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NEUROCOMPUTING

Artificial neural networks for feedback control of a human elbow hydraulic prosthesis

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ARTICLE INFO

Article history:
Received 2 January 2013
Received in revised form
8 April 2013
Accepted 11 May 2013
Communicated by D.-S. Huang

Keywords:
Human prosthesis
Forward kinematics
Artificial neural networks
Simulation
Control
Parallel mechanism

ABSTRACT

The paper addresses feedback control of actuated prostheses based on the Stewart platform parallel mechanism. In such a problem it is essential to apply a feasible numerical method to determine in real time the solution of the forward kinematics, which is highly nonlinear and characterized by analytical indetermination. In this paper, the forward kinematics problem for a human elbow hydraulic prosthesis developed by the research group of Polytechnic of Bari is solved using artificial neural networks as an effective and simple method to obtain in real time the solution of the problem while limiting the computational effort. We show the effectiveness of the technique by designing a PID controller that governs the arm motion thanks to the provided neural computation of the forward kinematics.

1. Introduction

The topic of actuated prostheses for human use is nowadays one of the most important branches of bio-robotics. The goal of giving back to amputees the possibility to carry out daily activities on their own represents a fascinating challenge for both medical and engineering researchers. The first studies about this topic started with the so-called “Utah Arm” (Late 70's, University of Utah), that was the first artificial limb able to decode myoelectric signals coming from nerves and still represents, in its latest version, one of the most diffused and commercially available architectures [27].

Nowadays, several solutions are available in the related literature to model and simulate the work of articulations in limb prostheses: the choices of research groups from all over the world concern both the mechanisms typology and energy supply. Two useful examples are the serial gas-actuated arm by Fite et al. [5] and the parallel architecture by Mendoza-Vázquez et al. [26], equipped with linear electrical actuators. The research group of the Polytechnic of Bari (Italy) developed a parallel simplified “Stewart platform like” mechanism [6], with a wire transmission that links the floating platform to three hydraulic cylinders. The device uses two cylindrical elementary hinges to connect forearm and arm, and three hydraulic actuators placed on the upper arm to reduce moving masses. These actuators are classified into two main ones (frontally placed) and a secondary one (placed in the rear of the prosthesis). Each frontal actuator is linked with two wires, one towards the front forearm and the other towards the rear part of the forearm. These two actuators are in charge of the positioning of the floating platform, connected to the forearm. The rear piston brings a pulley that forces another wire connected with the forearm.

This particular parallel geometry is characterized by the analytical indetermination of the forward kinematics problem, in spite of the solution of the inverse one. Indeed, the configuration required to the linear actuators for each position of the floating platform, and consequently their law of motion, is easily obtained analytically using rotation matrices with the required orientation angles. However, it is not possible to univocally determine the configuration of the mobile platform starting from the actuators' elongations. In fact, the forward kinematics problem of the Stewart platform consists in finding the position of the moving platform for a given set of limbs (connecting wires) lengths. The problem is to find the angular coordinates of the elbow prosthesis knowing the elongations of the rods of the hydraulic cylinders. The formulation of closure relations generates highly non-linear

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http://dx.doi.org/10.1016/j.neucom.2013.05.066
0925-2312

equations with multiple solutions [17]. Hence, in the literature different numerical methods have been studied to determine in real time the solution of the forward kinematics problem for parallel mechanisms such as the Stewart platform. Many contributions provide a solution to the forward kinematics problem based on numerical iterative schemes, such as the Newton–Raphson method, closed-form solutions, or approaches based on predictors. Innocenti and Parenti Castelli [21] proposed the formulation of a "closure equation" to solve the problem iteratively. This approach was further employed in [8,20,22,28,24,25,29,18,30] with different approximations and iterations. Moreover, Wen and Liang [31] provided the closed-form solutions for the general planar Stewart platform. Further contributions in this direction may be found in [4,19]. However, these methods are numerical, not strict closed-form methods.

In this paper, the problem is solved using artificial neural networks as an effective and simple method to obtain in real time the solution of the forward kinematics problem while limiting the computational effort. The proposed approach is applied to the hydraulic prosthesis developed by the research group of the Polytechnic of Bari [6] and we show the effectiveness of the method by designing a PID closed loop controller that effectively governs the arm motion thanks to the provided neural computation of the forward kinematics.

In the context of neural approaches, the first contribution was proposed by Lee and Han [23] who developed a technique based on linear predictors, where gains of each predictor are calculated by a neural network. Moreover, Geng and Haynes [7] used an innovative approach with neural networks with a relative error of few percents. In this paper we improve this result, achieving a better performance. More specifically, dealing with a particular Stewart-like parallel platform, we take a general way to solve the problem that can be extended to more general cases of multi-input–multi-output systems. In particular, the specificity of our system, featuring a joint in the center that is the prosthesis elbow, leads us to search for a suitable method to solve the forward kinematics problem. In fact, the system topology specificity lies in the fact that two hydraulic linear actuators govern, by some connecting rods, both the elbow motion (that is obtained by imposing suitable identical elongations to the pistons) and the wrist motion (that is obtained by imposing opposite motions to the pistons). Thus, the system features a complexity due to the simultaneous motion of elbow and wrist. Hence, we adopted a parallel mechanical structure that leads to equally partitioning the actuator effort between the two pistons, which operate concurrently. Such an energetic optimization, obtained by means of the Stewart platform, leads to a complex kinematics of the component. Using a modified platform also led to a simple determination of the component inverse kinematics, thus leading to a straightforward neural networks training. In fact, a neural approach was also proposed by Dehghani et al. [3] using a three layers network, while we employ a single layer one, with optimal performance and without unnecessary complications.

Summing up, the proposed solution leads to several advantages, namely:

1. the use of identical actuators working in parallel and not in series (which would lead to different actuators because of the different ranges of the kinematics variables);
2. a prosthesis behavior that is similar to that of the human limbs thanks to the double effect pistons, which can be assimilated to the bicep-quadricep group;
3. a suitable system robustness in the employment of oleo dynamics pistons (thus theoretically immovable after being elongated);
4. a limited computational complexity thanks to the artificial neural network use;
5. a more rapid response in simulation with respect to a numerical algorithm for determining the inverse kinematics, at the cost of a longer network training phase, which may however be carried out offline, disregarding time constraints; and
6. the ability to reconfigure the system according to the changes in its structure with a low computational effort (namely, by simply re-training the neural network on a new example set).

The remainder of the paper is organized as follows. Section 2 positions the paper in the related literature, discussing its contribution. In addition, Section 3 describes in detail the innovative elbow prosthetic device. Hence, the subsequent section describes the model of such a device and Section 4 addresses the solution of the forward kinematics problem by artificial neural networks. In addition, Section 4 develops a closed loop controller of the device. The paper ends with a concluding section and an up to date reference list.

2. The elbow prosthetic device

The architecture of the hydraulic prosthesis developed by the research group of Polytechnic of Bari is schematized in Fig. 1. The prosthesis concept is based on the replica of human articulations: the mechanism implements a cable transmission in order to mimic human body tendons and is based on a parallel mechanism, with the aim of maintaining coupled movements of flexion/extension and pronation/supination, so as to optimize the actuators' power consumption. In Fig. 1 a 3D kinematics scheme of the mechanism is shown: the upper and lower hinges allow respectively the flexion/extension and the pronation/supination movements. The two wished forearm Degrees Of Freedom (DOFs) are directly actuated by the coordinated motion of two hydraulic double effect cylinders. One more (rear) cylinder is equipped, as shown in Fig. 1, with a collaborative function during flexion movements. In this paper the device is considered actuated just by the two principal cylinders. A tendon-based transmission is set, to transmit the motion to the platform, to give stiffness to the mechanism in all directions during motion, and to take advantage of the third cylinder, as described in [6] in more detail.

The device is based on a parallel mechanism, in which the motion along the required DOF is obtained acting on the lengths of the links L_1 and L_2, that connect points B_1–P_1 and B_2–P_2 (see Fig. 2).

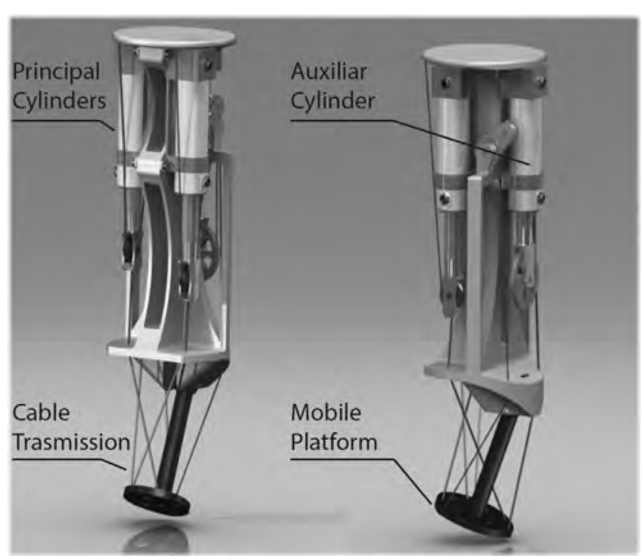

Fig. 1. 3D Scheme of the elbow prosthesis developed by the research group of Polytechnic of Bari (front and rear view).

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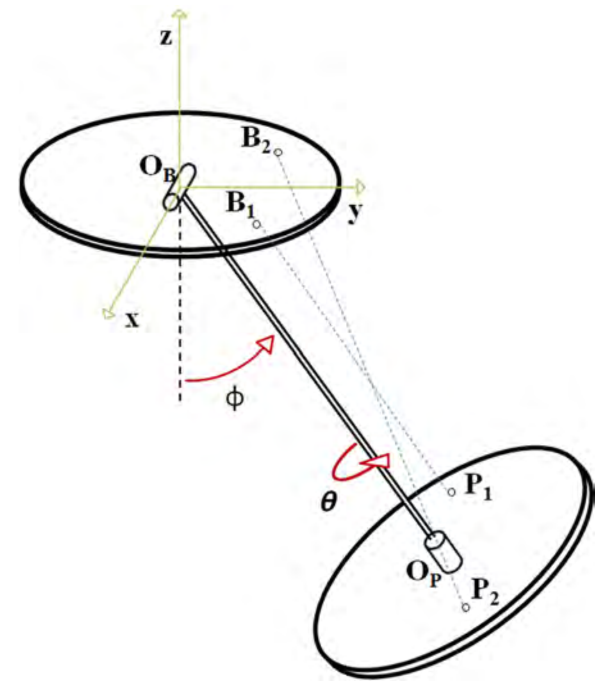

Fig. 2. The 3D kinematics scheme of the parallel mechanism of the actuated hydraulic prosthesis.

These points $B_{1/2}$ are connected to the fixed base that is the terminal part of the humerus of the arm, whereas points $P_{1/2}$ are a part of the floating platform that is connected to the forearm. The orientation of the floating platform toward the fixed frame is ruled by the 3×3 rotation matrix:

$$\mathbf{R}_{\varphi,\theta} = \begin{bmatrix} \cos[\theta] & -\sin[\theta] & 0 \\ \sin[\theta]\cos[\phi] & \cos[\theta]\cos[\phi] & -\sin[\phi] \\ \sin[\theta]\sin[\phi] & \cos[\theta]\sin[\phi] & \cos[\phi] \end{bmatrix} \quad (1)$$

where the range of motion of the two DOFs is $\theta \in [-70°, 70°]$, corresponding to the pronation/supination, and $\varphi \in [0°, 90°]$, for the flexion/extension.

The inverse kinematics of the device is described by the relations

$$l_1 = f_1(\varphi, \theta), \ l_2 = f_2(\varphi, \theta) \quad (2)$$

and may be analytically obtained by the matrix equation:

$$\mathbf{Links} = \mathbf{R}_{\varphi,\theta}\mathbf{Plat} - \mathbf{Base}. \quad (3)$$

In Eq. (3) the 3×2 matrix **Links** represents the components of l_1 and l_2, i.e., the cylinders rods elongations variables that rule the motion of the floating platform along the two DOFs. Moreover, the 3×2 **Plat** and **Base** matrices respectively represent the coordinates of the mobile platform and of the fixed upper base. So, the nonlinear equations coming out from Eq. (3) represent the relations between the anterior cylinders rods elongations and the two forearm rotations are plotted in Fig. 3a and b. As already stated, it is not possible to analytically determine the forward kinematic problem, which consists in the inversion of the relations (2) in order to get the relations:

$$\varphi = f_3(l_1, l_2), \theta = f_4(l_1, l_2). \quad (4)$$

The implemented neural network, subject of the present work, is suited to overcome this indetermination, in order to simulate the dynamics of the prosthetic device.

In order to design a controller able to handle the prosthesis, a correct model of the device is essential. Moreover, such a model must provide quick results in simulation in order to be useful to appreciate in real time the dynamical behavior of the entire system. Hence, the next section addresses the issue of modeling the prosthesis described in this section.

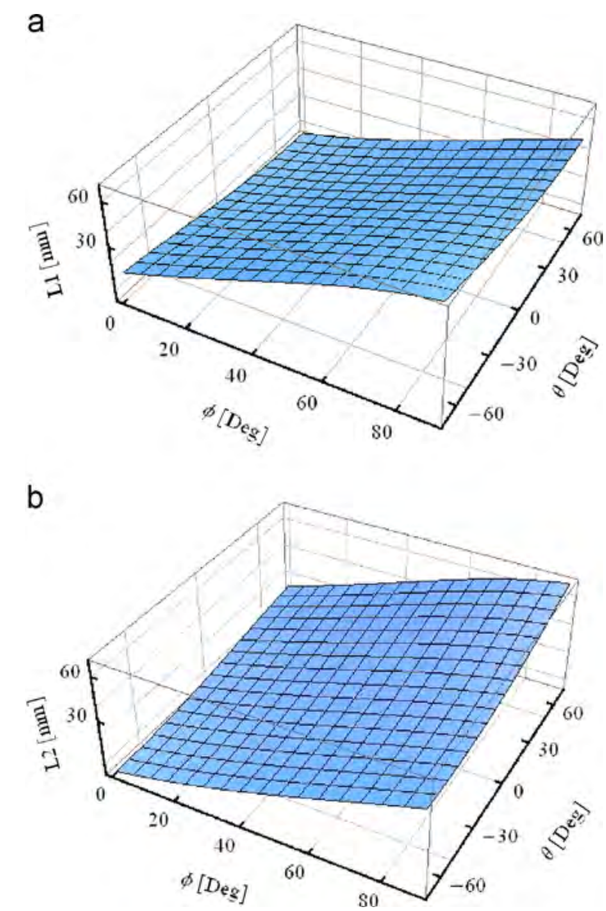

Fig. 3. The nonlinear relations between the two front cylinders rods elongations (left (a) and right (b)) and the forearm rotations of the hydraulic prosthetic device.

3. The controlled elbow prosthetic device model

The controlled prosthetic device model is composed of three fundamental blocks (see Fig. 4a): the references block, the control system block, and the plant block. Feedback is used to compare the output values of the two forearm rotations with the current input values and use the resulting error to define the control action.

In particular, the reference block provides the target values θ^* and φ^* that the closed loop system has to reach. In this block the signal containing the current value of the angles in output of the system is fed back. Since the actuation is provided by managing the elongations of the hydraulic pistons, the control system block in Fig. 4a performs a conversion of variables so as to produce in output the error relative to the elongations, evaluated as the difference between the reference signal and the feedback:

$$errorl_1 = l_1 - l_1^* \ \text{and} \ errorl_2 = l_2 - l_2^* \quad (5)$$

where l_1 and l_2 are the two elongations calculated from the value of the angles taken out of the system while l_1^* and l_2^* represent their reference values. This block produces as output the error signals called errorl_1 and errorl_2 which constitute the inputs of the control system block.

The control block includes two PID controllers, each associated to an error signal, i.e., to a hydraulic piston. This block controls the duty cycle of two electronic PWM (Pulse Width Modulation)

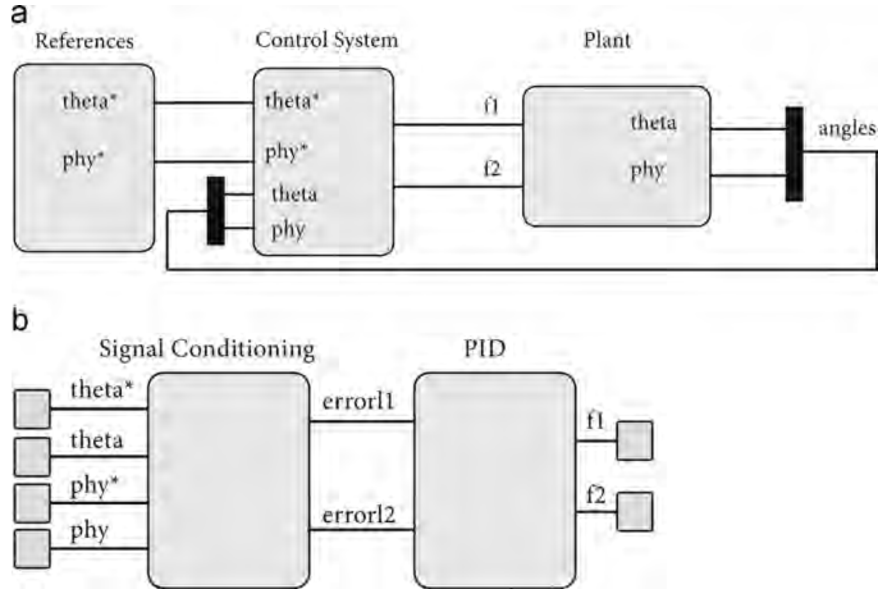

Fig. 4. A scheme of the controlled hydraulic prosthesis system (a) and of the control system block configuration with the errors and duty cycle signals (b).

valves controlling the oil flow rates of the two hydraulic pistons, so as to govern their elongations. Hence, the input variables of the plant of the physical model are the duty cycles f_1 and f_2 of two PWM valves. The control system block in Fig. 4a is represented in an extended form in Fig. 4b. So, to complete the mechanical model, in addition to the relations relative to the inverse kinematics, it is necessary to introduce the equations relative to the oil flow rate and its effect on the dynamic behavior through the hydraulic cylinders. For what concerns the valves, the usual relationship between flow rate and pressure losses is considered

$$Q^* = fK_v\sqrt{\Delta p} \tag{6}$$

where Q^* is the flow rate filling a cylinder, partialized by $f \in [0,1]$, that corresponds here to the duty cycle of a PWM valve, and K_v represents the flow coefficient of the valve. The same flow rate moves the rod of a hydraulic cylinder, so it can be expressed also as

$$Q^* = Av \tag{7}$$

being A the rod surface on which the fluid is acting and v the velocity of the rod.

Implementing a double PWM valve, one for each cylinder, the duty cycle value may be positive or negative in our formulation, depending on which chamber of the cylinder is being filled. With this approach, we can directly link the rod velocity sign (so, the direction of the movement) with the action on the valve. Hence, the considered rod surface depends on the direction of the movement, i.e., on the sign given to the variable associated to duty cycle. As a consequence, in the controlled prosthesis model the vector representing the stem velocities (v_1,v_2) is proportional to the instantaneous maximum available volumetric flow rate (Q_1,Q_2), suitably weighted by the duty cycle (f_1,f_2), by means of the piston area (A_{inf} and A_{sup}):

$$\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \frac{1}{A}\begin{bmatrix} f_1 Q_1 \\ f_2 Q_2 \end{bmatrix} \quad \text{with} \quad A = \begin{cases} A_{\mathrm{inf}} & f<0 \\ A_{\mathrm{sup}} & f>0 \end{cases} \tag{8}$$

Thanks to our formulation, which uses the same equation for each cylinder regardless of the chamber that is currently being filled, we can consider just one filling flow rate value for both movement directions of each piston. The two available volumetric flow rates may be expressed as a function of the pressure in the cylinder chamber that is filled (supposed the one with the highest pressure value) and the external pressure (p_{ext}) as follows:

$$\begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} = k\begin{bmatrix} \sqrt{p_{\mathrm{ext}} - \max(p_{\mathrm{inf1}}, p_{\mathrm{sup1}})} \\ \sqrt{p_{\mathrm{ext}} - \max(p_{\mathrm{inf2}}, p_{\mathrm{sup2}})} \end{bmatrix} \tag{9}$$

It is noteworthy that the dynamic balance of the rods of the two cylinders may be expressed as follows:

$$\begin{bmatrix} p_{\mathrm{sup1}}\,A_{\mathrm{sup}} - p_{\mathrm{inf1}}\,A_{\mathrm{inf}} - cv_1 + F_1 \\ p_{\mathrm{sup2}}\,A_{\mathrm{sup}} - p_{\mathrm{inf2}}\,A_{\mathrm{inf}} - cv_2 + F_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{10}$$

where the two forces F_1 and F_2 are the resultant forces of the system inertia and the applied load expressed as a function of the two arm rotations and their velocity and acceleration.

The presented model is implemented in the MATLAB Simulink environment. However, as previously discussed, the inversion of the forward kinematics problem leads to complex and nonlinear equations defining elongations (2). Hence, in the subsequent section we show how to design an artificial neural network in order to effectively and efficiently compute such an inversion, while keeping a good precision in order to avoid errors propagating through the feedback loop that would worsen the control action.

4. Solving the kinematics problem by neural networks

4.1. The ANN solution to the forward kinematics calculation

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way in which the biological nervous system processes information: ANN have been extensively used to model complex input/output relations for diverse aims, such as classification, control, optimization, estimation, in numerous applications fields, such as the medical, robotic, manufacturing, transportation, financial sectors and many more [1,2,9,11–16]. The key element of the ANN paradigm is the structure of the information processing system, which is composed of a large number of highly interconnected processing elements (neurons) that cooperate to solve specific problems. All connections among neurons are characterized by numerical values (weights) that are updated during the training.

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The computation performed by the ith neuron can be expressed as a nonlinear function of the weighted sum of the neuron outputs connected to the ith neuron.

The ANN is trained by a supervised learning process: in the training phase the network processes all the input–output pairs presented by the user, learning how to associate a particular input to a specific output and trying to extend the acquired information also to cases that do not belong to the training set spectrum. Typically, the ANN input dataset is subject to preprocessing. One such method is the normalization of variables so as to have a uniform distribution, with data that are normalized in the [0–1] range. Another type of preprocessing is the Gaussian distribution with zero mean and unit variance. Both methodologies are equivalent for the study presented in this paper.

In this paper ANN are used to invert the two non-linear algebraic functions that represent the elongations of the two pistons each as a function of the two forearm rotations by (2). Using these two relations we obtain all the values of elongations l_1 and l_2 with respect to the angles θ and φ: as a result, the ANN is used for solving the kinematics problem. Indeed, in the system model the variation of the elongations of the pistons are continuous, hence it is essential for the proper functioning of the prosthesis model that the ANN features a good generalization propriety, as well as the associative propriety. In other words, the ANN purpose is to obtain the inverse relation, so as to have the possibility of obtaining values of θ and φ from the network, by entering as an input the values of the elongations of the pistons l_1 and l_2.

The ANN simulation block is integrated into the plant block as shown in Fig. 5.

The first step for implementing the ANN is deciding which type of network is suitable for solving the problem. Hence, the ANN topology, layers number, neurons number in each layer, neurons transfer function, and training algorithm have to be selected.

After testing different kinds of solutions, we picked a two-layer, error back-propagation ANN. In particular, we chose error back-propagation since it tends to provide good responses when processing inputs that it has never processed before [9]. In fact, a new input will lead to an output that is similar to the correct input used in training similar to the one presented to the network.

Obviously, the network generalizes the solution, so we can train it using a representative set of input and target pairs, still getting good results without training the network with all possible input–output pairs. We used a vector of inputs and outputs uniformly distributed over the working range of the prosthesis, to have the best generalization performance.

To design the network we use the MATLAB neural network toolbox. The output layer contains 2 neurons, one for each DOF of the prosthesis, and each neuron uses the *purelin* transfer function of the neural network toolbox, because its output can be any value in the range $[-5, 69.98]$.

The hidden layer uses the *tansig* function of the neural network toolbox, because after trying it in comparison with other functions, it was shown that it achieves better performance.

For the training phase, we used an input data set of 12,831 elements, randomly divided into 3 subsets: the training set, containing 60% of the whole data-set, and the validation set and the test set, each containing 20% of the whole data set in their turn.

The bias learning function is *learngdm*, and the performance function is *mse*, the normalized mean squared error function (where *learngdm* and *mse* refer to the used neural network toolbox).

We start testing two different topologies: the feed forward back-propagation and the cascade forward back-propagation network [9–11]. In the first topology (see Fig. 6) the first layer weights the network input and each subsequent layer only weights the output of the previous layer. On the contrary, in the cascade forward topology (see Fig. 7) the first layer is the same as in the feed forward back-propagation one, while each subsequent layer weights both the network input and the output of all the previous layers. This topology has been demonstrated to be faster than the first type [9,15]. Both ANN topologies have the last layer as the network output.

The ranges of the outputs θ and φ are respectively $[-70^\circ, 70^\circ]$ and $[0^\circ, 90^\circ]$. Since the mechanical system has a low sensitivity, it was possible to construct the input vectors in steps of 1° and calculate the vector of the pistons elongations from the algebraic relations. This vector is the input vector of the ANN while the vector containing all possible combinations of the angles θ and φ is the target vector. The size of these two vectors is two rows and 12,831 columns.

Together with the ANN topology, we test the effects of preprocessing on the chosen topology and on the number of neurons necessary in the hidden layer. In order to choose the best topology and preprocessing combination, we consider 20 trainings

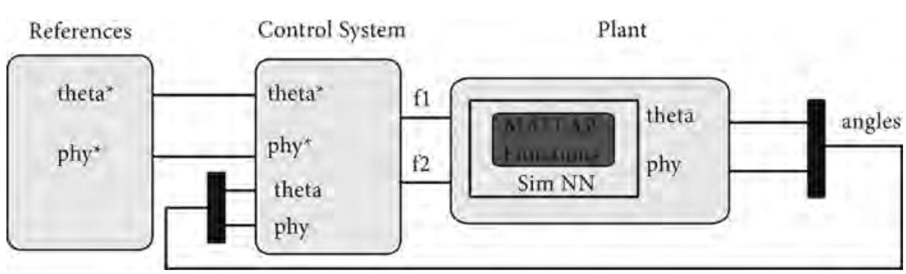

Fig. 5. A scheme of the controlled hydraulic prosthesis system with the ANN block integrated into the system plant.

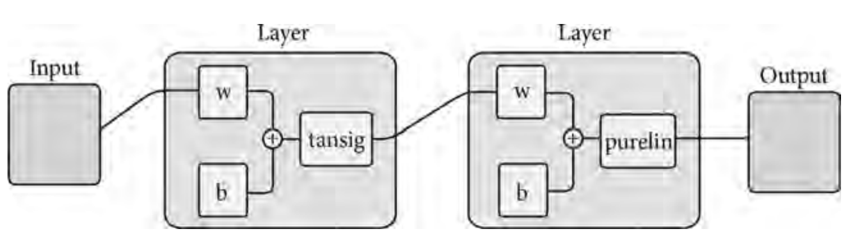

Fig. 6. Feed forward back-propagation network.

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of the two types of ANN by considering three preprocessing conditions in each case:

1. no preprocessing;
2. preprocessing such that the input vector is characterized by zero average and unitary standard deviation (zscore); and
3. normalization in the $[-1, 1]$ range of the input vector (mapminmax).

Such data elaborations are correspondingly applied also to the output vector (post-processing).

Table 1 shows the performance, measured in terms of mean and variance of number of epochs and mean of the mean square error (mse), of different 10 neurons ANN. The table shows that the difference in preprocessing can be disregarded with respect to precision (see the last row of the table, featuring similar values), while it affects significantly the number of epochs necessary for the training. Hence, while the ANN is robust from the precision point of view, the considerable variation in the (high) number of required epochs clearly indicates the necessity of preprocessing.

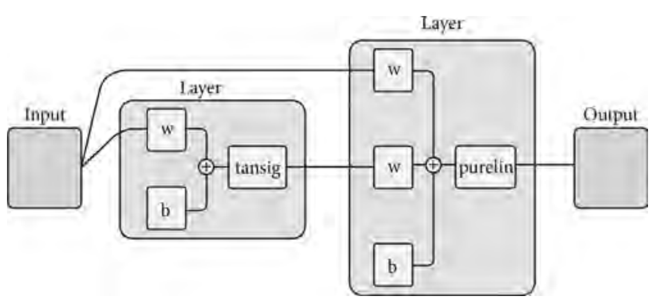

Fig. 7. Cascade forward back-propagation network.

On the other hand, it is important to remark that the high value of maximum number of epochs indicates that the number of neurons in the hidden layer is too low.

Hence, Table 2 shows the ANN performance as in Table 1 but with an enhanced number of neurons in the hidden layer, namely 30. The table shows on the one hand that the number of epochs is reduced by an order of magnitude with comparable results in all cases, showing the robustness of the approach. On the other hand, the obtained precision (last row of the table) is also increased of an order of magnitude on average with respect to the corresponding results in Table 1.

As a consequence, we choose a cascade forward network with a zscore preprocessing (second last column in Table 2) since this combination provides good results both in terms of low number of epochs necessary for the network training which indicates a good convergence and a smallest mean square error (mse), thus leading to a satisfactory compromise between performance and training time. Indeed, it is preferred to maximize precision in this design phase so as to be able to deal with uncertainty and the resulting loss in performance typically arising in the real system construction phase. We also remark that a further increase in the number of neurons does not correspond to a significant increase in performance but rather to a tendency to the overfitting behavior, which is a well known problem in ANN [9]. We do not report the corresponding tests for the sake of brevity: in particular, as we increase the epochs number, in such tests we observe a specialization of the ANN with respect to the training data, i.e., in the tests the network outputs are optimal only when the corresponding inputs are in the training set, otherwise outputs are affected by a significant error.

Having chosen the ANN topology detailed in the second last column of Table 2, we report in Table 3 the performance of the chosen ANN, corresponding to 108 epochs and a mean square

Table 1
Performance of 20 tested ANN with 10 neurons in the hidden layer.

Type	**Feed forward**	**Feed forward**	**Cascade forward**	**Cascade forward**	**Feed forward**
Output layer function	*purelin*	*purelin*	*purelin*	*purelin*	*purelin*
Hidden layer function	*tansig*	*tansig*	*tansig*	*tansig*	*tansig*
Neurons number	10	10	10	10	10
Preprocessing function	zscore	mapminmax	mapminmax	zscore	–
Mean epochs number	638	703	601	761	908
Variance epochs	1.232e+5	1.036e+5	1.338e+5	1.031e+5	4.274e+4
Mean mse error	1.428e−5	1.654e−5	1.282e−5	1.023e−5	1.53e−5

Table 2
Performance of 20 tested ANN with 30 neurons in the hidden layer.

Type	**Feed forward**	**Feed forward**	**Cascade forward**	**Cascade forward**	**Feed forward**
Output layer function	*purelin*	*purelin*	*purelin*	*purelin*	*purelin*
Hidden layer function	*tansig*	*tansig*	*tansig*	*tansig*	*tansig*
Neurons number	30	30	30	30	30
Preprocessing function	zscore	mapminmax	mapminmax	zscore	–
Mean epochs number	150	182	140	84	260
Variance epochs	3.859e+3	1.303e+4	1.622e+4	1.501e+3	6.262e+3
Mean mse error	1.428e−6	1.306e−6	1.259e−6	1.288e−6	9.921e−7

Table 3
Parameters and performance of the selected neural network.

Type	**Training function**	**Output layer function**	**Hidden layer function**	**Neurons number**	**Epochs number**	**Preprocessing function**	**Mean square error**
Cascade forward	Levenberg Marquardt	*purelin*	*tansig*	30	108	*zscore*	9.99e−7

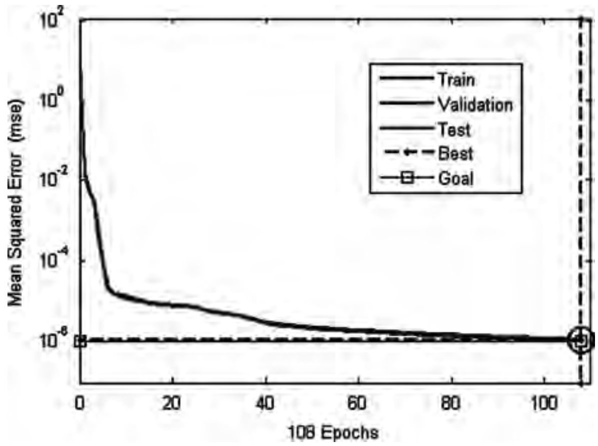

Fig. 8. Performance plot of the selected ANN: mean square error versus number of epochs.

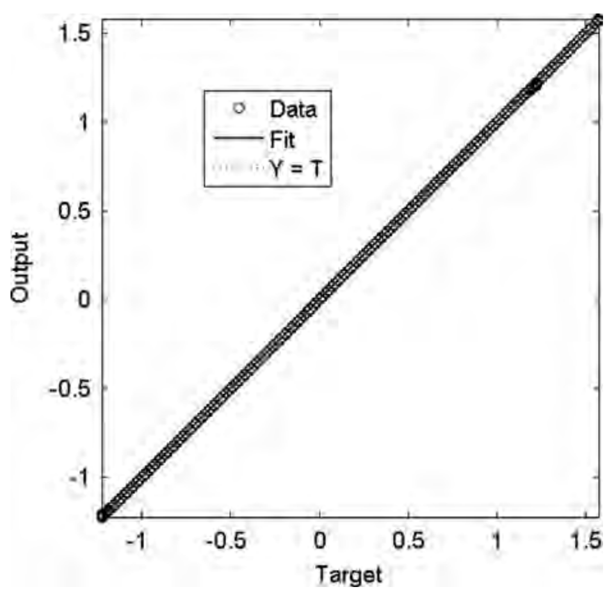

Fig. 9. Regression plot of the selected ANN target and outputs.

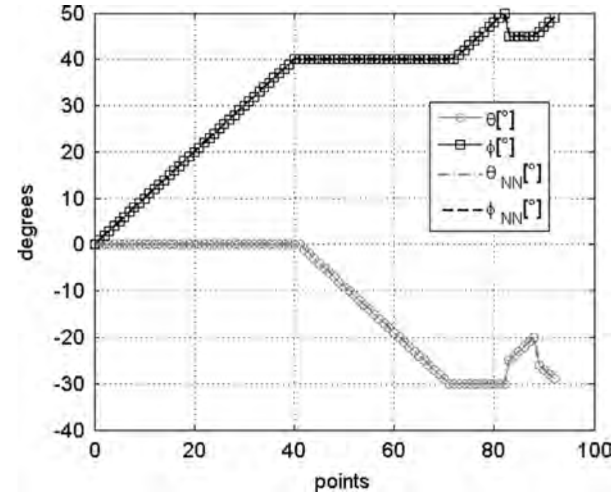

Fig. 10. Comparison of the ANN outputs with the exact inversion values.

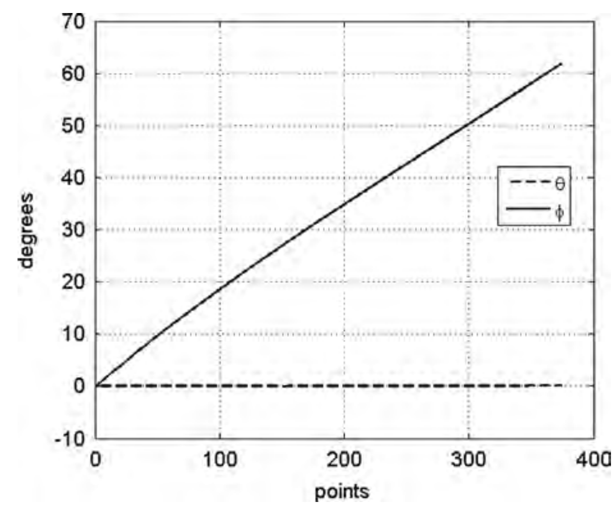

Fig. 11. Generalization test of the ANN.

error performance equaling 9.99e−7. Figs. 8 and 9 respectively report the mean square error variation with the number of epochs and the ANN regression plot: the solid line represents the best fit linear regression line between outputs and targets and the fact that all data are practically aligned on this plot confirms the extremely good fit of the training data.

4.2. The ANN test results

In this subsection we test the ANN effectiveness. In particular, Fig. 10 compares the network outputs (indicated by θNN and φNN) with the actual values of the two rotations obtained by using the exact inverse kinematics formula: it is apparent that the error is risible. Another important aspect is the ANN generalization property. Fig. 11, shows the network results obtained considering input values that were not used for training: the resulting performance is satisfactory, since the correct values of outputs are obtained. Moreover, we remark that, thanks to the recalled satisfactory generalization propriety of the designed network, even if we train the network with an input vector in steps equal to 1°, the error committed by the network is less than 1° (the worst case equals 0.35°). This can be shown comparing the ANN results with those obtained solving the direct kinematics problem by interpolation, i.e., using the so-called *solve* MATLAB function: indeed, the average error obtained by the ANN equals 0.7% and is much lower than the error obtained by such a function, equaling 9.4%, as shown in Tables 4 and 5.

4.3. Simulation results

After choosing the ANN, we design a classical PID controller in order to govern in closed loop the arm motion, according to Fig. 4a. Some simulation tests are carried out considering trapezoidal references for both arm rotations θ^* and φ^*. This type of input models simultaneously most of the possible motions of a human arm, namely, pronosupination and flexion. Moreover, such an input models simultaneously the arm and wrist movement and therefore justifies the use of a parallel architecture rather than a serial one. The controlled arm evolution is represented in Fig. 12: it is characterized by a satisfactory performance and a minimum error at the steady state. The figure represents the references θ^* and φ^* with the θ_{rif} and φ_{rif} labels and the controlled rotations θ and φ. It is apparent that the resulting errors are minimal.

Comparing the proposed approach with the recalled work [7] we remark that we take a general way to solve the problem that

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Table 4
Performance of the kinematic inversion achieved by neural network and *solve* matlab function.

Elongations (mm)		Correct degrees		Degrees calculated by the ANN		Degrees calculated by the *solve* function (Matlab)	
L_1	L_2	θ	φ	θ	φ	θ	φ
34.97	15.63	45	60	45.01	60.01	50.58	59.06
17.03	11.81	13	82	12.99	82.06	13.79	80.33
40.14	56.76	−43	25	−42.93	25.03	−49.10	24.64
34.09	33.63	1	50	0.9672	49.99	1.101	49.37
69.03	54.16	50	1	50.12	1.029	58.27	0.7140

Table 5
Relative error for ANN and solve solutions.

Elongations (mm)		Correct degrees		Relative error committed by ANN [%]		Relative error committed by the *solve* function (Matlab) [%]	
L_1	L_2	θ	φ	E_θ	E_φ	E_θ	E_φ
34.97	15.63	45	60	0.02	0.02	12.40	1.57
17.03	11.81	13	82	0.08	0.07	6.08	2.04
40.14	56.76	−43	25	0.16	0.12	14.19	1.44
34.09	33.63	1	50	3.28	0.02	10.10	1.26
69.03	54.16	50	1	0.24	2.90	16.54	28.60

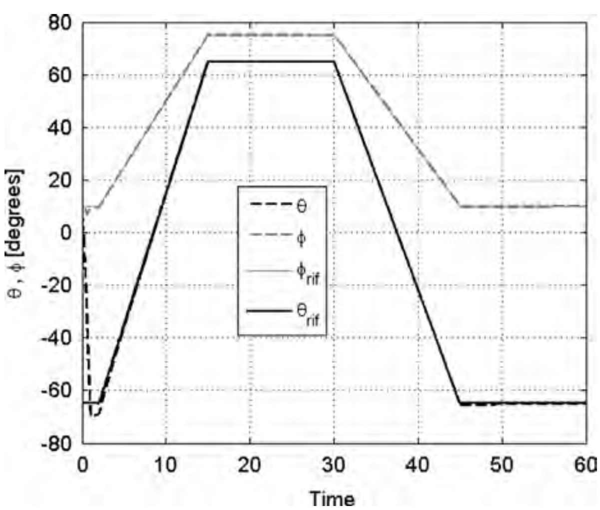

Fig. 12. Simulation tests of the controlled prosthetic device with trapezoidal references.

can be extended to more general cases of multi-input–multi-output systems. Moreover, we note that we obtain an average error of about 0.7% with a Stewart-like parallel platform while in [7] the authors declare an error lower than 1%. In our case, the employed numerical algorithm is the solve function of Matlab with the errors shown in Tables 4 and 5.

5. Conclusion

We present a novel approach for calculating the forward kinematics of a hydraulic prosthesis based on Artificial Neural Networks (ANN). The process is highly nonlinear and as such difficult to model and control, hence using an ANN allows solving the problem in real time with sufficient precision and limited computational effort. The procedure is innovative since it allows designers to test, by means of a robust trial and error procedure, the system behavior. In addition, it allows achieving good performance closed-form solutions. Moreover, even if the procedure requires time for training, after that the ANN response requires a short computation time. The proposed technique leads to straightforwardly design the control scheme in real time. Future research will be devoted to generalizing the procedure to different mechanical structures with two degrees of freedom, if the inverse kinematics of the system is well known. Moreover, further investigation will address limiting the required energy to move the prosthesis by employing genetic algorithms. Finally, an interesting field of future research is comparing the proposed PID linear control approach with nonlinear alternatives, e.g., using fuzzy control.

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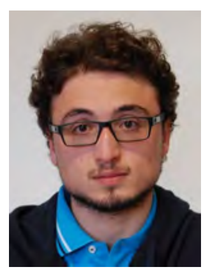

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