ESANN'1995 proceedings - European Symposium on Artificial Neural Networks
Brussels (Belgium), 19-20-21 April 1995, D-Facto public., ISBN 2-9600049-3-0, pp. 33-38

Identification of the Human Arm Kinetics using Dynamic Recurrent Neural Networks

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Abstract. Artificial neural networks offer an exciting alternative for modeling and identifying complex non-linear systems. This paper investigates the identification of discrete-time non-linear systems using dynamic recurrent neural networks. We use this kind of networks to efficiently identify the complex temporal relationship between the patterns of muscle activation represented by the electromyography signal (EMG) and their mechanical actions in three-dimensional space. The results show that dynamic neural networks provide a successful platform for biomechanical modeling and simulation including complex temporal relationships.

1. Introduction

The cause-and-effect sequence of events that takes place for a human movement to occur is complex : after a registration of the movement command in the central nervous system, there is a transmission of the movement signals to the peripherical nervous system; these signals induce the contraction of the muscles that develop tension (with concomitant generation of electromyographic signals). These contractions generate forces at synovial joints; these joints forces are regulated by the anthropometry of the skeleton and induce the movement of the rigid skeletal segments in a manner that it is recognized as the functional movement desired by the central nervous system. We are interested in the relationship between the electromyographic (EMG) signals (which are a reflect of the command signals sent by the central nervous system to the muscles) and the movements of the skeletal systems. Unfortunately, the application of traditional methods to explore this relationship (such as mechanical and statistical rules) lack the satisfaction of some required conditions : for example, in the case of biomechanics, some values cannot be measured (e.g. inner forces can only be estimated).

Nevertheless, the identification of this relationship enable to discern the role of each muscle during a particular movement. This is a particular important problem, e.g. in order to help persons with pathological movements (for example pathological gait) due to a bad synchronization of a particular muscle during the movement.

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. Unfor-

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tunately, all these techniques require important approximations on the EMG signals and/or provide poor simulation results.

We propose here an alternative approach based on artificial dynamic recurrent neural network (DRNN). The goal that we assign to our network is to map the biomechanical transformation : EMG signals to limb position. In particular, the network has to identify the complex relationship between muscle activity and upper-limb dynamics when subjects draw complex movements with the extended arm in free-space.

2. Methods and materials

Right-handed subjects were asked to draw as fast as possible a figure eight with the right extended arm in free-space. The range of duration of the figure eight movement oscillates between 1200 and 1500 ms. 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 (that means about 4000 sampled data points per sequence).

We collected the EMG signals from seven shoulder 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).

3. Architecture and learning algorithm

Some researches [3] propose to use feedforward networks to solve the identification task. Unfortunately, these networks do not include temporal relationships (i.e. parameters at time $t+1$ are a function of what happened at time t). As mentionned in [3], the feedforward models are inadequate for the problem.

As we will see below, DRNN will be able to circumvent the preceding drawback of the feedforward models and will hugely outperform them. The basic structure of the DRNN used in this study consists in an array of several neurons and interconnections between all elements. A new feature of the DRNN model is that it presents two types of adaptative parameters : the classical weights between the units and the time constants associated with each artificial neuron. The time constants hugely increase the dynamical features of the network. Dynamical recurrent neural networks are thus much more adapted to temporal treatment than the classical feedforward ones which are much more adapted to classification tasks. Moreover, they can deal with non-fixpoint learning algorithms and it was proven that these networks are universal approximators of dynamical system [1].

The network has to treat temporal sequences, it follows that the learning equations will be continuous in time and time will appear explicitly.

Dynamic neural networks are governed by the following equations :

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

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

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

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After the introduction of new variables $z_i(t)$, we can derive the learning equations :

$$\frac{\partial E}{\partial w_{ij}} = \frac{1}{T_i} \int_{t_0}^{t_1} y_i . F'(x_j) . z_j \, dt \tag{3}$$

$$\frac{\partial E}{\partial T_i} = \frac{1}{T_i} \int_{t_0}^{t_1} z_i . \frac{dy_i}{dt} \, dt \tag{4}$$

It is important to notice that these equations 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 Pontryaguin Maximum Principle. A thorough presentation of the learning algorithm and a comparison of some acceleration techniques can be found in [2].

4. Training, validation, and results

As outlined above, we develop a network that gives the position (y_x, y_y, y_z) of the wrist versus time thanks to the temporal evolution of the EMG.

All positions y_x, y_y and y_z were normalized between 0.2 and 0.8 to avoid the system to enter the saturation zones of the sigmoid function. Indeed, normalization was required since the activation function used (sigmoid) only yields values between zero and one.

4.1 Validation - Theory of identification

A rigorous validation of a model tends to be an extremely difficult task : a mathematical model can only be validated in a given number of known situations, whereas its purpose is to predict behaviour in unknown situations. It is the classical problem of duality between adjustment and prevision. In fact, no perfect validation is possible; however, we will give below the issue of validity of our network.

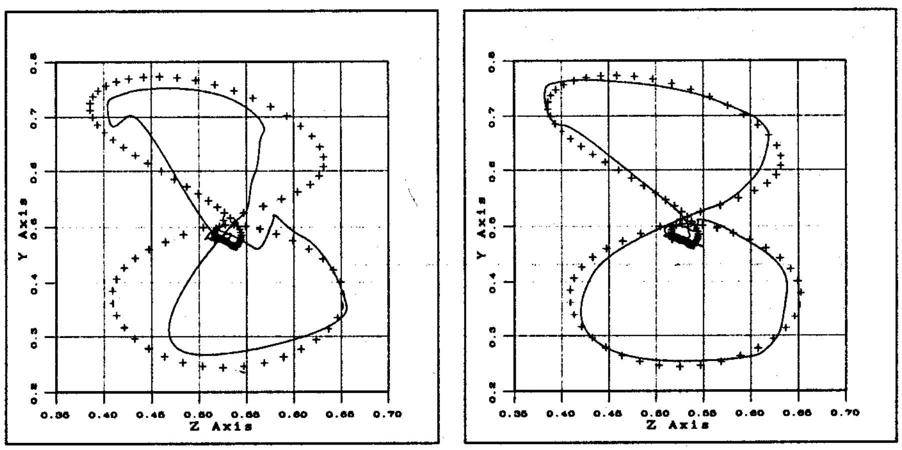
First, we have to distinguish between all the different identification situations the human arm's case. The system is :

- nonlinear : we cannot apply the linearity properties of superposition.
- stationary : we assume that the parameters of the systems remain constant through time.
- deterministic : there is no probabilistic knowledge of the exact state of the system, as in stochastic systems.
- continuous : the system is continuous but we will have to discretize it for the purpose of the computer simulation.
- multi-input, multi-output (MIMO) : several input EMG signals and several position coordinates.

A neural network model can deal with all the above design features of the system. Indeed, nonlinearity will be introduced with the excursions of the activation function (sigmoid) into nonlinear regions. A neural network is by definition multi-input and multi-output, the stationary and deterministic aspects are some of the basic concepts of our model. Continuity is the last feature to be respected. As the network simulation on a digital computer requires a discrete-time model,it is imperative that the discrete-time (DT) model, when derived as a numerical approximation to a continuous-time model, preserves the dynamical features of the continuous-time (CT) model (not only asymptotic attractors and local stabilities but also asymptotic stability of fixpoints). Moreover, we have to keep in mind that numerically, any discretization method of solving ordinary differential equations tends to generate spurious asymptotic points (fixpoints, quasi-periodic points,...) and the resulting difference equations may be less stable than the underlying ordinary differential equation. To be sure that there is a correct analogy between the DT and CT behaviours, our network must respect a criterion known as the *Asymptotic Consistency Criterion* [4].

4.2 Results

The training of the network requires about 8000 to 10,000 epochs (that means an average of 24 hours of continuous running on a SUN 670MP machine). Our results provide ample evidence that a dynamic recurrent neural network algorithm can be used to identify the arm complex dynamics and predict arm trajectories using the muscles EMG signals as inputs (see Figure 1).



(a) (b)

Figure 1: Example of network prediction during the learning process: (a) 5000 iterations after initial randomized weights; and (b) prediction of the trajectory after the tolerance was reached 4500 iterations later. Both figures present the experimental (cross) and predicted values (solid line).

Once the network was trained, we subjected it to perturbations on all the input muscle EMG (see Table 1).

We alter the signal with random perturbations in the range ±20 % on all the input signals. The network exhibits its robustness : the positions varied no more than ±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 strengthen the biologically plausible features of the model : one knows that while

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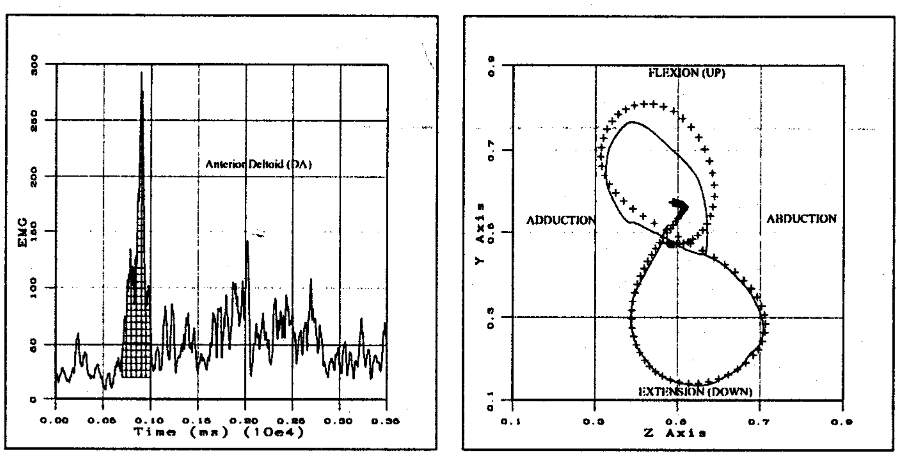
EMG data tend to be quite variable, positions are far more consistent. The perturbation experiments reported in Table 1 provide some more evidence that the model is valid.

Perturbations	*Position y* (mm) Mean	*Position y* (mm) Std Dev.	*Position z* (mm) Mean	*Position z* (mm) Std Dev.
Random noise (in the range ± 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	

Table 1 : Mean absolute differences and standard deviations between the actual and the output predicted by the model for random perturbations on all the muscles' EMG. These values are computed over 50 drawings of the trajectory.

4.3 Automatic identification of the muscles

One of the basic problem of biomechanics is *distribution* (also referred as *redundancy*) : how are the large number of muscle forces distributed over the shoulder joint? We found that our network is able to identify the correlation between EMG and wrist position. If we modify one of the input EMG signal, the resulting trajectory drawn by the network clearly shows that the model has identified the impact of each muscle on the movement.



(a) (b)

Figure 2: Lesion of the anterior deltoid. The trajectories begin towards flexion-abduction direction. (a) shows the burst that we annihilate (filled) and (b) shows the comparison between the normal (cross) and abnormal (solid line) trajectories.

For example, on Figure 2, we suppress the first burst of the EMG signal of the anterior deltoid muscle (AD). This one has its origin at the clavicle and its insertion at the lateral humerus. It has a great role in the abduction-flexion movement of the arm (to move the arm up and towards the external side of the body). Note that the flexion,

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extension, adduction and abduction sides of the subject are shown on Figure 2b. We see that if we annihilate the principal burst occuring during the drawing of the first lobe of the lemniscate, the curve is reshaped following the biomechanical rules of the movement. The model has identified the EMG signal corresponding to the anterior deltoid has a controller of the abduction and flexion movement, a fact that is biologically plausible !

5. Conclusion

In the introduction, we conjecture that artificial neural networks could provide a fruitful method to identify complex temporal systems as the relationship between the electromyography signals and their mechanical actions. The success of the neural computing solution can be judged from the previous results: the network converges to a plausible dynamical behaviour, random perturbations to the EMG input signals lead to similar output predictions and changes to a single muscle EMG give biomechanically plausible trajectories. Moreover, we have also shown that the network can generate unlearned trajectories.

The main interest of the study lies in the insight it gives about the mapping from arm muscle activation states to arm motion. As presented in Section 4.3, 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 also prove that, as opposed to simply replicating training examples, the network can generalize the behaviour of the human arm.

Furthermore, due to their dynamical features and to their abilities, dynamic recurrent neural networks can be applied to several other research fields. We have already successfully used this kind of network to simulate the neural integrator of the human oculomotor system. We are presently studying some other applications of dynamic neural networks in the field of mathematics (such as interpolation tasks i.e., for the forecasting of stock market value) and of engineering (active noise control).

Acknowledgements

This work is supported by the Belgian National Fund for Scientific Research (F.N.R.S.) and by the Research Fund of the University of Brussels (U.L.B.)

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