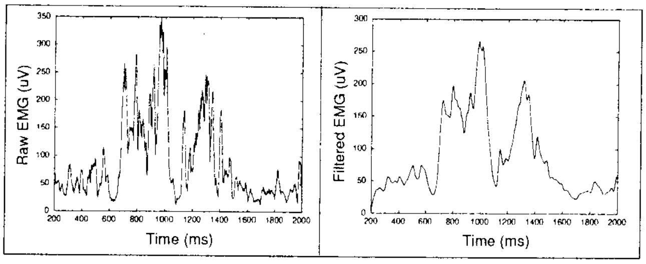


**Fig. 2.** *Raw EMG signal of the anterior deltoid (left) and its filtered version (right) at 5 Hz.*

The first obvious preprocessing that one could apply to the EMG signals is of course to model this transfer function. This treatment is illustrated on Figure 2 where the raw EMG signal of the anterior deltoid (left) and its filtered version (right) at 5 Hz are plotted versus time.

### 3.2 Sign adjusted EMG input signals

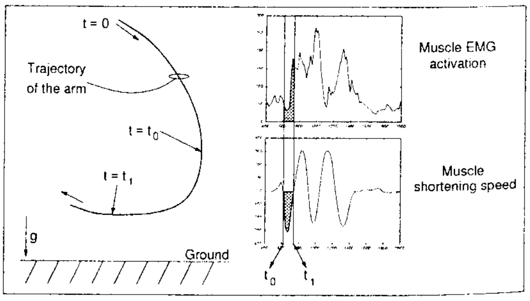


**Fig. 3.** *Illustration of the concept of passive burst.*

One important problem arises when using raw or filtered EMG signals. Indeed, the interpretation of a particular burst of a muscle EMG activation can be very difficult for an identification process. Let us take the example of the part of figure eight trajectory depicted on Figure 3. The experimenter begins to draw the trajectory at time $t = 0$ and lets his (her) arm going down toward the ground thanks to the action of the extensor muscles (which preferential field is directed toward the bottom). Due to gravity, the speed of the limb increases and at time $t = t_0$ the central nervous system sends a command to slow down the movement. This slowing down is induced by the activation of muscles which have a flexor preferential field (their action is directed toward the top). When such a muscle is activated, its effect is not to move the limb upward but to slow down the movement downward. The action of such a muscle is depicted on right-up corner of the figure. The speed of shortening of this particular muscle is also depicted just below. We note that the burst occurs when the speed of shortening of the muscle is negative : that means that the muscle was lengthening when the activation happened. We can also note that, at time $t = t_1$, the muscle speed of shortening becomes positive : the muscle acts again in its preferential field and the limb begins to move upward. One solution to help the identification system to identify *active bursts* (the limb move in the direction of the preferential field of the muscle) or *passive bursts* (the limb is slowed down in the opposite direction of the preferential field of the muscle) is to look at the speed of muscles. When the speed is negative, we can consider that the burst as a brake action and *invert it.*

The corrected EMG signal is constructed using the following procedure. When the speed becomes negative, we revert the EMG activation. Nevertheless, in order to keep a continuous signal, we do not flip the signal with respect to the X axis but with respect to the line that joins EMG activation of the instants of null speed. The resulting EMG signal (dashed line) has been named the *sign-adjusted EMG signal.*

### 3.3 Muscle forces using biological filters

The different preprocessing methods described in the previous section attempt to get closer reflections of the force generated by muscles. We will present here a much more efficient way to obtain these force signals by using biological filters. These filters will be applied to raw EMG signals to give muscle forces and will be derived using two well-known muscle models : Lumped parameter models and cross-bridge models.

**Lumped Parameter models - Hill models** The filters are based on descriptions which resulted in muscle models that were composed of viscoelastic elements. The most widely applicable of these models is that of A. V. Hill.

They can be described as follows [6] : muscle is composed operationally of three elements (see Figure 4) : *(i)* a contractive element (CE) that acts as an active force generator; *(ii)* an elastic element (SE) that represents the combined stiffness of tendon and cross-bridges in series with the force generator; *(iii)* a second elastic element on parallel with the previous two elements (PE) that represents the passive tissue contribution to muscle force. Hill has proved that this model explained the force-velocity relation of a muscle. This relation consists of separate equations for lengthening and shortening muscle.

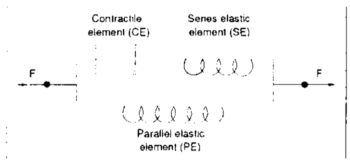


**Fig. 4.** *Schematic representation of Hill model structure.*

**Cross-bridge models** Together with the tension-velocity, there exists a tension-length relation of a muscle; this latter one will be derived using cross-bridge models. Muscle force exhibits a pronounced length dependence which can be explained by the sliding filament theory. As muscle length changes, the relative overlap of the actin and myosin filaments in each sarcomere changes because of telescoping of the sarcomere structure; this overlap determines the maximum number of available cross-bridges at any given muscle length. Figure 9.12a shows the idealized length-tension curve measured during steady-state isometric contraction when the muscle is fully active.

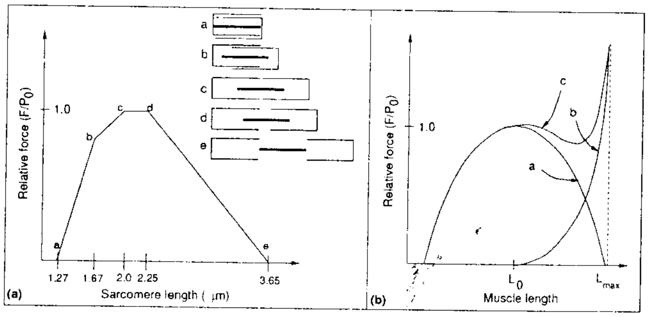


**Fig. 5.** *Force-length relation. (a) isometric force length relation of a sarcomere and the corresponding sarcomere geometry responsible for this effect. (b) the generalization to the force-length relation of a muscle.*

In contrast to lumped-parameter models which try to reproduce macroscopic behaviour with discrete mechanical elements, cross-bridges models strive to incorporate the known micro-structure of the sarcomere together with metabolic kinetics of muscle to predict macroscopic variables such as whole muscle force, stiffness, shortening velocity, energy consumption, heat liberation, etc.

Concerning the force-length relation of a muscle, it is the perfect image of the same relation of a sarcomere (see Figure 5a, curve $a$) except that we must take into account the passive tissue contribution to muscle force. Indeed, when a muscle is fully extended, the sarcomere can not develop a force anymore but the passive elasticity of the tissue gives rise to an increasing force which tend to infinity (see Figure 5b, curve $b$). The complete force-length relation is obtained by the cumulative effect of curve $a$ and $b$ (i.e. their addition) : curve $c$.

**Computation of the muscle biological filters** This section is devoted to the description of our muscle filter model (the reflection of our EMG to force processing approach).

The main attribute of this muscle filter model considered here is based on two different complex filters which are used in series : a *static filter* (active and passive) and a *dynamic filter*. The first one represents the idealized tension-length relationship (see Figure 5), the second one the idealized force-velocity curve. The current activation level of each muscle during the complex movement is defined by a normalization of the absolute EMG value in percentage of the maximal voluntary contraction (MVC) of the muscle tested in the primary position of the studied movement (extended arm at horizontal).

Classically, the total tendon force $F^T$ is defined by the following *product* relationship [1] : $F^T = a\, F_0^M\, F_l\, F_v\, \cos\alpha$ where $F_0^M$ is the peak isometric force at rest length, $F_l$ the force-length component, $F_v$ the force-velocity component, $\alpha$ the pennation angle and $a$ the normalized activation level which is bounded by the inequality : $0 \leq \alpha \leq 1$. The pennation angle $\alpha$ gives the angle between the position of the muscle (defined by its two tendons) and its effective action direction. For simplicity, we do not take $\alpha$ into account because this coefficient remains constant throughout the figure eight movement.

In order to determine the filters, we have to compute the actual length of the different muscles; this one is calculated on the basis of current kinematics data that provide the shoulder angles in 3D space. These experimental data are combined with a set of musculotendon actuator parameters [13].

*Static filter :* The static filter is divided into two components : the *active tension static filter* (ATSF) and the *passive tension static filter* (PTSF).

The *active tension static filter* (ATSF) is defined by the relation : ATSF= $k_0 L^2(t) + k_1 L(t) + k_2$ where $L(t)$ corresponds to the current length of the musculotendon actuator and $k_0$, $k_1$, $k_2$ are the parameters of the idealized parabolic function (which corresponds to the curve $a$ of Figure 5).

The *passive tension static filter* (PTSF) is defined as : PTSF= $p_0 L^2(t) + p_1 L(t) + p_2$ where $L(t)$ corresponds to the current length of the musculotendon actuator and $p_0$, $p_1$, $p_2$ are the parameters of the idealized parabolic function (which corresponds to the curve $b$ of Figure 5). The component PTSF is only taken into account if $L(t) > L_0$ (see Figure 5).

*Dynamic filter :* The dynamic filter includes only one component due to the force-velocity relationship. This relation is denoted DTF : *dynamic tension filter*.

*Force computation :* The expression of the force has been given below. Nevertheless, we will prefer a more simple expression to calculate the different forces using the three filters : ATSF, PTSF and DTF using the expression : $F$ = [(EMG × ATSF) + PTSF] × DTF. The interpretation of this relation is quite simple : the raw EMG signal must, in a first phase, be modulated by the active force-length relation (thus modulated by the ATSF filter); this latter term must be increased by the passive PTSF if the length of the muscle is greater than $L_0$. This latter value is then modulated by the force-velocity relation (DTF filter) to give *an approximation* of the muscle force.

We wish to emphasize that this procedure gives an approximation of the real force and not its absolute value. Each approximated force is equivalent to the real force times an unknown constant (this constant is the same for all the muscles). Nevertheless, if the computed values are relative, the different ratios between the muscles are absolute and it is these different ratios that are important for the DRNN identification.

| *Type of inputs* | *Root mean square error* |
|---|---|
| Raw EMG | $14.5\ 10^{-3}$ |
| Filtered EMG | $11.4\ 10^{-3}$ |
| Sign adjusted EMG | $7.4\ 10^{-3}$ |
| Force | $5.9\ 10^{-3}$ |

**Table 1.** *Root mean square error according to different types of inputs.*

### 3.4 Results

The results of the computation of the real muscle forces and their use as inputs of the DRNN identification are depicted in the following figures (Figures 6). After having trained the network for 5,000 epochs (with each type of inputs), we computed the mean trajectory for each type of training to get the curves of Figure 6 (left curves) For each mean trajectory, we took the error vectors between the experimentally recorded trajectory and the simulated one (see Figure 6, curve *b* of the top figure). We then shifted these error vectors in order that their origins coincide with (0,0) (Figure 6, right). The improvements in the quality of the simulated curve can be visually observed.

The root mean square amplitude of these vectors can be computed. Table 1 shows that identification process benefits from the EMG input signals preprocessing.

## 4 Conclusion

The present results show that dynamic recurrent neural networks are successful in identifying the complex mapping between full-wave rectified EMG signals and upper-limb trajectory. Moreover, it has been proved that the quality of the identification of the mapping will allow to clearly interpret the role of each muscle in any particular movement. Our method succeeds whereas several others (estimating individual muscle forces by means of mathematical optimization theory, study of the mechanical action of each muscle, ...) have failed or gave poor results to solve the complex problem of muscular redundancy.

We have shown in this paper that the quality and the speed of the complex identification process can be improved by applying some treatments to the input

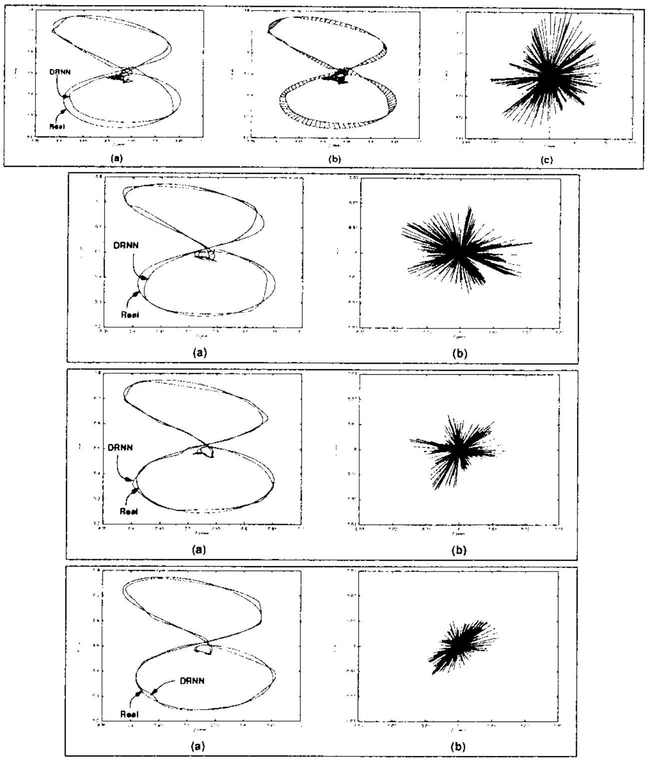


**Fig. 6.** *From top to bottom : training with the raw EMG as inputs, with filtered EMG as inputs, with sign adjusted EMG as inputs and with the forces as inputs.*

signals (i.e. the raw EMG signal). These treatments, applied on raw EMG signals, help to get signals that are better reflections of muscle forces which are the real actuators of the movements.

There are number of research avenues that have potential in future applications of the dynamic recurrent neural network 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.

The performance of this neural identification also reinforces 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 and in particular will help to understand the *internal models* acquired by the brain through motor learning.

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