Combining Neural Tracking and Control to Improve Rehabilitation of Upper Limb Movements in Hemiplegia

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Abstract. This paper aims at introducing a novel approach for assisting and restoring upper arm movements in stroke patients. The presented system integrates advanced markerless motion analysis together with an artificial neural network controller for a biomechanical arm model. The keypoint of the project is to acquire kinematics information from the healthy arm of a stroke patient during planar arm movements and elaborate them in order to obtain a self-rehabilitative stimulation of the plegic arm of the same patient. The first experimental tests show good results and allow to define working direction for the extension of the work and for its application in clinical contexts.

1 Introduction

Rehabilitative practice in stroke patients has strengthened its empirical foundation on the basis of the recent advances in neuroscience methods, which led to deeper understanding of motor control and learning mechanisms [1]. Among them, long-term potentiation (i.e. synapses are able to encode new information to represent a movement skill) has been considered to play a relevant role in restoring functions. A critical element for the success of these mechanisms resides in the repetition of inputs for the motor cortex, which serves as a biological teacher for the neurons acquiring novel skills. This process could easily be implemented through experience and training, which induce physiological and morphological plasticity, by strengthening synaptic connections between neurons encoding more common functions [2]. In this context, the key concept behind rehabilitation is, from a neural network point of view, the repetition of movements in a learning-by-examples paradigm: by repeating movements in either passive or assisted way, the brain is exposed to different examples, and its neurons adapt their connections to the newly presented conditions. In this general context, the Functional Electrical Stimulation (FES) could heavily enhance its role in rehabilitation, since it can be considered as an artificial teacher that allows exploration of the workspace, thus representing a driver for different examples: following this perspective, FES has broken the walls of simple functional substitution [3] to come up to the requirements of rehabilitation, and has been proven as successful both in lower [4] and in upper limb movements [5]. These encouraging findings

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recently brought to the development of FES-assisted rehabilitation programs in hemiplegic patients [6]. Some of the limitations driven by FES in rehabilitation programs reside both in the rather raw and un-physiological control of the stimulation, and in the invasiveness of the approach. While for the latter issue, advancements in technology made it possible to obtain efficient non-invasive stimulators (see e.g. Handmaster [7] and the Bionic Glove [8]), the issue of biological plausibility of stimulation waveforms has not yet been deeply investigated, though some pioneering work has been found in literature [9]. The resolution of the inverse dynamics, i.e. extracting the muscular forces needed to obtain a specific movement from a starting point to a desired endpoint is one of the problems to be solved to efficiently drive the stimulation: to this end, artificial neural networks have been hypothesized as biologically plausible controllers [10], and then shown as efficient in the resolution of the problem [11]. Moreover, if a stand alone system has to be used for an effective self-rehabilitation exercise, one point to be addressed resides in the information regarding starting position and desired endpoint to be provided to the controller. Among the possible sensors that can efficiently gather these data, one can cite goniometers and motion capture systems, being the latter less invasive if no markers are to be applied on the body surface.

Following this perspective, the aim of the current work is to provide a general framework for the integration of three blocks that could constitute a stand-alone self-rehabilitation system: a motion tracking system for the estimation of the desired trajectory obtained from movement of the sound arm, relying on silhouette tracking through a novel markerless motion estimation method; a neural controller for the resolution of the inverse dynamics to obtain the desired stimulation; the stimulator block, that serves as effector to drive the plegic arm. The FES is driven by the integration between a markerless system for tracking movement and a neural network for controlling the muscular stimulations. The overall system to be realised has been named TwinN-FES (Tracking with neural Network-FES). In particular, this work will deal with the first two blocks of the system.

2 Methods

Figure 1 shows a non formal flow diagram of the proposed method, while in the following subparagraphs the first two blocks are described in detail.

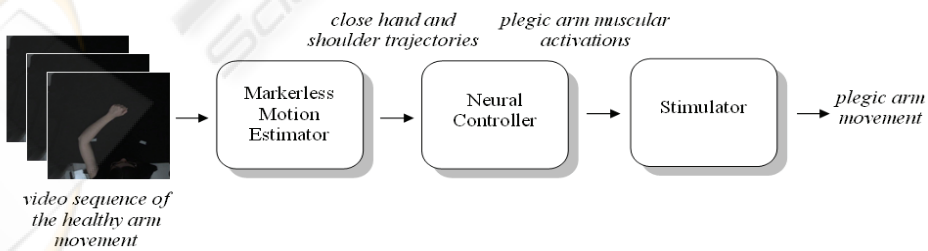

Fig. 1. The proposed method.

2.1 The Markerless Motion Estimation Method

The markerless motion estimation method, proposed to track the upper limb during the execution of planar movements, aims at estimating the movement of the entire arm. The high deformability of human silhouette and consequently the unacceptability of a rigid body approximation are critical problems in markerless motion analysis [12], [13], [14]. In this context, energy-minimising deformable models offer a partial solution. The widely used Active Contour Model, called Snake, is driven by a cost function generated by processing an image. The Snakes [15] are widely used in literature for segmentation and contour detection but they are not applied to track silhouettes subtly changing their shapes during the movement. For this reason they are not successfully applicable for human tracking.

This paper introduces a new deformable model for contour tracing that allows to track a deformable silhouette, i.e. the upper limb movement. The method is based on a closed Snake predicted by an Artificial Neural Network (ANN) and then called Neural Snake. The neural approach is based on a multilayer Perceptron (2 hidden layers with 15 neurons each) trained for snake configuration prediction. The horizontal and vertical components of position, velocity and acceleration of each contour point in the current frame are the ANN inputs (number points x 6), while the output is constituted by the horizontal and vertical components of the position of each contour point in the subsequent frame (number points x 2). The training set is obtained by analysing several ad-hoc video sequences: they are characterised by slow upper limb planar movements with high frame rate on a dark background. Figure 2 shows a flow diagram of the proposed algorithm which extracts the training set from a video sequence.

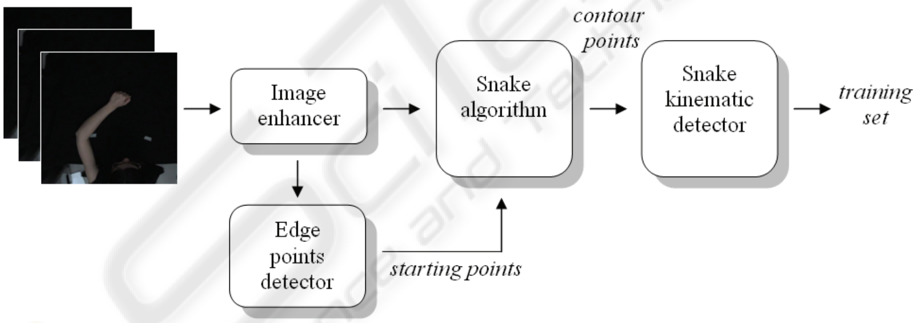

Fig. 2. Graphical representation of the proposed algorithm for the training set achievement.

The frames of the video sequences are analysed first by the image enhancer and edge detector block in order to determine the upper limb edge over time (figure 3). At first the input RGB sequence is converted to greyscale, then the distribution of its histogram is modified by using the VirtualDub program [16]. In particular, the contrast filter (200%) and the sharper filter (maximum) are used. After filtering the image by a two-dimensional median filter (5-by-5 filter window), the arm silhouette is extracted with an edge detection procedure, as reported in Canny [17]. The upper limb edge is then uniformly sub-sampled by choosing an Euclidean distance between consecutive points. The sub-sampling procedure aims at keeping constant over time the number of edge-points (i.e. in figure 3 the number of points is 22).

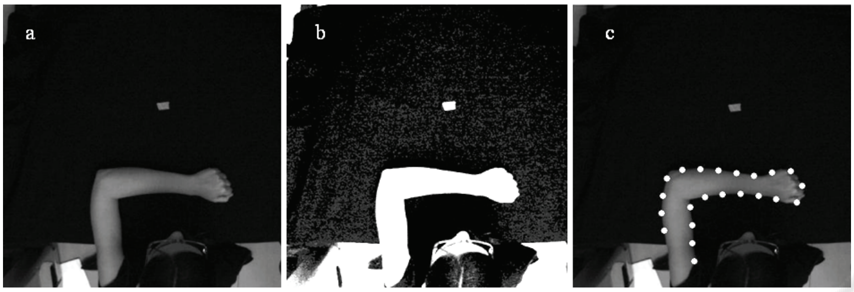

Fig. 3. 66th frame of one of the video sequences used for training the ANN. a) Original frame. b) Frame after the application of the image enhancer. c) Points obtained after the sub-sampled edge detector.

The edge-points are then used as starting points for the Snake algorithm as reported in Kass [15]. Then the obtained horizontal and vertical positions of the contour points are processed in order to obtain their velocities and accelerations over time. These measures generate the training set of the ANN so that its neurons specialise in snake configuration prediction. After training, the ANN is used, frame by frame, to pre-collocate the snake near the silhouette before the application of the traditional snake model (figure 4).

The contour-points positions prediction, obtained through the ANN, is significant especially in case of fast movements (ballistic) or video sequences with low frame rate (i.e. webcams). Therefore, the usage of the trained ANN before the application of the Snake algorithm allows to track the silhouette also in these situations. Since the ANN inputs are constituted by the horizontal and vertical components of position, velocity and acceleration of each contour point, the first three frames of the video sequence are necessary for the initialization phase. In this stage the M starting points are chosen in the first frame and the following two frames are elaborated with the Snake algorithm obtaining the horizontal and vertical positions (P_x and P_y), velocities (v_x and v_y) and accelerations (a_x and a_y). Then, the subsequent i frames ($i=4,\ldots,N$, where N is the total number of frames of the video sequence) are elaborated by applying the Snake algorithm on the output of the ANN (the M predicted contour points P^*_x and P^*_y). The result is the estimation of the silhouette over time. The spatial extremities of the M contour points, obtained by the Neural Snake approach, are then found in order to estimate the close hand and shoulder trajectories. The positions of these joints are in fact the inputs of the second block of the proposed method: the Neural Controller.

2.2 The Proposed Neural Controller of the Upper Limb Model

The second part of the present work concerns the use of the trajectory's parameter information extracted by the Neural Snake algorithm. In order to simulate the activation of the plegic arm, a neural approach for modelling of the motor control of a human arm during planar movements has been used. For this purpose the Neural Snake processing block has been integrated with a second system including a NN with a biomechanical arm model [11].

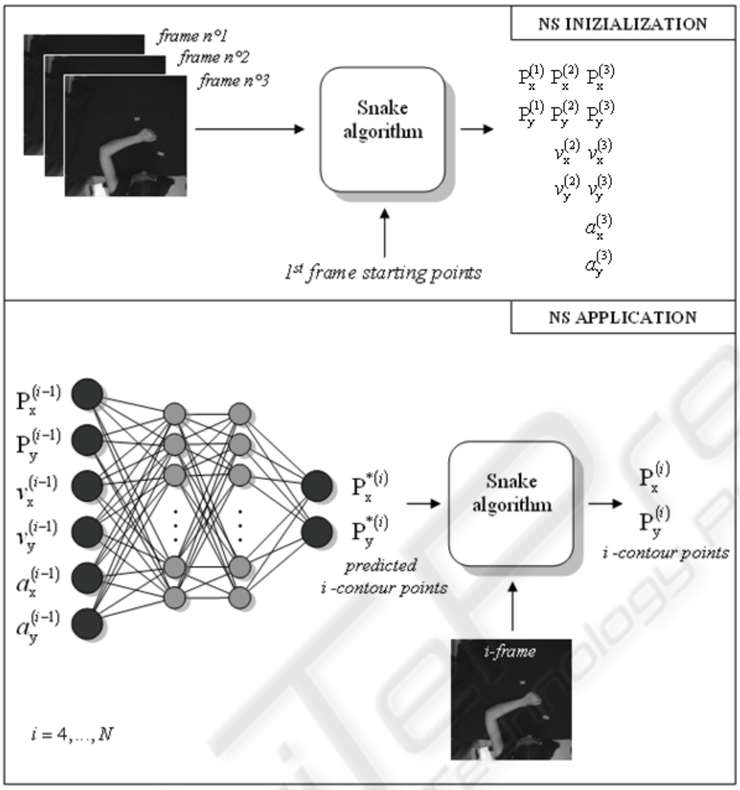

Fig. 4. Graphical representation of the proposed algorithm for upper arm silhouette tracking.

This linked system is based on three main computational blocks (figure 5): 1) a parallel distributed learning scheme that simulates the internal inverse model in the trajectory formation process; 2) the Pulse Generator, which is responsible for the creation of muscular synergies; and 3) the limb model based on two joints (two degrees of freedom) and four muscle-like actuators.

An ANN (a Multi-Layer Perceptron, MLP-ANN with one input layer, one output layer and two internal layers) has been used to represent the first computational block.

This first block represents the inverse internal model of the upper limb. It collects proprioceptive information from the environment, and generates the specific neural inputs necessary to obtain the desired motor task which should be carried out by the arm. The Artificial Neural Network (ANN) can accomplish to this task on the basis of its adaptation and plasticity features. The first layer of the ANN used for this model is composed by 4 input units, representing the spatial information (in joints coordinates) of the starting and the ending points gained by the analysis of the movement of the real arm by means of the Neural Snake algorithm.

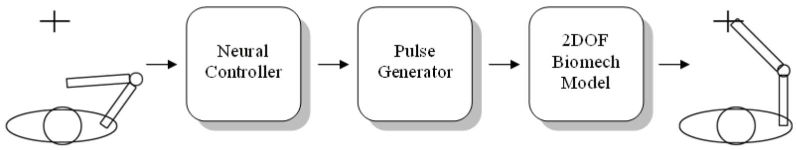

Fig. 5. Graphical representation of the proposed method for neural controller of the upper limb model.

The transfer function chosen for every unit is the hyperbolic tangent: the output n_i^m of the i^{th} neuron at the m^{th} level is obtained from the weighted outputs of the $(m - 1)^{th}$ level, according to equation

$$n_i^m = \frac{2}{1 + e^{-\sum_{j=0}^{N_m} w_j^{m-1} \cdot n_j^{m-1}}} - 1$$

After the elaboration of two hidden layers composed by 20 neurons each, the output layer provides 3 values, passed to the Pulse generator block, which transforms them in the model of the train of the efferent nervous spikes necessary to activate the bio-mechanical arm, thus inducing the generation of the planar movement.

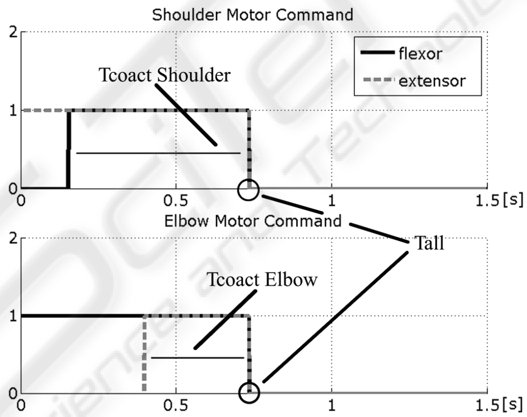

Fig. 6. Neural activations of both the shoulder and the elbow muscle pair. Tall, total time of neural activations, is the same for the two joints; the two Tcoact represent the interval of co-activation of flexor and extensor muscle. The value of 1.5 s is the total observation time.

The third module corresponds to the model of a human upper limb, composed of a skeletal structure together with a muscular structure. The skeletal model has a plant structure composed of two segments (because the close hand joint is not considered), with lengths *L1* and *L2*, which represent the forearm and the upper arm respectively, connected with two rotoidal joint. The planar joints that connect the two segments can assume values in the angular range [*0*, *π*]. These values univocally identify the

Cartesian coordinates of the free end in the working plane by means of well known direct kinematic transformation. The muscular system is thus based on 4 Hill's type muscle-like actuators, and establishes the dynamic relationship between the position of the arm and the torques acting on each single joint [18].

The next figure depicts the profile of these neural activations having rectangular shapes, and shows the duration of the entire voluntary task ranging in the interval 300 ms - 1 s. The three parameters generated by the ANN are: $T_{coact\ shoulder}$, that defines the time of co-contraction between the agonist muscle and the antagonist muscle of the shoulder joint, $T_{coact\ elbow}$, giving the same information for the elbow joint, and *Tall* that specifies the duration of the overall neural activations.

Body segment anthropometrics and inertias of both upper arm and forearm are now taken from the scientific literature, taking into account the specific body height and weight [19], but a key feature of the proposed approach is that an adequate model of the arm of any specific subject can be obtained and used in the Neural Net.

The integration of the Neural Snake and the Neural Controller, that constitute the first two blocks of the proposed stand-alone self-rehabilitation system, has been tested on several experimental trials. The next paragraph describes the obtained results.

3 Experimental Results

The markerless method has been firstly tested on synthetic video sequences in order to evaluate its accuracy in tracking the arm silhouette, and after on a real context. The synthetic videos, obtained with the program Poser®, present one virtual subject executing movements similar to the real ones (that will be described below). Figure 7 depicts the model on which the method has been applied. A first video sequence, with an high temporal resolution (60 fps) has been created as the training set for the snake predictor ANN. Subsequently the proposed method has been tested on six different videos, each one having a particular value of Gaussian noise (mean = 0, and variable variance) added to it, and a temporal resolution of 30 fps. In literature results of the application of contour detection algorithms are usually presented in a qualitative way [15], [20]. In the present work the use of these synthetic videos makes it possible to achieve quantitative results in terms of RMSE. Figure 8 shows the RMSE value for each video sequence. The values obtained with the test carried out on synthetic videos allow us to extend the application of the markerless technique to video sequences, where real subjects are filmed by means of digital cameras.

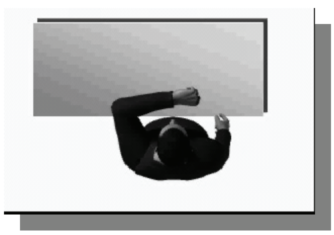

Fig. 7. Upper view of the synthetic model used to test the proposed tracking system.

The tests have been done by recruiting 2 healthy subjects. During tests, the subject sits on a chair in front of a desk whose height is the same of the subject's armpit. In this way the upper limb movements on the desk are planar. The subject's trunk is close to the desk border.

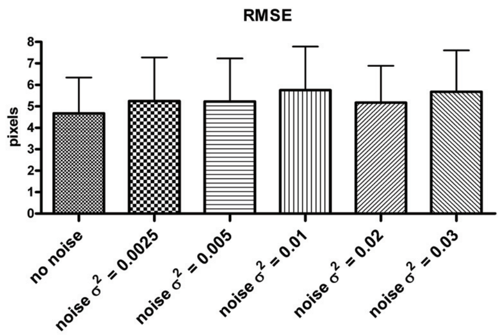

Fig. 8. RMSE values obtained from the analysis of the synthetic video sequences using the tracking system. Pixel/cm ratio is 2.7. This means that the mean error value is less than 3 cm.

Three target points are set on the table surface and a digital video camera (Silicon Imaging MegaCameras SI-3300RGB) records movements from an upper view. The experimental protocol consists of a series of 3 fast reaching movements executed with the left arm towards three different targets considering the centre of the closed hand as the end-effector. The video sequence used for training the Snake predictor ANN has been acquired with the temporal resolution of 60 frame/s. The proposed Neural Snake technique has been applied on two video sequences acquired with the 30 frame/s sampling rate. The spatial resolution of the frames is 1024x1020 pixels. The pixel/cm ratio is 13.5. Figure 9 shows the experimental setup.
The Neural Snake method has been applied on the video sequences and the close hand and shoulder positions have been estimated over time. Figure 9 shows the results of the proposed silhouette detector and the obtained trajectories on the last frame of the video sequence. The Cartesian coordinates of the three targets reached by the subject's arm are evaluated considering the shoulder as the centre of the reference system. The new positions values are subsequently sagittally mirrored and passed to the right arm Neural controller. For each pair of starting and target points of the three trajectories, the motor control simulator generates the neural excitations that permit the biomechanical right arm model to execute a movement similar to the one experimentally acquired (figure 10).

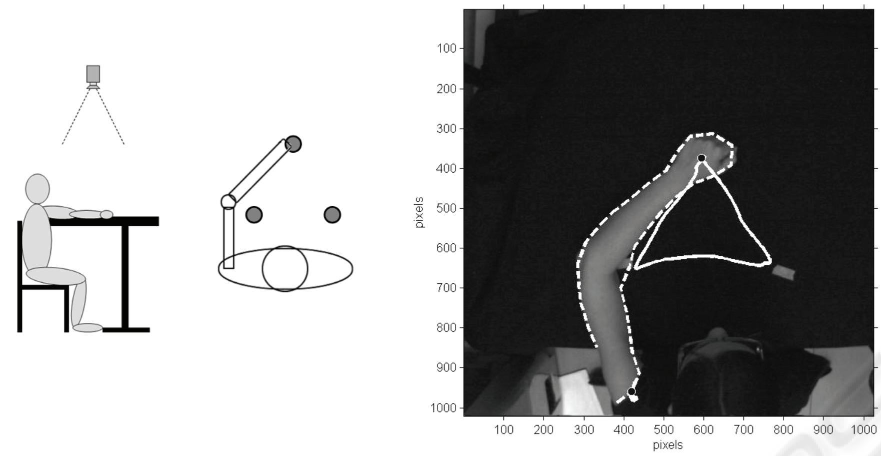

Fig. 9. On the left , experimental setup; on the right, upper limb Neural Snake (dot line) and close hand and shoulder trajectories (solid line) on the last frame of the video sequence.

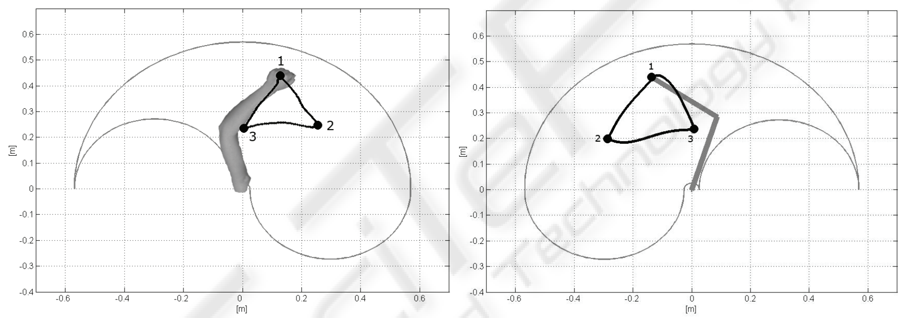

Fig. 10. Solid close hand trajectory (left) and the output of the Neural Controller: “plegic” arm trajectory (right).

4 Conclusions

A new method finalised to the self-rehabilitation of the arm movements of hemiplegic patients has been presented. The overall system is composed by three main blocks. The first one is dedicated to the markerless analysis of the healthy arm during planar movements and the extraction of kinematics parameters. In the second block a neural controller makes use of these information in order to generate specific outputs necessary to pilot a biomechanical arm model. First experimental results are particularly encouraging: in the future the outputs gained by the neural controller will be used for generating the electrical stimuli of the FES system which represents the third block of the proposed approach, called TwinN-FES.

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