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Qualitative approach for forward kinematic modeling of a Compact Bionic Handling Assistant trunk ⋆

A. MELINGUI * **C. ESCANDE** * **N. BENOUDJIT** **
R. MERZOUKI * **J. B. MBEDE** ***

* *LAGIS, (UMR), (CNRS) 8219, Ecole Polytechnique de Lille,59655 Villeneuve d'Ascq, France, (achille.melingui@etudiant.univ-lille1.fr, rochdi.merzouki@polytech-lille.fr, coralie.escande@polytech-lille.net)*
** *Department of Electronics, University of Batna, Algeria, (e-mail: nbenoudjit@gmail.com)*
*** *Electrical Engineering and Telecommunications Department of Polytechnic National School, University of Yaounde 1, PO. Box: 8390 Yaounde, Cameroon, (e-mail: mbede@neuf.fr)*

Abstract: This paper addresses the forward kinematic model of a class of hyper-redundant continuum robot, namely Compact Bionic Handling Assistant (CBHA). Inspired from the elephant trunk, it can reproduce some biological behaviors of trunks, tentacles, or snakes. Such systems, like the CBHA are subjected to a set of nonlinearities (flexibility, elasticity, redundancy,...) and uncertainties (parameters and modeling), making difficult to build an accurate analytical model, which can be used to develop control strategies. Hence, learning method becomes a suitable approach for such scenarios in order to capture un-modeled nonlinear behaviors of this continuum arm. The proposed approach makes use of Multilayer Perceptron (MLP) and Radial Basis Function (RBF) Neural Networks for the approximation of forward kinematic model (FKM) of CBHA trunk. The experiments have been conducted on the CBHA in order to validate the forward kinematic model where the arm trajectories are generated using a physical coupling with a rigid manipulator. A comparison of both qualitative approaches with a quantitative geometric approach, according to the model accuracy is given at the end of the experiment.

1. INTRODUCTION

Unlike traditional rigid link robots, continuum robots present some features (flexibility, redundancy,...) which can be exploited for singularities elimination, obstacle avoidance, various criteria performance enhancing, and as well as for smooth motion. However, these features can be a source of nonlinearities, making difficult the development of a precise model-based control for such type of robots. Potential applications include navigation and operation in complex and congested environments such as search and rescue operations and surgical interventions. If suitable methods to model closed and open rigid robots kinematic chain mechanisms exist (Denavit et al. [1955], Khalil et al. [1986],...), the kinematic model of continuum robots remains difficult to obtain with high accuracy, because, they are often under-determined systems, due to their redundancy or hyper-redundancy with high number of parameters.

Considerable efforts have been focused on the design and construction of continuum robots. The use of the latter for practical applications requires modeling and development of real-time algorithms to extract their full physical potential. Focusing on their forward kinematic modeling, in the literature, two modeling approaches have been addressed; model-based approach and learning-based approach. A large proportion of efforts in the area have been focused on model-based approach (Gravagne et al. [2000], Jones et al. [2002], Jones et al. [2006], Rolf et al. [2012],...). In the learning-based approach, almost contributions focused on the inverse kinematic modeling (Rolf et al. [2009], Reinhart et al. [2011],...). The present paper focuses on forward kinematic modeling of continuum robots.

Trivedi et al. [2008], Rucker et al. [2010] and He et al. [2013] considered a more detailed model of material physics and bending processes, based on the Euler Bernoulli beam and Lagrange equations. They proposed an analytic method respectively for kinematics and dynamics modeling of continuum robots. However, these models do not provide closed-form solutions. They require an iterative solution of differential equation systems, which make them computationally expensive. Webster III et al. [2010] and Mahl et al. [2012], investigated the use of hyper redundant rigid-link models. A section kinematics is built connecting several 3-DOF parallel mechanisms in series. Afterwards, these section kinematics are combined to the manipulator arm kinematics as an open chain model. However, it is difficult to relate the CBHA links such to a rigid-link model which often gives imprecise results (Jones et al. [2002]). In addition, the CBHA trunk is made almost

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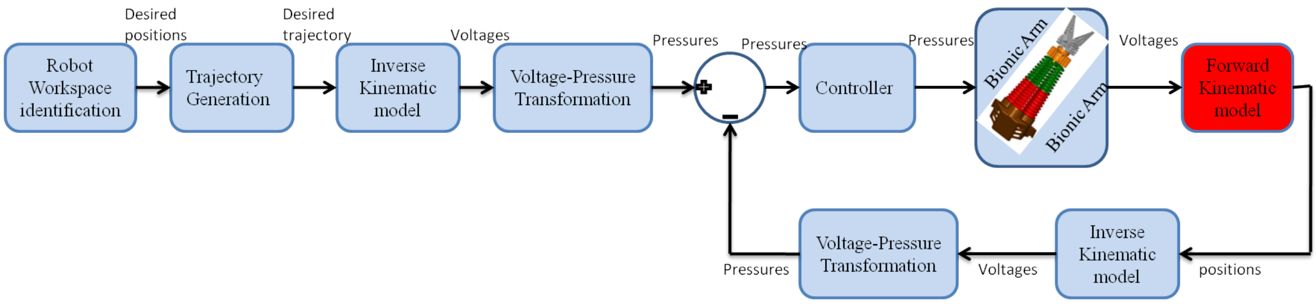

Fig. 1. Overall autonomous control scheme of the CBHA

completely out of polyamide. Jones et al. [2002], Rolf et al. [2012] and Chirikjian et al. [1994] focus on the continuum deformation of the entire robot arm section. They define a class of functions to describe all possible deformations of the section. The most used class of deformation functions is circular shapes (Jones et al. [2002], Jones et al. [2006], Bailly et al. [2005]). Circular shapes correspond to a constant curvature of the continuum robot and describe the energy minimum without gravitational or other external forces (Gravagne et al. [2000]). Jones et al. [2002] has pointed out the central problem of circular approaches through a numerical investigation. The difficulty occurs when one or more of the sections of the trunk does not bend, in which case the bending radius of the trunk section becomes infinite. This gives rise to two problems (Jones et al. [2002]): The numerical evaluation of the kinematics at this point (the kinematics model involves terms including the radius) and the evaluation near the limiting case of a straight trunk (a finite-precision machine arithmetic produces numerical instability). The authors only deal with the straight positions, but they do not apply if a section is not bent. Godage et al. [2011]prevented this problem by choosing a more general class of functions. Their model successfully describes elongation, but encounters estimation problem in a high-dimensional parameters. Rolf et al. [2012] proposed a new parameterless method to deal with geometric singularities in stretched positions, which allow to capture pure elongations that are not naturally expressed by the toroidal deformations underlying the constant curvature assumption. However, examining the physics of flexible structures demonstrates that continuum trunks bend with constant curvature, forming an arc of a circle, only in the absence of external forces such as gravity (Gravagne et al. [2011]).

In order to capture the full complexity of continuous deformations and un-modeled nonlinear behaviors of the continuous robots, a learning-based approach is developed in this paper for modeling the forward kinematic of the CBHA. This choice is motivated by the fact that:

- the learning approaches are free from assumptions (constant curvature, the toroidal deformations,...), they use the sampled input-output data pairs to estimate the FKM.
- continuum robots deformations are potentially infinite dimensional since the entire arm's material is deformable. This kind of deformation could only be reconstructed using redundant sensors. Therefore, they are under-determined systems with high number of parameters.

For a reliable CBHA positioning, it is not efficient to control the pressure alone. Friction and hysteresis related to CBHA structure can cause largely different postures when applying the same pressure several times. Since pressure does not provide reliable information about the robots position and movement in space, reaching solely concerns the geometric information (length sensors). These geometric information (length sensor values) can be controlled by dynamically adjusting the pressure in each actuator (Rolf [2012]). CBHA robot can be controlled by the following control scheme Fig. 1. The control scheme comprises:

- An inverse kinematic model to evaluate the geometric information (robot posture) from workspace coordinates;
- A pressure transformation system to provide the pressure necessary to achieve the robot posture;
- A controller to compensate uncertainties and modeling errors;
- A FKM to evaluate the workspace coordinates from geometric information.

The contribution of this work can be summarized in three points:

(1) Development of the FKM of CHBA based on learning approach;
(2) Identification of the CHBA workspace;
(3) comparison of the proposed approach with a model-based approach using an appropriate test-bench for calibration.

In Park et al. [1991] and Hornik et al. [1989], RBF and MLP neural networks are respectively considered as the universal approximators. They can approximate any nonlinear functional relationship with an arbitrary accuracy, provided that enough hidden neurons are available. In this work, RBF and MLP neural networks are used to model the forward kinematic of the CBHA. The remainder of this paper is presented are followed: Section 2 describes the CBHA robot. Section 3 presents the MLP and RBF neural networks. Section 4 describes the experimental platform and provides experimental results and discussions. Section 5 gives the conclusions and future works.

2. PROBLEM FORMULATION

The CBHA depicted in Fig. 2 is attached to an omnidirectional mobile robot called Robotino Fig. 3. It comprises two main segments, each with three pneumatic-actuated bellow, a ball-joint as wrist, controlled using two actuators, and two compliant jaws constituting a gipper controlled by

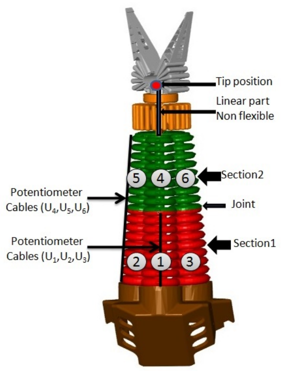

Fig. 2. CBHA manipulator

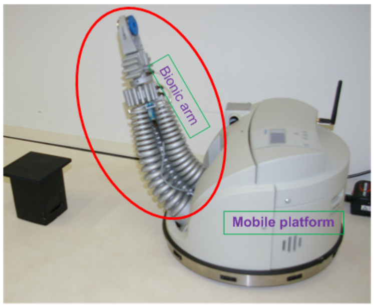

Fig. 3. Robotino XT platform

one actuator. Each actuator can be controlled separately. The venting of the backbone tubes allows resetting its shape; hence supplying it with compressed air leads to its expansion. The bionic trunk consists of nine sensors; six wire-potentiometers, installed on the surface of each flexible backbone tubes, in order to measure their elongations. Two sensors are used for the rotating part and the last one to detect the gripper status. Nowadays, the CBHA placed on the Robotino mobile robot platform is controlled in an open-loop configuration using a joystick interface. The problem is to keep this control autonomous and in closed-loop Fig. 1. The main difficulty is the establishment of an accurate FKM allowing obtaining the relationship between Cartesian coordinates of the tip of the arm and the tube-lengths. Thus, this is our main interest in this work. We study the FKM of the two jointed segments (red and green segments of the Fig. 2), so that 6 actuated inputs are used. We consider only Cartesian tip position, so that 3 measured outputs are used.

3. MLP AND RBF NEURAL NETWORKS

Typical examples of ANNs are MLP and RBF neural networks. They are different from each other in both the architecture as well as the training procedure. ANNs are universal approximators, they can approximate any non-linear functional relationship (mapping) with an arbitrary accuracy, provided that enough hidden neuron is available (Hornik et al. [1989], Benoudjit et al. [2003]). This supports the success of the ANNs in numerous fields of application of regression problems. A MLP neural network Fig. 4 is composed of an input layer, an output layer, and one or more hidden layers. The signals flow consecutively through the different layers from the input to the output layer. For each layer, each elementary unit calculates a scalar product between a vector of weights and the output vector given by the previous layer. A transfer function (sigmoid, hyperbolic tangent,...) is then applied to the result to produce an input for the next layer.

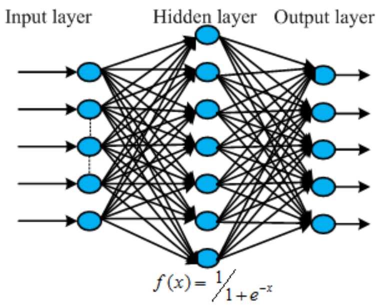

Fig. 4. MLP Neural Network topology

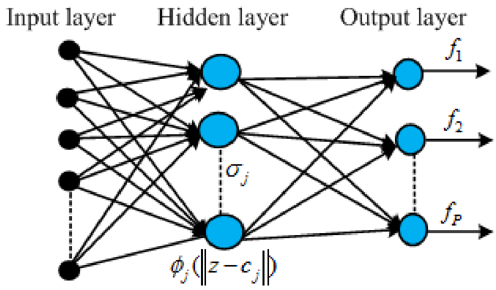

Fig. 5. RBF Neural Network topology

RBF neural network Fig. 5 is composed of three layers (input, a hidden, and an output layer). Input neurons propagate input variables z_j to the next layer. Each neuron in the hidden layer is associated with a kernel function φ_j (usually a Gaussian function) characterized by a center c_j and a width σ_j.

$$\varphi_j(\|z-c_j\|) = \exp\left(-\frac{1}{2}\left(\frac{\|z-c_j\|}{\sigma_j}\right)^2\right). \quad (1)$$

The output function is given by:

$$f(z) = \sum_{j=1}^{P} \lambda_j \varphi_j\left(\|z-c_j\|\right). \quad (2)$$

Where P and λ_j are respectively the number and the weight of the radial functions. For more details about ANNs, we refer the reader to (Hornik et al. [1989], Benoudjit et al. [2003], Bishop [1995]).

4. EXPERIMENTAL RESULTS

To verify the performances of the proposed approach, the validation of the FKM based on MLP and RBF Neural Networks is achieved using a rigid six degrees-of-freedom manipulator. In this section, we first provide a description of the sample data acquisition followed by the learning phase result. Finally, the experimental platform and the obtained results are described, which illustrate the effectiveness of the proposed approach for the case of the CBHA system.

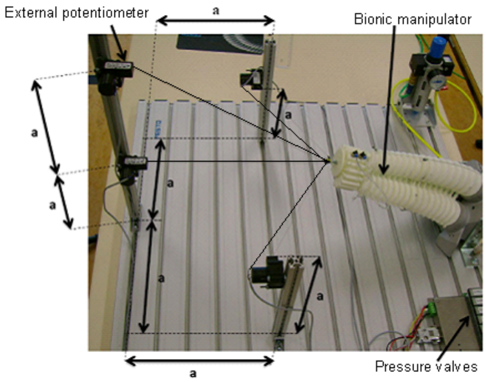

Fig. 6. Trilateration process

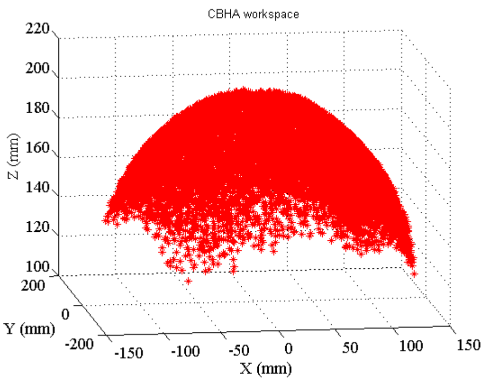

Fig. 7. Bionic arm workspace

4.1 Data acquisition

To build the learning data base, the tip of arm position is evaluated experimentally by means of a trilateration system developed in (Escande et al. [2012]) Fig. 6. The test bench consists of:

- 1 profiled metallic platform,
- 4 external proportional potentiometers
- 6 wire-potentiometers placed along of each tube.

From the 4 values of the external potentiometers and using the simple trigonometry transformation, we evaluate the tip position of CBHA arm. The learning base is built as followed: The CBHA posture (wire-potentiometer values) is varying proportionally with the pressure used to control tube-lengths. The pressure in each tube is controlled using internal PID-control. The range of each pressure is [0; 1.5]bars. By using a step size of 0.5, each tube can be controlled by one of these values $(0; 0.5; 1; 1.5)$. With 6 controlled inputs, we have a learning base of $4^6 = 4096$ samples. The workspace of CBHA arm is depicted in Fig. 7.

4.2 Learning procedure

The forward kinematics neural network model is consisted of 6 inputs of wire-potentiometer $(U_1, U_2, ..., U_6)$ and 3 outputs (Tip of arm position). The both neural networks regressors (MLP and RBF) were trained on their corresponding training sets. The learning data base is divided randomly; 70 percent for training set, 15 percent for validation and test sets. The training set is used during learning

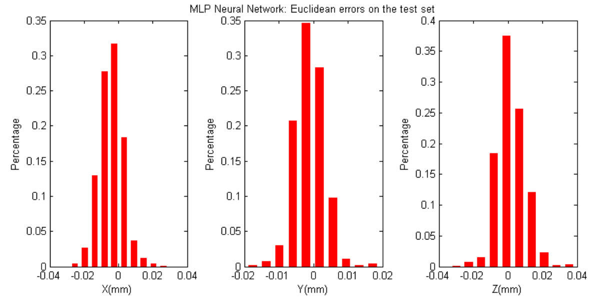

Fig. 8. MLP neural network: Test set results

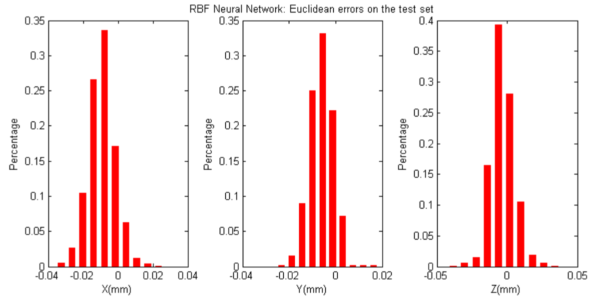

Fig. 9. RBF neural network: Test set results

Table 1. Results achieved on the forward kinematic by the MLP and RBF neural networks

Neural networks topologies	Number of neurons	MSE
MLP (2 hidden layers)	36	$3.0890.10^{-5}$
RBF ($\sigma = 0.5$)	72	$5.2664.10^{-5}$

phase and the test set is only employed to evaluate the performance of the networks. The validation set is used during the learning phase to avoid the overfitting. In order to empirically select the best model for each regressor, the value of each parameter was varied in a given predefined range according to a grid search over the validation set. We tested the MLP with 2 up to 40 neurons in the hidden layers. Concerning the RBF model, we varied the number of neurons in the hidden layer from 2 to 90, and the width of the Gaussian kernel from 0.01 to 2. The assessment of the trained regressors in terms of MSE (mean square error) on the test samples yielded the values reported in Table. 1. Note that, the length-sensors are given in volt, because they are provided by the wire-potentiometers. By simple transformation, these voltages are transformed into length. We use the wire-potentiometer voltages to avoid the uncertainties related to the transformation from voltage to length. The obtained results from a test set of 614 samples for MLP and RBF neural networks are depicted respectively in Fig. 8 and Fig. 9. They present the percentage error between the desired and predicted CBHA tip positions over the samples of the test set.

4.3 Model validation and results

To collect a time-domain Cartesian position of the tip of the CBHA and its tube-lengths, we used an external rigid robot (Kuka KR6 Arc) to generate the bionic arm trajectories. This 6 DoF robot is also used as an external sensor, allowing measurement of the tip of the bionic arm position according to that of Kuka end-effector, which are

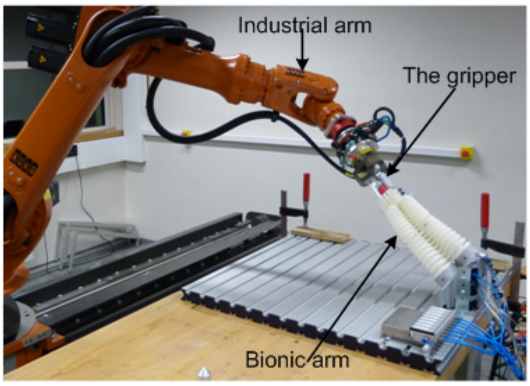

Fig. 10. Experimental test environment

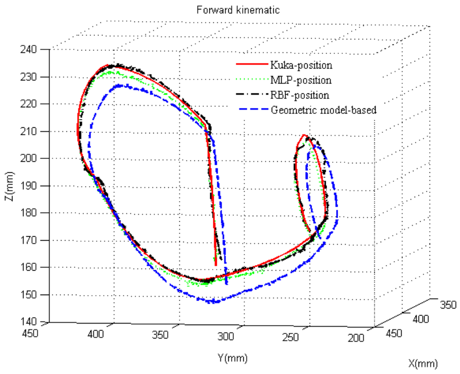

Fig. 11. Industrial trajectory estimation

superposed. The industrial arm grippes the extremity of the bionic trunk to generate the desired trajectory Fig. 10. For this purpose, programming Kuka Robot Language (KRL) is used. The algorithm is implemented through the Kuka Control Software (KSS) which is running on VxWorks. Remote Sensor Interface(RSI) is considered to exchange data between the robot and a remote server using an Ethernet connection. From the Kuka robot side, the Cartesian coordinates of the end effector in acquired for a specific generated trajectory inside the workspace. On the side of the bionic arm, during the trajectory generation, a DSpace Input/Output board receives the length measurements of the bionic arm and sends a trigger signal to Kuka Robot for the synchronization of the starting time. In this section, a comparative study between two learning neural networks method with a geometric model-based is addressed. The qualitative and quantitative approaches are used to validate the estimated FKM of the CBHA, based on trajectories generated from the industrial robot manipulator. The geometric model-based approach is based on a constant curvature principle (Webster III et al. [2010]). The development of two sections bionic arm FKM is presented in details in (Escande et al. [2012]). The method assumes that the curvature of the sections and the tubes describes a perfect arc of a circle which is an imposed assumption inducing some modeling uncertainties. The robot trajectory, the estimated neural networks trajectories (MLP and RBF) and the estimated geometric model-based trajectory are depicted in Fig. 11. The estimation errors in X, Y and Z are respectively represented in Fig. 12, Fig. 13, and Fig. 14. Table. 2 rank the performances of each approach.

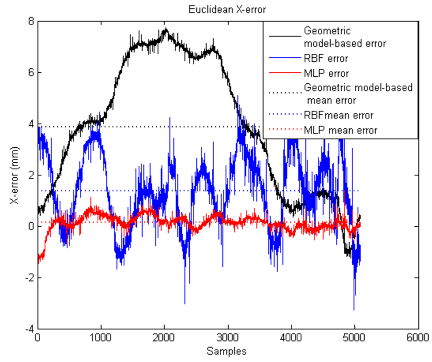

Fig. 12. Euclidean error in X axis

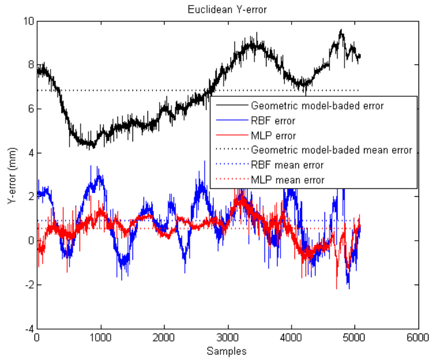

Fig. 13. Euclidean error in Y axis

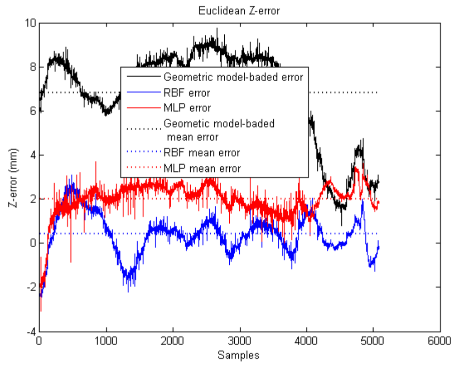

Fig. 14. Euclidean error in Z axis

Table 2. Results achieved on the FKM by Geometric model-based, MLP and RBF neural networks

Modeling approach	Mean of Euclidean error(mm)		
	X	Y	Z
Geometric model-based	3.8614	6.8089	6.8115
RBF Neural Networks	1.3772	0.8860	0.4165
MLP Neural Networks	0.1283	0.5527	1.9877

On the whole, the results of different approaches are satisfactory in terms of trajectory estimation and position errors convergence. We have a mean error of $5.82mm$, $0.89mm$ and $0.88mm$ respectively for geometric model-based approach, RBF and MLP neural networks approach. As we are pointed out previously, the problem of constant curvature based-methods occurs when one or more of the sections of the trunk does not bend, in such case the bending radius of the trunk section becomes infinite. This leads to two problems: The numerical evaluation of the kinematics at this point and the evaluation near the limiting case of a straight trunk. This justifies imprecise estimation for some trajectory portions using the geometric model-based approach. We notice that the estimated trajectories using neural network and the imposed industrial robot trajectory are very close. However, we observe some differences which are mainly due to the trunk composite flexion memory and uncertainty length measurements issued from the wire-potentiometers. In this work, we demonstrate that without the quantitative assumptions of the constant curvature, the toroidal deformations..., the MLP and RBF neural networks can approximate accurately the tip of bionic arm position while dealing with geometry singularities and stretched positions. Thereby, the proposed qualitative modeling approach, compared to those developed in (Mahl et al. [2012], Rolf et al. [2012], Jones et al. [2006]) gives improvement in the forward model estimation, with consideration of the undesired nonlinearities of the trunk. Comparing the performances of two neural networks, we notice that, MLP outperforms their RBF counterparts, in term of MSE, because the MLP uses an additional layer of neurons.

5. CONCLUSIONS

In this paper, a learning-based qualitative approach is used for elaboration of the FKM of a CBHA manipulator. MLP and RBF neural networks are trained to approximate the FKM. The experiments have been performed using the CBHA of the Robotino XT robot, in order to validate the accuracy of the learning-based models, through the two neural network topologies. A comparison with a geometric-based quantitative approach shows the accuracy of the qualitative methods in the presence of nonlinearities and uncertainties. In future work, we should integrate the kinematic of the mobile platform to the CBHA kinematic model, to generalize the study for the overall RobotinoXT, the mobile-bionic manipulator robot.

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REFERENCES

B. A. Jones, and I. D. Walker. Kinematics for multisection continuum robots. *IEEE Trans. on Robotics*, 22:1, 2006.

B. A. Jones, and I. D. Walker. Limiting-case analysis of continuum trunk kinematics. *in ICRA*, 10:117–127, April 2002.

B. He, Z. Wang, Q. Li, H. Xie, and R. Shen. Design and kinematic modeling of constant curvature continuum robots: A review. *International Journal of Advanced Robotic Systems*, 10:1–13, 2013.

C. Escande, P. M. Pathak, R. Merzouki, and V. Coelen. Geometric modeling of multisection bionic manipulator: Experimental validation on robotinoxt. *In Robotics and Biomimetics (ROBIO), 2012 IEEE Int.Conference on*, December 2012.

C. M. Bishop. Neural Networks for Pattern Recognition. *Oxford University press*, 1995.

D. Rucker, B. Jones, and R. Webster. A geometrically exact model for externally loaded concentric-tube continuum robots. *IEEE Trans. on Robotics*, 26:2, 2010.

D. Trivedi, A. Lotfi, and C. Rahn. Geometrically exact models for soft robotic manipulators. *IEEE Transactions on Robotics*, 24:2, 2008.

G. Chirikjian and J. Burdick. A modal approach to hyper-redundant manipulator kinematics. *IEEE Transactions on Robotics and Automation*, 10:3, 1994.

I. A. Gravagne and I. D. Walker. On the kinematics of remotely-actuated continuum robots. *in ICRA*, 2000.

I. S. Godage, D. T. Branson, E. Guglielmino, G. A. Medrano-Cerda, and D. G. Caldwell. Shape function-based kinematics and dynamics for variable length continuum robotic arms. *in ICRA*, 2011.

I. A. Gravagne, C. D. Rahn, and I. D. Walker. Large deflection dynamics and control for planar continuum robots. *IEEE/ASME Trans-actions on Mechatronics*, 1–7, July 2011.

J. Denavit, and R.S. Hartenberg. A kinematic notation for lower-pair mechanisms based on matrices. *Journal of Applied Mechanics*, 22:215–221, 1955.

J. Park, and I. W. Sandberg. Universal approximation using radial basis function networks. *Neural computation*, 3 (2):246–257, 1991.

K. Hornik, M. Stinchcombe, and H. White. Multilayer feedforward networks are universal approximators. *In Intelligent Robots and Systems*, 2(5):359–366, 1989.

M. Rolf. Goal balbing for and efficient bootstrapping of inverse models in high dimensions. *Dissertation, Faculty of technology, Bielefeld University*, 2012.

M. Rolf, and J. J. Steil. Constant curvature continuum kinematics as fast approximate model for the Bionic Handling Assistant. *In Intelligent Robots and Systems*, 10:3440–3446, October 2012.

M. Rolf, J. J. Steil, and M. Gienger. Efficient exploration and learning of whole body kinematics. *IEEE 8th Int. Conference on Development and Learning*, 1–7, Shanghai, 2009.

N. Benoudjit, and M. Verleysen. On the kernel widths in radial basis function networks. *Neural Process Lett.*, 28: 139–154, 2003.

R. F.Reinhart, and J. J. Steil. Neural learning and dynamical selection of redundant solutions for inverse kinematic control. *In Humanoid Robots, 2011 11th IEEE-RAS Int. Conference on*, 10:564–569, October 2011.

R. J. Webster III and B. A. Jones. Design and kinematic modeling of constant curvature continuum robots: A review. *The International Journal of Robotics Research*, 29(13):1661–1683, June 2010.

T. Mahl, A. Hildebrandt, and O. Sawodny. Forward Kinematics of a Compliant Pneumatically Actuated Redundant Manipulator. *7th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, 1267–1273, 2012.

Y. Bailly and Y. Amirat. Modeling and control of a hybrid continuum active catheter for aortic aneurysm treatment. *in ICRA*, 2005.

W. Khalil, and J.F. Kleinfinger. A new geometric notation for open and closed-loop robots. *IEEE Int. Conf. on Robotics and Aut.*, 3:1174–1179, 1986.