SOFT ROBOT POSITIONING
USING ARTIFICIAL NEURAL NETWORK

UDC (((681.58:004.89)+681.5.01):(004.032.26+004.8))

Marko Kovandžić, Vlastimir Nikolić, Miloš Simonović, Ivan Ćirić, Abdulathim Al-Noori

University of Niš, Faculty of Mechanical Engineering,
Department of Mechatronic and Control, Niš, Serbia

Abstract. *The experiment investigated the performance of an artificial neural network in solving the inverse kinematic problem of a soft robot. For this purpose, a simple soft robot was designed of building blocks, stringed on three rubber hoses, and an actuating system, to provide the hydraulic pressure. An axial extending of a hose, while the others are in the relaxed state, results in bending of the robot. The network was employed, as a black box, to approximate the behavior of the system. In accordance with the purpose, the input consisted of the desired spatial coordinates and the output of the step motor angular displacements. The network was trained and tested using records collected at 200 randomly chosen robot positions. The relative testing error of positioning, about 5%, confirmed a predictable robot behavior. The solution proposed is competitive in terms of simplicity, safety and price of realization. The experiment provided basics for the future research of the design of modular soft robots.*

Key words: *robotics, soft robot, automatic control, neural networks, artificial intelligence, spatial positioning*

1. INTRODUCTION

Nowadays, robots are widely present, especially in manufacturing, because of their ability to perform plenty of different tasks in a more accurate and efficient way than humans. However, the extensive robotic practice revealed some of their shortcomings too, like limited adaptability and insufficient safety. Conventional robots are rigid, which makes them dangerous in interaction with humans and other living creatures. In such a scenario, human and robotic moving zones have to be separated explicitly in order to provide a safe working environment. As the time passes, robots take over more and more

activities from humans. The range of their application spreads from production to other areas of human activity and demands for the interaction with humans constantly grow. In order to bridge the gap between robots and humans engineers turn to construction of soft robotic systems. Representative examples of these are presented in Fig. 1. The first image (a) shows a vine-like robot developed by the Stanford University. It works on the principle of inversion and accomplishes a friction-independent movement. The robot can move, easily, trough caves, ruins, interiors of living creatures and other restricted and unpredictable spaces. It is ideal for diagnostics, resolving failures, delivery of goods and assistance under extremely limited conditions [2]. The second image (b) presents the first functional soft robot powered entirely by vacuum, developed by the École Polytechnique Fédérale De Lausanne. It moves by having air sucked out of it. Thanks to the modularity, the robot can be easily reconfigured to perform different tasks such as climbing vertical walls and grabbing objects [3]. A team of engineers, at the University of California San Diego created a soft robot that can walk on sand, pebbles, rocks and up inclines (c). It moves using four hollow limbs which are pumped full of air. The limbs are much lighter and more maneuverable than standard limbs made of rigid structures [4]. The last image, (d), presents a platform for creating soft robots developed by the Harvard John A. Paulson School of Engineering and Applied Sciences. It is equipped with sensors for registering movement, pressure, touch and temperature [5]. The platform enables complex sensing motifs to be easily integrated into soft robotic systems. Inspired by the structure of biological organisms, all of the robots presented are made of soft elements which are able to bend and twist with a high curvature. Using this fact, soft robots can be defined as systems with autonomous behavior primarily composed of the materials with tensile modulus of elasticity in the range of the soft biological materials (10^4-10^9Pa) (Fig. 2). The soft structure makes them continuously deformable with the theoretically infinite degrees of freedom [6]. They can adapt their shape to confined spaces (engines, mechanisms, interior of buildings, caves, pipe lines, human and animal body cavities, etc.). In such surroundings, soft robots exceed the performance of conventional robotic systems, made of rigid materials. One of the greatest advantages of the soft construction is that these robots are harmless in contact with humans, other living creatures and other sensitive objects.
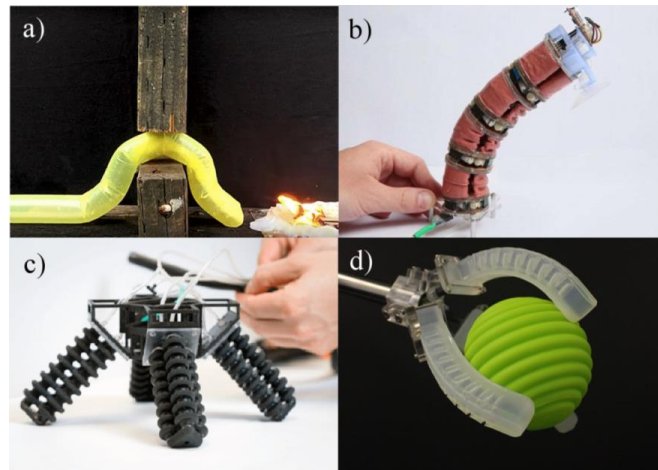

Fig. 1 Soft robot examples

The basic challenge in making a predictable robotic system is determining the mathematical model. Calculating kinematic parameters (position, orientation, velocity and acceleration) of the effector, on the basis of joint positions, is called the direct kinematic problem. In the standard robotics, it is a trivial, straightforward problem which always has a solution. Inverse kinematics implies determining joint parameters that provide a desired spatial position of the effector. It is a much more difficult and computationally expensive problem, accompanied by nonlinearities, singularities, redundancy and collision avoidance. Only a small percent of manipulators have a unique analytical solution [7]. If the kinematic parameters are known, dynamic equations are used to link them with the forces. Thus, a direct dynamic is calculation of accelerations caused by applied forces and an inverse dynamic is calculation of forces needed to provide a desired acceleration. The first procedure is used in simulation and the second in control algorithms. Soft robot modeling is even more complex, because of the absence of rigid joints and links. The concept of soft robot is relatively new but previous experience revealed control algorithms [7-11] which are similar to conventional ones, intended for rigid robots. These are obtained by involving the principle of piecewise constant curvature [1, 6-11]. It implies that each body segment of a multi-segment robot deforms with a constant curvature. Under this assumption, N-link soft manipulator can be determined uniquely by 2N joint variables. A common practice is dividing a mathematical model into two separate sub mappings [12]. The first is universal, applicable to soft robots generally, and the second is robot-specific. Another way of soft robot modeling is the discrete Cosserat approach based on the micropolar elasticity [6]. The model incorporates a local rotation of points as well as the translation assumed in the classical elasticity. It inherits the geometrical and mechanical properties of the continuous Cosserat model, making the natural soft robotics a counterpart of the traditional rigid robotics. In the lack of analytical solutions, an accurate model can be obtained using numerical methods [13-15], such as the Finite Element method [16-17]. These methods perform the feedforward control of robot using an inverse optimal model. In his research [18], Zhang extended the method to the real-time closed-loop control. However, the solutions employ a quasi-static model, which limits the control to low velocity trajectories. There are even some on-line software frameworks published, based on the numerical techniques, intended for the simulation of soft robots [13-14].
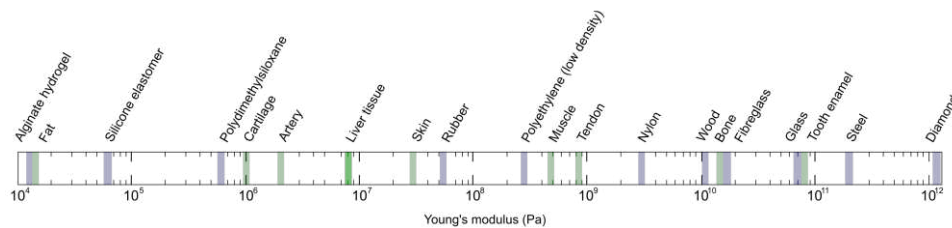

Fig. 2 Tensile modulus (Young's modulus) of engineering and biological materials [1]

The research suggested a universal method of soft robot control using artificial neural network. The procedure is well established in the conventional robotics [19-22]. Neural networks are proven approximators distinguished by simple implementation and excellent speed of performance [23]. They are employed as a black box, which means that a certain input produces a desired output, but how the network achieves the result is left to a self-organizing (artificial intelligence) algorithm [24]. The last property makes

them suitable for a broad range of users, who are not necessarily familiar with the control theory, robotics or mechanics at all. The purpose of the experiment was to prove that an artificial neural network can be trained to perform a predictable soft robot control by approximating the inverse kinematic problem.

2. METHOD

The experiment was performed with the simple soft robot design (a) assembled of building blocks. The building block (b) is constructed of three, identical, conveniently shaped and radially disposed, hollow cylinders and a coupling element in the centre. The cylinder hole fits the diameter of a rubber hose, in the all images marked with black. The construction was obtained by stringing 15 identical building blocks (b) on the three rubber hoses. One end of the each hose was sealed with a cup and the other was used for the hydraulic power supply. The cross section of the construction, in the relaxed state, is presented in the image (c) and the same cross section in the pressurized state in the image (d). From the last, it is obvious how the robot works. Expanding one hose, while the opposite is in relaxed state, results in bending of the whole structure.
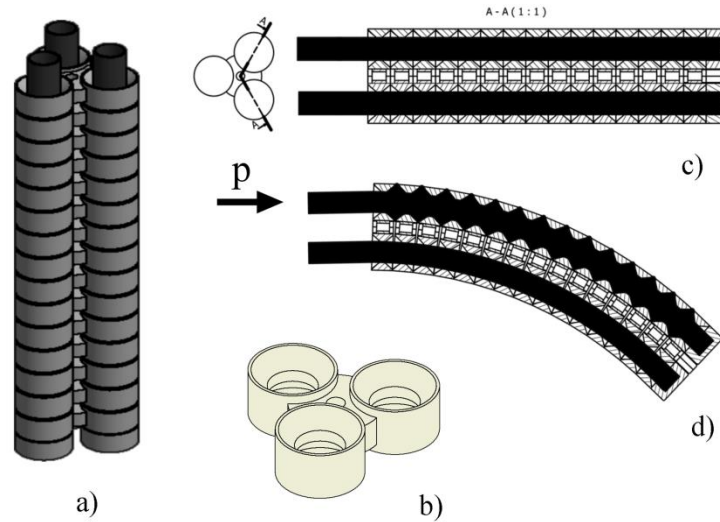

Fig. 3 Soft robot: a) design, b) building block, c) cross section – relax state, d) cross section – tense state

There are two functional zones on the rubber hose surface. One, where the hose touches the walls of the building block, can be considered as a passive zone. In this zone, any radial expanding is absolutely prevented by the block geometry and an axial expanding is suppressed by the friction force. Out of the passive zone, the hose is spreading unhindered, if interior elastic forces are ignored. As a consequence of spreading, one hose becomes longer than the other (d) which causes the overall construction to bend to the opposite side, with respect to the center of symmetry. An additional modeling problem is that the zones are not constant. As the pressure increases,

from the zero state, the contact surface between the hose and walls of the building block is spreading. It happens until the entire hollow is filled totally with the rubber hose. It can be designated as a charging pressure. The behavior of the free hose with respect to the pressure is not easy to predict. It depends on hydraulic forces, elastic forces and the block geometry. The other point of interest is the pressure level when the gap between building blocks start to appear. This pressure can be named an activating pressure. The element can be considered as inactive until it reaches the activation pressure. The activation pressure cannot be higher than the charging pressure and it depends on the same parameters. The existence of different working regimes implies huge nonlinearities in the mathematical model of the soft robot.
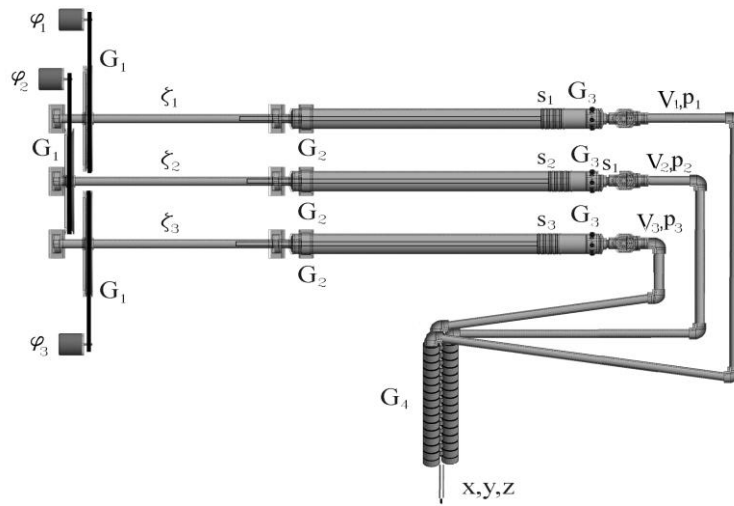

Fig. 4 Soft robot and electro-hydraulic actuator

The robot was pressurized using an electro-hydraulic system, presented by the block diagram on the Fig. 4. The actuating system was designed of three identical lines, each of them intended for supplying one rubber hose of the soft robot. At the beginning of the line, the mechanical input was achieved by a step motor, with the angular displacement, φ. The motor was controlled using the A4988 CNC driver and the driver was governed by a PC through the USB connection with the AT- mega328P microcontroller. A time belt drive was employed to multiply the step motor torque. The transfer function, G_1, of the time belt drive, was defined as a ratio between the output angular movement, ζ, and the input angular movement, φ. A thread (G_2), at the input of hydraulic cylinder, had to transform the angular movement ζ to the linear displacement, s, of the piston. The cylinder was used to transform mechanical to hydraulic energy. Its transfer function was defined as the ratio between output volume, V, displaced by the hydraulic cylinder, and the input linear displacement, s. Finally, the soft robot, including pipelines, was observed as a multivariable system with three input and as many output variables. It was described by transfer matrix H with 3x3 elements. The analysis of the working principle already revealed the existence of nonlinearities in this matrix. The input vector consisted of volumes (V_1, V_2 and V_3) which

were displaced by hydraulic cylinders. The output variables (x, z, y) were spatial coordinates of the control mark, placed at the top of the soft robot. The whole system, consisting of actuating and executive organs, was represented by the transfer function [25]

$$G = G_1 G_2 G_3 \begin{bmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{bmatrix} \tag{1}$$

The above transfer function describes the direct kinematic problem, in a general form. The transfer functions of the amplifiers, G_1 G_2 G_3, are easy to be calculated, on the basis of geometric parameters, or determined using an identification procedure. However it is extremely complex to analytically model the transfer function H, because of the above mentioned nonlinearities.

Fig. 5 An appearance of the employed soft robot

In the experiment, analytical modeling was avoided completely by observing the whole system (Fig 4.) as a black box. Since the intention was to solve the inverse kinematic problem, a neural network was trained to approximate the inversion of the transfer function (1). The input was the robot position (x, y and z) and the output was the control signal made of angular displacements of the step motors that provide the position. For the training purpose approximately 200 control vectors were chosen randomly, each with the angular displacements between 0 and 60 revolutions. The values were determined experimentally, the first as a control level in the relaxation state and the second as the level that causes full bending (limited at 135°). For each vector geometrical coordinates of the led diode, at the top of soft robot, was recorded by the total station Sokkia SET630R. The instrument allows laser measuring of distances with the accuracy of +/-3mm, at the used range of lengths, memorization and automatic data transfer through a RS-232 port. Actually, after several attempts the diode had to be colored opaque because the laser beam had passed through its

transparent body. The network was trained, on the basis of experimentally obtained records (Fig.6), using the back propagation algorithm with momentum. The results were evaluated for the range of different configurations and training parameters, in order to find an optimal solution. Both the training and the testing were performed by software designed for the purpose of the previous experiment [23].
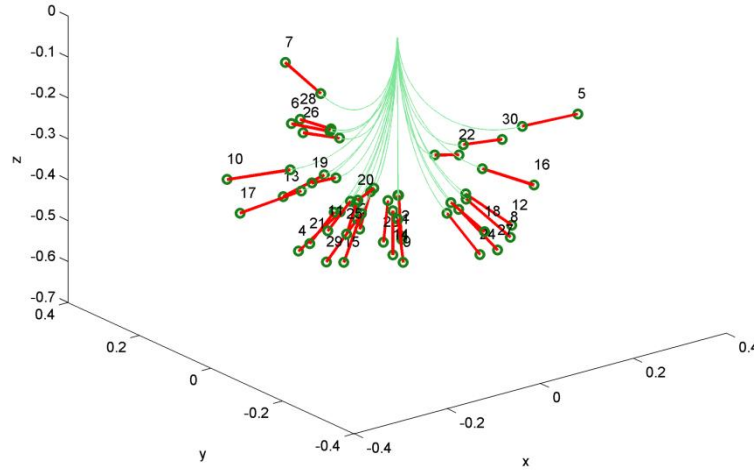

Fig. 6 The first 30 positions of the soft robot recorded

3. RESULTS

The experiment started with the structure of a neural network. The size of the input layer was determined by the number of executive channels, in the soft robot construction, and the size of the output layer is determined by the number of space coordinates. In both cases it is three. At first, a single hidden layer neural network was examined with the number of hidden neurons within the range between 1 and 40. The resulting mean squared errors and their approximations, using two term exponential function, are presented in Fig. 7. The other parameters were fixed at the optimal values, obtained successive through the series of experimental cycles. Both errors decrease down to approximately 10 neurons and then start to rise. The consistency of the results is better for the lower numbers of neurons so the network with 12 neurons in a single hidden layer was adopted as an optimally configured neural network. Any attempt of employing a multi-layered neural network gave no improvements with respect to the results obtained using a single-layered neural network with the same number of neurons.

The influence of training parameters on the accuracy of the positioning was tested for 33x34 different, logarithmically distributed, combinations of values. The value of learning coefficient was in the range between 0.01 and 0.999, and the momentum factor, between 0 and 0.999. Experimental results and appropriate approximations, using the local linear regression model, are presented on the Fig.8, for the training error and Fig.9 for the testing error. The errors were big and the results were inconsistent only for the small values of the training parameters. The optimal values were adopted at 0.6 for both,

learning coefficient and momentum factor. During the test, the rest of the parameters were fixed at the optimal values.
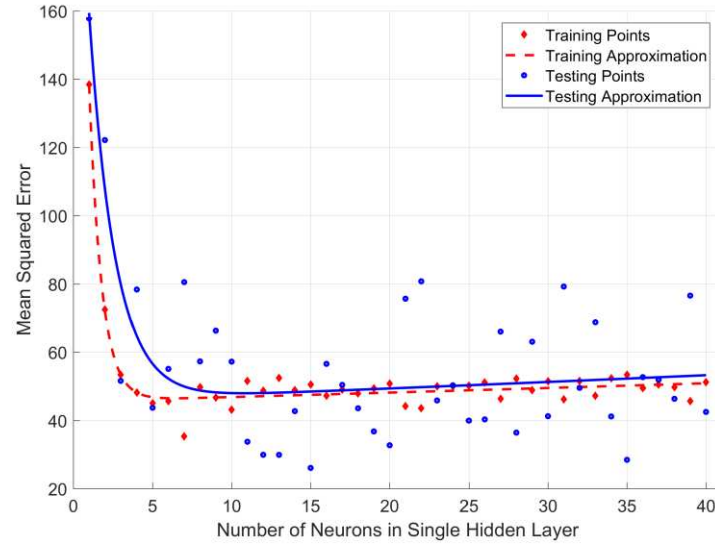

Fig. 7 Mean squared errors with respect to the number of neurons in a single hidden layer
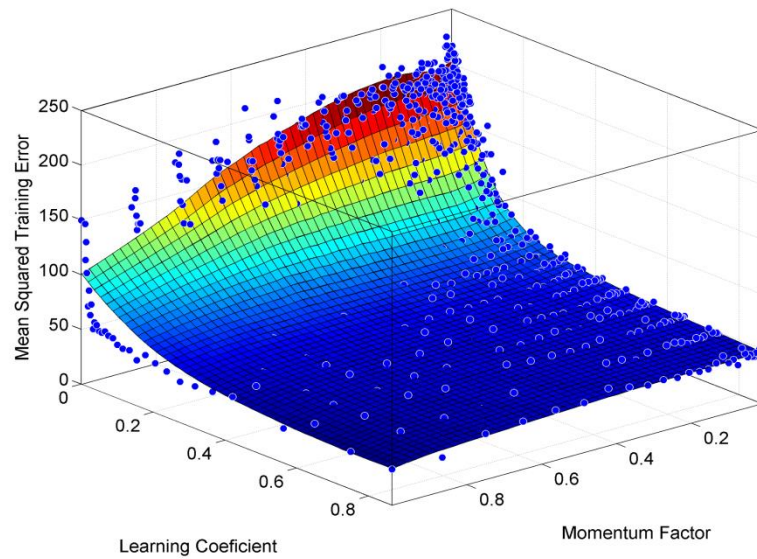

Fig. 8 Mean squared training error with respect to the training parameters
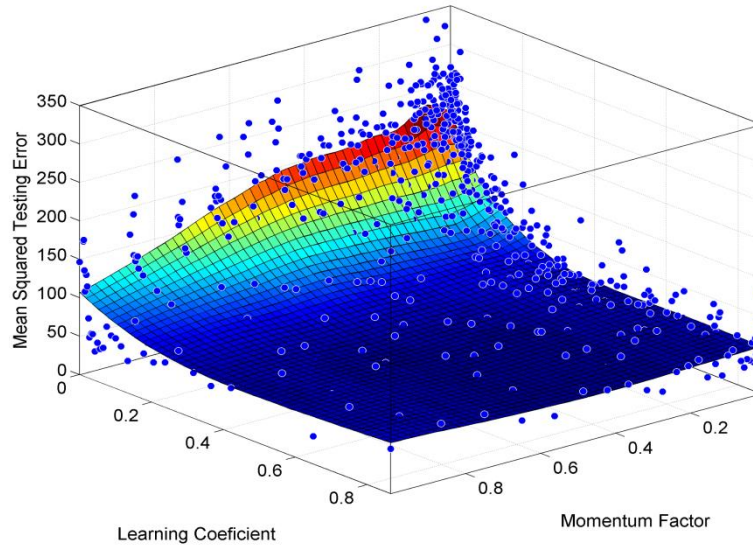
Fig. 9 Mean squared testing error with respect to the training parameters

The accuracy achieved in positioning with respect to the number of backpropagation epochs, in the logarithmic scale, was presented on the Fig. 10. It shows that training error decreases constantly with the number of epochs. The testing error decreases up to some value and then stagnates or even increases. Such a case is known as over-trained neural network [24]. The approximations were performed using two term exponential function.
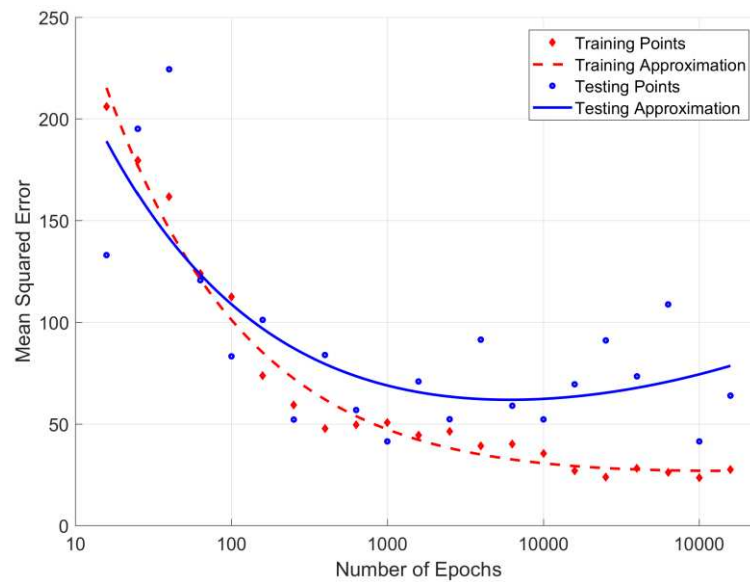

Fig. 10 Mean squared errors with respect to the number of training epochs
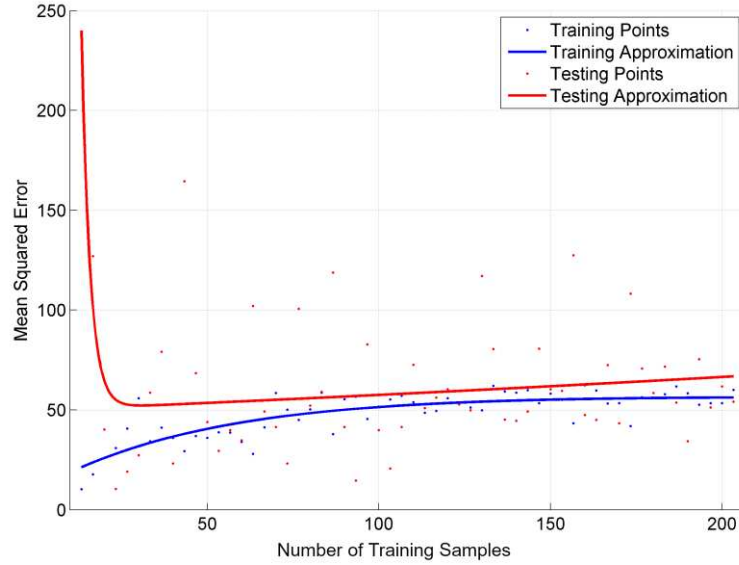
Fig. 11 Mean squared errors with respect to the number of training samples

The dependency of the training and testing errors with respect to the number of training points, presented in Fig. 10, shows that the training error decreases and the testing error increases with respect to the number of training points. The consistency of the errors increases, naturally, with higher numbers of training points. However, after a certain number, despite involving more and more samples, improvement becomes negligible. So, an optimal number of training points is a compromise between the anticipated accuracy and available training resources. The approximations were performed, again, using a two term exponential function.

After optimal parameters were chosen, the system was tested employing 15% of randomly chosen samples. These samples had not been used, previously, for the training of the neural network. In such a way the concern is avoided for all training positions to belong to the moving range of the robot. The soft robot achieved a mean absolute error around 48 mm in tracing of the given spatial positions.

4. DISCUSSION

The experiment confirmed that a feedforward neural network can be trained for solving the inverse kinematic problem of the soft robot. The mean absolute positioning error of 48 mm in comparison with the 1000 mm long moving zone gave the relative positioning error of about 5%. The error might seem too big, in comparison with the classic positioning systems, but it proved a predictable robot behavior. If the error is acceptable, from the standpoint of the robot function, the solution provides a high rate between performances achieved and utilized resources. The construction was designed, completely, of the most frequent and the most accessible materials. In such a way, the price of the realization was dramatically decreased. The control of the robot, by self-

organizing algorithm, eliminated identification as a phase in the system modeling. Thus, it is acceptable even for the users who are not familiar with the classic robotic theory. The selection of soft materials for the robot construction is expected to provide good safety in the interaction with humans.

The biggest drawback of the proposed solution is that it works for the constant dynamic conditions only. It can be adapted to the change of load only by renewing the training procedure using a new set of training data. So, the ultimate goal of further research should be designing a positioning control which is adaptable to the dynamic conditions. Such a system should be capable to collect information about the loads, using several sensors mostly placed at the robot body. The network should generate the control signal, by solving the inverse dynamic problem, on the basis of the desired coordinates and the current loads. Another solution for improving the positioning accuracy can be involvement of a closed-loop control but it requires an efficient procedure for the determining robot position in real time. The increase of positioning error with the increase of training samples (Fig. 11) indicates that the error originates from the nonlinearities and redundancy in the robot behavior that cannot be approximated by a neural network. The research will be used as a model for further experiments with different constructions of modular soft robots. The experiments are expected to minimize deformities (nonlinearities, redundancy and singularities) in the robot behavior and consequently improve the positioning accuracy.

REFERENCES

[1] D. Rus, M. T. Tolley, "Design, fabrication and control of soft robots", Nature, vol. 521, pp. 467-475, 2015. [Online]. Available: http://dx.doi.org/10.1038/nature14543

[2] Stanford researchers develop a new type of soft, growing robot, 2017. [Online]. Available: https://news.stanford.edu/2017/07/19/stanford-researchers-develop-new-type-soft-growing-robot/ [Accessed on July 2018].

[3] Soft robot powered by vacuum can climb walls, grab objects, 2017. [Online]. Available: http://www.dnaindia.com/technology/report-soft-robot-powered-by-vacuum-can-climb-walls-grab-objects-2542831[Accessed on July 2018].

[4] Soft Robots Disrupting Robotics, 2017. [Online]. Available: https://disruptionhub.com/5-soft-bots-disrupting-robotics/[Accessed on July 2018].

[5] R. L. Truby, M. Wehner, A. K. Grosskopf, D. M. Vogt, S. G. M. Uzel, R. J. Wood, J. A. Lewis, "Soft Somatosensitive Actuators via Embedded 3D Printing", Advanced Materials, vol. 30, 2018. [Online]. Available: https://doi.org/10.1002/adma.201706383

[6] F. Renda, F. Boyer, J. Dias, L. Seneviratne,"Discrete Cosserat Approach for Multi-Section Soft Robots Dynamics", Transaction on Robotics, [Online]. Available: http://arxiv.org/abs/1702.03660 [Accessed on July 2018]

[7] S. Cubero, *Industrial Robotics: Theory, Modeling and Control.* pIV pro literatur Verlag Robert Mayer-Scholz, 2007. [Online]. Available: http://zums.ac.ir/files/research/site/ebooks/Robotics/Industrial%20Robotics%20Theory%20Modelling%20and%20Control.pdf

[8] A. D.Marchese, D. Rus, "Design, kinematics, and control of a soft spatial fluidic elastomer manipulator" . International Journal Of Robotics Research, vol. 35(7), pp. 840-869, 2016. [Online]. Available: http://dx.doi.org/10.1177/0278364915587925

[9] A. D.Marchese, R.Tedrake, D. Rus, "Dynamics and trajectory optimization for a soft spatial fluidic elastomer manipulator", The International Journal Of Robotics Research, no. 8, p. 1000, 2016.[Online]. Available:http://groups.csail.mit.edu/robotics-center/public_papers/Marchese15a.pdf

[10] S. Wolf, "Soft Robotics with Variable Stiffness Actuators: Tough Robots for Soft Human Robot Interaction",Soft Robotics. Springer, 2015. [Online]. Available∶https://doi.org/10.1007/978-3-662-44506-8_20

[11] L. Ming, A. Mahdi, O. D. Cagdas, "Theoretical Modeling and Experimental Analysis of a Pressure-Operated Soft Robotic Snake", Soft Robotics, vol. 1(2), 2014. [Online]. Available: https://doi.org/10.1089/ soro.2013.0011

[12] R. J. Webster, B. A. Jones. "Design and Kinematic Modeling of Constant Curvature Continuum Robots: A Review", International Journal Of Robotics Research, vol. 29(13), pp. 1661-1683, 2010. [Online]. Available: http://dx.doi.org/10.1177/0278364910368147

[13] E.Coevoet, T. Morales-Bieze, F. Largilliere, Z. Zhang, M. Thieffry, M. Sanz-Lopez, C. Duriez, "Software toolkit for modeling, simulation, and control of soft robots", Advanced Robotics, vol. 31(22), pp. 1208-1224, 2017. [Online]. Available: http://dx.doi.org/10.1080/01691864.2017.1395362

[14] E. G Kaigom, J. Roßmann, "Physics-based simulation for manual robot guidance", An eRobotics approach. Robotics And Computer Integrated Manufacturing,vol. 43 (Special Issue:Extended Papers Selected from FAIM 2014), pp. 155-163. [Online]. Available: http://dx.doi.org/10.1016/j.rcim.2015.09.015

[15] M. Thieffry, A. Kruszewski, O. Goury, T. M. Guerra, C. Duriez. "Dynamic Control of Soft Robots", IFAC World Congress, 2017. [Online]. Available: https://hal.archives-ouvertes.fr/hal-01558844/file/ DynamicControlSoftRobots.pdf

[16] C. Duriez,"Control of elastic soft robots based on real-time finite element method". 2013 IEEE International Conference On Robotics & Automation, 3982, 2013.[Online]. Available:http://dx.doi.org/10.1109/ICRA. 2013.6631138

[17] F.Largilliere, V. Verona, E. Coevoet, M. Sanz-Lopez, J.Dequidt, "Real-time control of soft-robots using asynchronous finite element modeling", ICRA, IEEE International Conference on Robotics andAutomation, pp. 6, 2015. [Online]. Available:https://hal.inria.fr/hal-01163760/document

[18] Z.Zhang, J. Dequidt, A. Kruszewski, F. Largilliere, C. Duriez,"Kinematic modeling and observer based control of soft robot using real-time Finite Element Method", 2016 IEEE/RSJ International Conference On Intelligent Robots & Systems (IROS), 5509, 2016.[Online]. Available:http://dx.doi.org/10.1109/IROS.2016.7759810

[19] Ç.Nihat, B. Veli, "Artificial Neural Networks Based Inverse Kinematics Solution and Simulation of a Six Degree of Freedom Lighting Manipulator", Gazi Üniversitesi Fen Bilimleri Dergisi, Vol 6(1), pp 117-125, 2018. [Online]. Available:http://dx.doi.org/10.29109/http-gujsc-gazi-edu-tr.328422

[20] L.Aggarwal, K.Aggarwal, R. J. Urbanic. "Use of Artificial Neural Networks for the Development of an Inverse Kinematic Solution and Visual Identification of Singularity Zone(s)", Procedia CIRP, vol. 17(Variety Management in Manufacturing), pp. 812-817, 2014. http://dx.doi.org/10.1016/j.procir.2014.01.107

[21] M. Asadi-Eydivand, M.Ebadzadeh, M. Solati-Hashjin, C.Darlot, N. A. Abu Osman,"Cerebellum-inspired neural network solution of the inverse kinematics problem", Biological Cybernetics, vol. 109(6), pp. 561-574, 2015. http://dx.doi.org/10.1007/s00422-015-0661-7

[22] M.Soylak, T. Oktay, İ. Turkmen, "A simulation-based method using artificial neural networks for solving the inverse kinematic problem of articulated robots", Proceedings Of The Institution Of Mechanical Engineers -- Part E -- Journal Of Process Mechanical Engineering (Sage Publications, Ltd.), vol. 231(3), p. 470, 2017. http://dx.doi.org/10.1177/054408915608755

[23] M. Kovandžić, V.Nikolić, A. Al-Noori, I. Ćirić, M. Simonović, "Near field acoustic localization under unfavorable conditions using feedforward neural network for processing time difference of arrival", Expert Systems With Applications, 71138-146, 2017. [Online]. Available:http://dx.doi.org/10.1016/j.eswa.2016.11.030

[24] R. Rojas R, *Neural Networks*. Springer-Verlag, 1996.[Online]. Available:http://dx.doi.org/10.1016/ j.eswa.2016.11.030

[25] V. Nikolić, Ž. Čojbašić, D. Pajović, *Automatsko upravljanje: Analiza sistema,* Nova Jugoslavija, 1996.