Design and Experimentation of a Neural Network Controller for a Spherical Parallel Robot

Donatello Tina, Luca Carbonari and Massimo Callegari
Department of Industrial Engineering & Mathematical Sciences, Polytechnic University of Marche, Ancona, Italy

Keywords: Neural Networks, Robot Control, Parallel Kinematics Machines.

Abstract: The paper deals with a neural network control for the gravity compensation of a parallel kinematics robot. The network has been designed in a simulation environment then it has been implemented in robot's controller by using an FPGA device that is part of an embedded system. After the training phase, several experiments have been performed on the prototype manipulator and the related datasets have been collected and elaborated. In the end, a comparative analysis has shown the improved performance of the neural network controller with respect to the inverse dynamics one, mainly due to the well-known difficulties in deriving explicit models of friction and play in the joints.

1 INTRODUCTION

During the last two decades, research in the Artificial Neural Network (ANN) field has increased significantly in different branches of science. To the best of our knowledge, King and Hwang (1989) first theorized the application of ANN for robotics applications; Narendra and Parthasarathy (1990) demonstrated that Neural Networks can be also usefully exploited for the modelling of dynamic systems as well as for the control of automated machinery. Other recent robotics applications for neural networks are the solution of the kinematics of a parallel manipulator (Zhang and Lei, 2011) and the control of a planar robot (Serrano, 2011).

Field Programmable Gate Arrays (FPGA) can perform a large number of parallel operations at very high time rates and their architecture is very suitable for the implementation of real time neural networks. As a matter of fact remarkable realisations are available already in scientific literature, e.g. Orlowska-Kowalska et al. (2011) used an FPGA-based ANN for the state estimation of a two mass system with elastic couplings.

The main target of the present work is the realisation of a gravity compensation module for the control of a prototype parallel manipulator, named Sphe.I.Ro. whose kinematics allows only motions of pure rotation. The computation of the analytic model of machine's statics is quite burdensome due to the presence of the closed kinematics chains. Therefore an ANN has been created in order to obtain a reliable and efficient static model of the robot, that is able to provide the actuation forces needed to maintain a certain configuration in the orientation space.

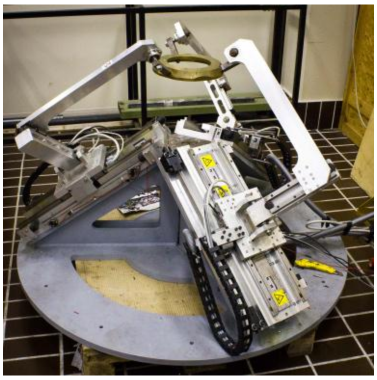


Figure 1: Photograph of the Sphe.I.Ro. robot.

2 THE Sphe.I.Ro. ROBOT

Sphe.I.Ro. (Spherical Innovative Robot) is a parallel kinematic machine developed at the robotics laboratory of the Polytechnic University of Marche. It is made by three identical serial chains connecting the moving platform to the fixed base, as shown in Figure 1; each leg is composed of two links: the first one is connected to the base by a cylindrical joint (C) while the second link is connected to the first

Tina D., Carbonari L. and Callegari M..
Design and Experimentation of a Neural Network Controller for a Spherical Parallel Robot.
DOI: 10.5220/0004047602500255
In *Proceedings of the 9th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2012), pages 250-255
ISBN: 978-989-8565-21-1

one by a prismatic joint (P) and to the end-effector by a universal joint (U); for this reason its mechanical architecture is commonly called 3-CPU. Figure 2 shows a sketch of robot's kinematics: when the translations of the three cylindrical joints are actuated, the end effector is only allowed to perform pure rotations around a fixed point of the space (Callegari et al., 2004). The large number of passive prismatic pairs, typical of parallel kinematics, causes high friction losses, which represent a relevant disturbance for motion control and make quite difficult the realisation of a good dynamic model of the robot. Therefore the A.'s decided to turn to an empirical model that could robustly take into account these phenomena; in particular, the resort to ANN's systems proved able to fit the physical behaviour of machine, obviously after a proper training phase.

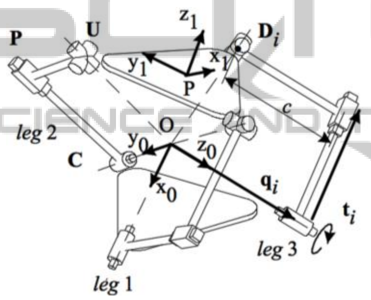


Figure 2: Schematic representation of robot's kinematics.

3 DESIGN OF THE ANN SYSTEM

3.1 ANN Model

If the model of a single neuron is taken into consideration, its output can be expressed as:

$$y = \sigma(\boldsymbol{W}^T \boldsymbol{x} + b) \qquad (1)$$

where $\boldsymbol{x}$ is the input vector, $\boldsymbol{W}$ is a weighting vector, b is the bias number and σ is the activation function. According to Cybenko's theorem (Cybenko, 1989) a static feedforward net with one hidden layer of neurons has been chosen, with the number of neurons n to be selected after some simulation trials, as explained in the following section; the input of the net are the 3 displacements q_i of the actuators while the output is represented by the 3 forces f_i that keep the robot at rest in the assigned configuration.
The resulting model of the whole net has the form:

$$\boldsymbol{y} = \boldsymbol{\sigma}_O (W_O^T \boldsymbol{\sigma}_H (W_H^T \boldsymbol{x} + \boldsymbol{b}_H) + \boldsymbol{b}_O) \qquad (2)$$

where: $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{\sigma}_O, \boldsymbol{b_O} \in \mathcal{R}^{3x1}$; $W_O \in \mathcal{R}^{nx3}$; $W_H \in \mathcal{R}^{3xn}$; $\boldsymbol{b}_H, \boldsymbol{\sigma}_H \in \mathcal{R}^{nx1}$.

3.2 Simulation Network

A simulation model of the network was developed in order to select the appropriate number of neurons for the hidden layer and to tune the training procedures. Both kinematic and dynamic models of the robot were available already (Callegari et al., 2004, 2012): it is remarked that the latter has been built according to the virtual work principle, therefore resulting very compact and efficient, potentially allowing a real-time use.

Once set up the simulation environment, several parameters of the ANN have been changed to look for best gravity compensation performance. Every net configuration has been tested after a proper training, realized by using data sets of about 3 500 different orientations inside robot's workspace. If the latter is mapped into the joint space, it is represented by a tetrahedron whose lateral faces are singularity surfaces (Carbonari, 2012). For each test configuration, the gravity force reflected to the actuators was calculated by using the mathematical model, therefore obtaining both input (joint positions) and output (reflected gravity forces) data set for the training of the net.

The ANN training has been performed by means of the Levemberg-Marquard back-propagation algorithm (Hagan and Menhai, 1994). The back-propagation algorithm needs data to be pre-processed in order to normalize the input of the net.

Nets with different numbers of neurons have been investigated (see Table 1 for details); in each case, the training has been interrupted when the output error or the gradient became lower than a given threshold. Simulation results showed that 20 neurons are a good compromise between net complexity and net performance. It is noted that a mean square error of about *26 mN* has been achieved throughout the workspace for the 20 neurons net: this, for a mean actuation effort of about *48 N*, corresponds to a relative error lower than *1%*.

Table 1: Training performance of different nets (simulation).

	Training stop criterion		
No. of neurons	*Gradient threshold*	*Actual gradient*	*Performance (mean square error)*
15	0.009	0.0090	0.0429
20	0.009	0.0080	0.0263
25	0.009	0.0500	0.0268
30	0.009	0.0072	0.0314
40	0.009	0.0088	0.0198

4 ANN IMPLEMENTATION ON FPGA

The performance of the artificial neural network has been experimented on the Sphe.I.Ro. robot, whose control architecture is briefly described in the following. The parallel robot is actuated by three brushless linear motors, whose drivers are connected to a PXI platform (by National Instruments) which performs both control and supervision tasks. The PXI device hosts an FPGA board, which deals with several processes, such as managing encoders signals, commanding the brakes of the 3 linear axes, running the neural network and operating the pre- and post-processing of network's input and output.

By grouping the elementary operations of the ANN for layers, it is possible to implement the net in LabView by means of two nested "*for loops*", as shown in Figure 3: the inner one for the multiplication between the input and the corresponding weight, and the outer one for the implementation of neuron's calculations. Figure 3 shows the hidden layer of the ANN, in case 20 neurons are used: $\boldsymbol{x}$ is the input vector of the net and $\boldsymbol{W}$ is the weights matrix, where w_{ij} represents the j^{th} weight of i^{th} neuron. It is noted that the activation function σ_H is the same for all the neurons. The activation function has been realised by means of the sigmoid *tanh(x)*. According to Kwan (1992) an approximation of a sigmoid function can be implemented by using a sigmoid-like second-order piecewise function Γ:

$$\Gamma(x) = \begin{cases} x(\beta - \theta x), & 0 \le x \le L \\ x(\beta + \theta x), & -L \le x \le 0 \end{cases} \tag{3}$$

where β and θ determine respectively the slope and the gain of the nonlinear function (3) while L represents the amplitude of the non-linear region.

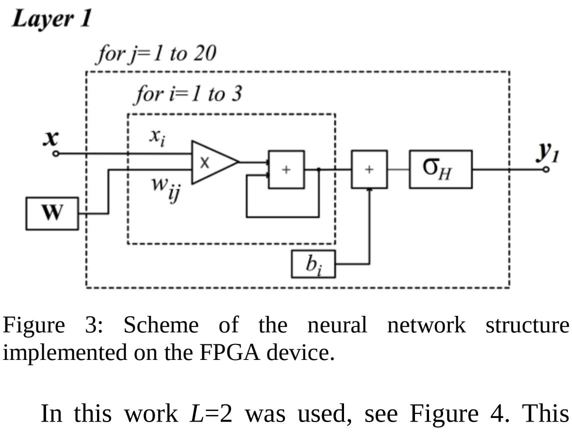


Figure 3: Scheme of the neural network structure implemented on the FPGA device.

In this work L=2 was used, see Figure 4. This makes possible to evaluate the activation function by means of two multiplications and one summation.

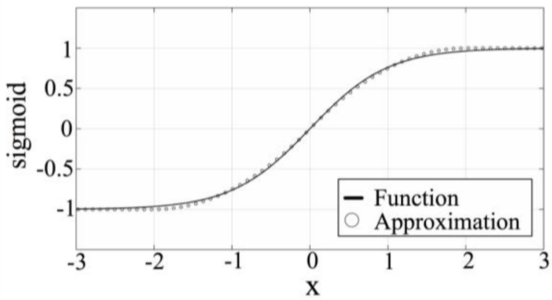


Figure 4: Sigmoid activation function σ_H (x) and its approximation Γ(x).

5 CONTROL ALGORITHM DESCRIPTION

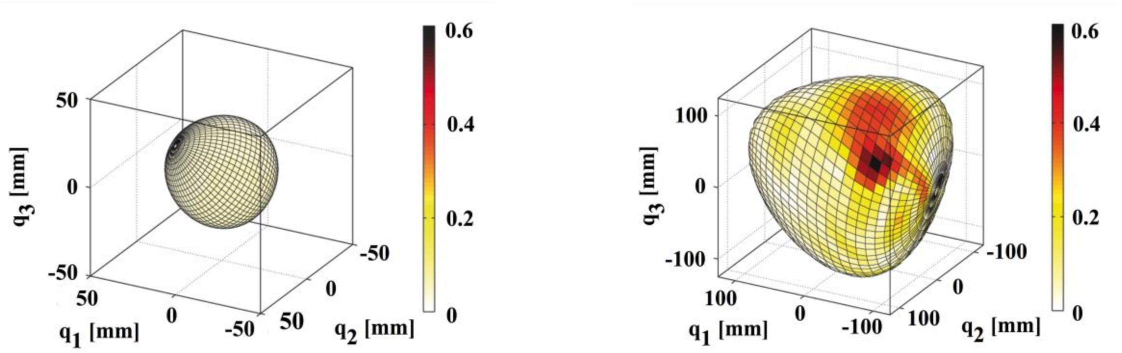
The implementation of the software in the LabView environment has been made through its typical graphic language. Two types of code had to be written: the ANN has been implemented on the FPGA board while all other control software had to run on the PXI controller, which supervises the user interface and manages the manipulator's control system.

Furthermore an interrupt-based procedure ensures the synchronization between the different hardware components: in fact, the two devices run at different clock rates, i.e. a maximum clock rate of *40 MHz* for the FPGA board and *10 MHz* for the PXI controller. In order to optimize the FPGA performance, the code has been partitioned into different processes, able to perform in-parallel different real-time tasks, i.e. encoder's signals processing, motor driving, ANN system computation and safety procedures management.

In the PXI controller a Virtual Instrument was implemented, by exploiting a series of routines that guarantee the correct execution of the ANN on the FPGA. In fact the net was designed and tuned in Matlab and then adapted for real-time execution in the LabView environment. Thus relevant data of the net, such as weights matrix, bias vector, pre-process and post process settings, were first set up in the Matlab simulation environment and then exported to the LabView one.

It is useful to assess and compare the computation efforts needed by both gravitational compensation models.

As for the ANN model, of course the computation burden depends upon the number of neurons that compose the net. For the net that has



(a) (b)

Figure 5: Norm of the error on different surfaces of joints space (different scales are used): (a) surface close to home configuration, (b) surface close to workspace boundaries.

been actually implemented on robot's controller (one hidden layer with 20 neurons, 3 input and 3 output), the computation of gravity forces requires 166 multiplications and 43 summations.

If the analytical model is used, a huge number of non linear operations must be used. In particular, an algorithm based on this model involves 8305 operations, of which 532 are trigonometric operation.

6 RESULTS

6.1 Simulation Tests

Several tests have been performed in order to estimate the performances of the ANN gravity compensation module. First, the entire workspace of the Sphe.I.Ro. robot has been investigated through computer simulation, by computing the gravity compensation forces with the two available models, i.e. the analytical model and the neural network model. The deviation between the two models can be evaluated as:

$$\mathbf{E}_{sim} = \boldsymbol{F}_{math} - \boldsymbol{F}_{ANNsim} = [e_{s1} \quad e_{s2} \quad e_{s3}]^T \qquad (4)$$

where $\boldsymbol{F}_{math}$ are the 3 motor thrusts compensating the gravity force computed by the mathematical model while $\boldsymbol{F}_{ANNsim}$ is the corresponding force vector evaluated by the ANN in the simulation tests.

Each point of the surface visible in Figure 5a represents a specific robot's pose in the neighbourhood of home configuration while the surface of Figure 5b lays closer to workspace boundaries. In both cases the norm of error vector (4) is represented by different colour levels. Since darker regions mean higher error values, it is apparent that the error is relevant ($\approx 0.4\ N$) only within a very limited region of the space. As a matter of fact, the error becomes lower and lower as the home configuration is approached: this is due both to the choice of the training points and to the increasing isotropy of robot kinematics. In fact, during training, the points of the dataset have been made denser in this part of the workspace, where most operations are carried on.

The behaviour of both the neural network and the analytical model can be better visualized in the task space. To this aim, the orientation of the platform is described by means of the elevation, azimuth and torsion angles (α, β, γ). By keeping the torsion angle (γ) as a parameter, the error in the orientation space can be represented as a function of elevation and azimuth only: for instance, each point of the surface in Figure 6a represents the norm of the error for a configuration that is given by elevation α (the angle around the base circle) and azimuth β (the polar distance from the centre of the base circle). Figure 6 and Figure 7 represent the error evaluated in simulation for a null torsion angle ($\gamma=0$) and for a torsion angle $\gamma=15°$ respectively: this task space representation clearly shows how the error increases while workspace boundaries are approached, even if it is pretty limited anyhow. It is noted that the peak error values emerging in these figures are higher than the errors that can be read in Figure 5 because the corresponding points are external to those surfaces and therefore they are not mapped there.

The prototypal machine is affected by significant friction forces and bodies deformations, which can be hardly evaluated in symbolic models, therefore it was expected that the ANN based model would perform better than the analytic model: the following experimental tests aimed at assessing this point.

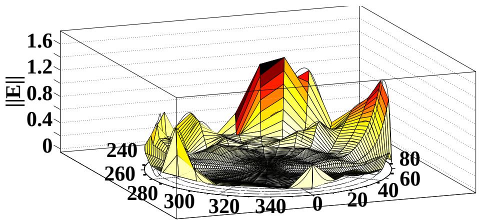


Figure 6: Error plot in the orientation space for γ=*0* (simulation tests).

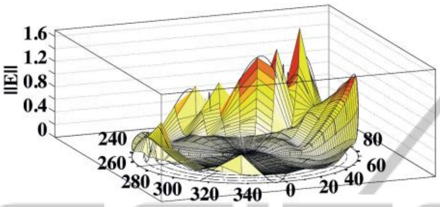


Figure 7: Error plot in the orientation space for *"γ=15°* (simulation tests).

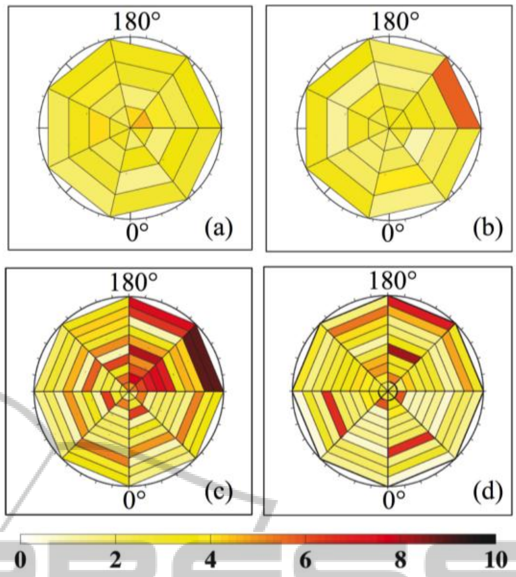


Figure 8: Actuation forces errors in different points of the α–β space: $|\mathbf{E}_{math}|$ (a) and $|\mathbf{E}_{ann}|$ (b) for γ=0; $|\mathbf{E}_{math}|$ (c) and $|\mathbf{E}_{ann}|$ (d) for γ=15°.

6.2 Experimental Tests

In order to collect the experimental dataset for the training of the net, a PID controller has been used to bring (and keep) the manipulator in all the selected points of the workspace. Once Sphe.I.Ro. had been driven to a new pose, the forces necessary to maintain the robot in such configuration have been recorded by measuring the current absorbed by motors. The brushless linear motors used to drive the rig have a proportional dependence between current and force: the related constant is called *"thrust constant"* (K_t) and is provided by the manufacturer.

During the experimental tests, the robot has been commanded to attain several orientations in the workspace (different from the ones in the training set) and the actual forces required by the actuators, $\boldsymbol{F}_{exp}$, have been compared with both the forces estimated by the ANN, $\boldsymbol{F}_{ANNexp}$, and the ones provided by the analytical model, $\boldsymbol{F}_{math}$. The arising errors are:

$$\mathbf{E}_{ann} = \boldsymbol{F}_{exp} - \boldsymbol{F}_{ANNexp} = [e_{a1} \quad e_{a2} \quad e_{a3}]^T \qquad (5)$$

$$\mathbf{E}_{math} = \boldsymbol{F}_{exp} - \boldsymbol{F}_{math} = [e_{m1} \quad e_{m2} \quad e_{m3}]^T \qquad (6)$$

Figure 8 allows a comparison between the behaviours of the two models of gravity compensation (analytical and ANN based): since the two graphs have quite similar values, some critical indicators are collected in Table 2.

In order to get more insight into this key issue, Table 2 also presents the experimental performance of the ANN based controller, in case the training is performed on the simulation data set (in place of the on-field training); all the data are provided for both torsion angles (*γ=0°* and *γ =15°*). It can be seen that the performance of the ANN controller is better than the analytical based one in all conditions tests, but the difference is scarcely substantial. As could be expected, such difference in performance becomes smaller as the boundaries of the workspace are approached and/or the values of the torsion angle increases since less points have been taken in these conditions for ANN training and, on the other hand, the analytical model is able to capture, at least partially, the rapidly changing manipulator's dynamics close to singular configurations.

In the end, it can be useful to investigate the causes of the not completely satisfying behaviour of the ANN based compensation: first of all, due to the relevant time needed by on-line experiments, only 100 points have been considered to build the experimental data set for net training (while 3000 points have been used in the simulations). Secondly, due to the lag induced by static friction, for any configuration of the manipulator there exist a whole range of actuation forces that keep the machine in equilibrium under the effect of gravitational force: such effect surely affected the training phase and thus the performance of the ANN compensation.

Table 2: Performance indexes of gravity compensation models.

		Max error[%]	Ave error[%]
ANN compensation (on-field training)	$\gamma=0°$	7,0	2,8
	$\gamma=15°$	11,5	4,6
ANN compensation (simulation training)	$\gamma=0°$	9,0	3,8
	$\gamma=15°$	13,6	4,9
Analytical model compensation	$\gamma=0°$	8,5	3,8
	$\gamma=15°$	12,6	5,4

7 CONCLUSIONS

The aim of this work was to investigate the performance of ANN's for the gravity compensation of a spherical parallel manipulator. The availability of an analytical model of robot's dynamics allowed to design the net through computer simulation and to port the software to the real-time control hardware after a first (preliminary) tuning.

After the on-field net training phase, more tests have been performed to evaluate the compensation effectiveness: the manipulator has been commanded to reach several poses in the task space and the output of the ANN has been compared with the actuation forces actually needed; the same comparison has been made with the actuation forces provided by the analytical model of robot's inverse dynamics.

The results of the tests showed that the ANN controller behaves better than the algorithmic one, even if the improvements are not very relevant. It is reckoned that better performances could be obtained by a more extensive training on the field and in case the mechanical structure were less influenced by static friction, as is the present case: the influence of this factor could be assessed by further experimentation, by measuring the gravitational actions with the manipulator in (slow) motion.

From the computational point of view, on the other hand, the ANN based compensation overperforms the analytical model, whose computation is rather time consuming indeed.

REFERENCES

Callegari, M., Carbonari, L., Palmieri, G. and Palpacelli, M.-C. (2012). Parallel Wrists for Enhancing Grasping Performances. In: *Grasping in Robotics*, G. Carbone ed., Springer, 2012. (In press)

Callegari, M., Marzetti, P., Olivieri, B. (2004). Kinematics of a Parallel Mechanism for the Generation of Spherical Motions, in J. Lenarcic and C. Galletti (eds), *On Advances in Robot Kinematics*, Kluwer, pp.449-458.

Carbonari, L. (2012). Extended analysis of the 3-CPU reconfigurable class of parallel robotic manipulators. *Ph.D. Thesis, Polytechnic University of Marche, Ancona*, Italy

Cybenco, G. (1989). Approximation by Superpositions of a Sigmoidal Function. *Mathematics Control, Signals and Systems*, Vol. 4, no. 2, pp. 303-314.

Hagan, M.T. & Menhai, M. (1994). Training feed-forward networks with the Marquardt algorithm, *IEEE Transactions on Neural Networks*, Vol.5, No. 6, pp.989-993

King, S.-Y., and Hwang, J. -N. (1989). Neural network architectures for robotic applications. *IEEE Transactions on Robotics and Automation*, Vol. *5*, no. 5, pp. 641-657.

Kwan, H. K. (D. of E. E.). (1992). Simple sigmoid-like activation function for digital hardware implementation. *Electronics Letters*, Vol. 28, no. 15, pp. 1379-1380.

Narendra, K. S. and Parthasarathy, K. (1990). Identification and control of dynamical systems using neural networks, *IEEE Transaction on Neural Networks*, Vol. 1, no. 1, pp. 4-27.

Orlowska-Kowalska, K and Kaminski, M, (2011). FPGA Implementation of the Multilayer Neural Network for speed estimation of the Two-Mass Drive System. *IEEE Transaction on Industrial Informatics*, Vol. 7, no.3, pp. 436–445.

Serrano, F. E. (2011). Neural Networks Models for Control and Identification of a Two Links Robotics Manipulator. *Proceedings CONCAPAN XXXI*.

Zhang, D., & Lei, J. (2011). Kinematic analysis of a novel 3-DOF actuation redundant parallel manipulator using artificial intelligence approach. *Robotics and Computer-Integrated Manufacturing*, Vol. 27, no. 1, pp. 157-163.