2018 18th International Conference on Control, Automation and Systems (ICCAS 2018)
Oct. 17–20, 2018; YongPyong Resort, PyeongChang, GangWon, Korea

Use of Deep Learning for Position Estimation and Control of Soft Glove

Jeesoo Ha[1], Dooyoung Kim[1] and Sungho Jo[2*]

[1]School of Computing, Korea Advanced Institute of Science and Technology,
Daejeon 305-701, Korea (jsha2913@kaist.ac.kr, dykim07@kaist.ac.kr)
[2]School of Computing, Korea Advanced Institute of Science and Technology,
Daejeon 305-701, Korea (shjo@kaist.ac.kr) * Corresponding author

Abstract: Soft wearable robots comprised of deformable materials have recently attracted much attention in the field of applications for its lightness and elasticity. However, there exist some limitation to the control of wearable robots due to the complexity of the model and the conditions of the wearer. In this paper, we propose a learning-based position control method of soft wearable glove using a deep neural network (DNN). To analyze our proposed method, we fabricated a soft pneumatic glove and a control board for the glove based on open hardware platform data. With our developed system, we collected the pressure and position data of the soft glove using a Leap Motion sensor to train our soft glove position network (SGPN). Along with our proposed DNN model, we could enable open-loop control on the joint positions of the soft glove by supplying pressure to the actuator without prior knowledge of the wearer or the wearable robot such as hand size of the wearer or the stiffness of pneumatic actuator.

Keywords: soft wearable robot, robotic glove, deep learning, learning-based control

1. INTRODUCTION

Soft robots, one of the specific types of robots composed of soft materials such as silicone rubber or tendons, have recently gained much attention in the application field of robots due to their relatively high degree of freedom and deformability [1,2]. Especially, since it is lighter and more elastic than conventional robots, the number of researches applying soft robotics to wearable robots have drastically increased. Some of the previous researches include soft gloves for rehabilitation [3–5] and soft wearable suits for reducing human metabolic costs [6]. These soft wearable robots can safely interact with the wearer because of its lightweight and high compliance, and it is relatively inexpensive to manufacture compared to traditional exoskeletons.

Despite these advantages, the functionality of soft wearable robots is still limited because they are difficult to model and control. Unlike conventional robots with fixed shapes and limited movements, soft robots made of deformable materials have very high degrees of freedom, making it difficult to create an analytical model for soft robots and to use existing rigid robot control methods immediately [1, 7].

One common way of modeling soft robots is constant curvature approximation, which simplifies the model by assuming that the soft robot has a constant curvature. This method is able to model and control the soft robot by reducing the dimension of the soft robot to 3-D. However, such method only shows good performance when the external force is small and the shape is uniform. For robots with the complex shape, such as wearable gloves, computational costs and predicted parameters dramatically increase [7]. Especially, it is more complicated for soft gloves, which have different hand shapes and movements depending on the sex, age and health condition of the user [5]. Some studies on soft gloves were conducted to change the design of actuators depending on the shape of a wearer's hand and desired behavior [3,5,8], however, these solutions require information about the user's hands to control the gloves and should change the model to suit the user.

In this research, we propose a learning-based modeling method of soft pneumatic glove using a deep neural network (DNN), to estimate and control each joint positions of the glove with pressure sensors attached to the glove without an analytical model, as shown in Fig. 1. For

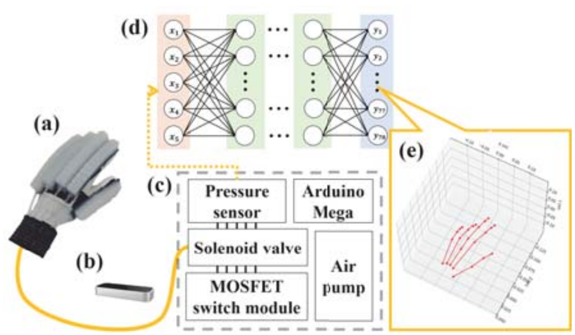


Fig. 1 Schematic diagram of the soft glove controller architecture; (a) soft pneumatic glove, (b) Leap Motion sensor, (c) pneumatic control board, (d) soft glove position network (SGPN), (e) result of position estimation

the experiment, a soft pneumatic glove was fabricated using five pneumatic networks bending actuators (PNBA); the manufactured glove is driven through a pneumatic

This paper is supported by the National Research Foundation of Korea Grant funded by the Korean Government (MSIT) under Grant NRF-2016R1A5A1938472.

control board; pressure data and each joint positions of the glove were collected when operating the glove using pressure sensors and a Leap Motion sensor, respectively; and the collected data is used to learn our proposed soft glove position network (SGPN). The trained model enables open-loop control to the finger joint positions of the soft glove according to the pressure supplied to the actuator without prior knowledge of the wearer or the robot model. The performance of the proposed algorithm was evaluated by comparing the estimated position and the actual fingertip positions of the glove according to the pressure for grasping motion of the glove.

The paper is organized as follows. Section II describe the architecture of the soft glove and its control system used in this paper. Section III propose data acquisition method and structures of our model. In Section IV, we presents analysis of the experimental results. We discuss limitation of current approach and future work in Section V, and finally conclude our research in Section VI.

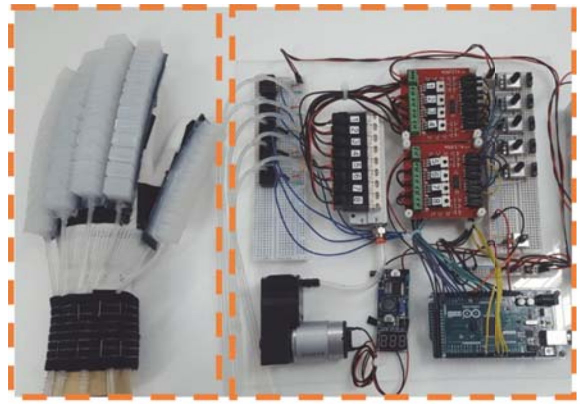
2. MATERIALS

Soft robots composed of flexible materials have difficulty in estimating the state or position of robots, considering their high degree of freedom and variable stiffness. Especially in the case of wearable robots such as gloves, having to adjust the model suitable for the wearer increases complexity. Therefore, we suggest a learning-based modeling approach for estimating and controlling the position of soft gloves based on data without specific model information. In order to make this possible, we made a soft pneumatic glove and a pneumatic control system capable of measuring the position of the soft glove.

2.1 Soft Pneumatic Glove

The soft pneumatic glove used in the experiment was fabricated using the pneumatic networks bending actuator (PNBA) proposed by Mosadegh et al. The PNBA is an actuator made by connecting sequence of air chambers. The chambers are manufactured by curing silicone elastomers using molds made from a 3-D printer. The serially connected chambers are inflated during air injection, thereby creating a bending motion of the actuator. Materials that does not stretch like paper are added to prevent unnecessary movement such as extending at the bottom of the actuator.

To make a soft pneumatic glove, two types of PNBA were produced considering the differences in the length of each finger of the human hand. One ($112 \times 17 \times 15$ mm) had eleven air chambers for bending the thumb. The other ($146 \times 17 \times 15$ mm) was consist of twelve air chambers for the rest of the fingers (index finger, middle finger, ring finger, and pinky finger). The actuators made of silicon material (DragonSkin30, Smooth-On Inc.) were attached to each finger position of a cloth glove using Velcro, as shown in Fig. 2 (a). To drive the glove, tubes were connected to one end of each actuator



(a) (b)

Fig. 2 Experimental equipment (a) soft pneumatic glove, (b) pneumatic control board

to allow air to flow in and out.

2.2 Pneumatic Control System

1) Hardware

To control the pressure supplied to the glove, we used a pneumatic control board proposed by the soft robotics toolkit [9] as shown in Fig. 2 (b). The board was consists of several parts: a micro controller (Arduino MEGA 2560 R3, Arduino), eight solenoid valves (VA100U-5M, SMC), two MOSFET switch module (SZH-AT021, SZH), an air pump (DAP-3043, MotorBank), and five pressure sensors (100PGAA5, Honeywell). The air from the motor is supplied to the soft pneumatic glove through the tubes connected to the actuator of the glove. The pneumatic pressure supplied to PNBA of the soft glove was measured using the pressure sensors connected on the tube of the actuators.

To adjust the air supply on the actuator, the controller generated the pulse with modulation (PWM) signal, which were transferred to the MOSFET switch module. Depending on the PWM signal, the MOSFET switch module regulated the amount of air supplied by opening and closing the solenoid valves connected to the actuators. By consistently retrieving the measured pressure and generating PWM signal the pneumatic board, the pressure was adjusted to control the soft glove.

2) Control System

We created a control system for pneumatic board control using the Robot Operating System (ROS) [10] to collect position data and pressure from the soft glove. Along with the generation of PWM signals from the controller of the board, the joint position data of each finger of the soft glove was utilized for the control system. The joint positions of each finger were acquired using the Leap Motion sensor, which is a device capable of measuring 3-D hand position with a position accuracy of up to 1.2 mm for moving objects [11].

For the experiment, we presented hand position information on the 78-dimensional data format composed of each finger joint and the palm-center coordinate as shown in Fig. 3. Because the thumb does not have metacarpals, Leap Motion sensor publishes the same position about proximal phalanx and metacarpal [12]. For this reason, the data representing the hand position by combining each 3-D coordinate and the palm-center coordinate at each five-finger joint position had 78 dimensions ($5 \times 5 \times 3 + 3 = 78$). The position information was converted into TF topics, the data format representing the 3-D coordinate in ROS, and then changed into relative coordinates centered on the palm. By transforming to relative coordinates in this way, errors due to translation and rotation of the hand can be reduced. The hand position data were used to train our deep neural network with pressure sensor information.

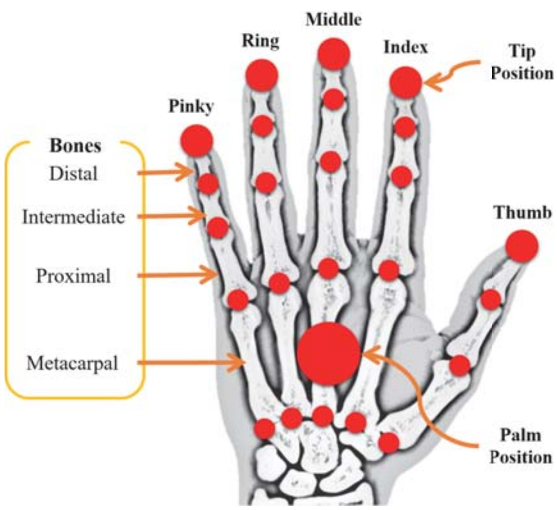


Fig. 3 The positions of each finger joint and palm-center position of soft glove

3. METHOD

3.1 Data Acquisition

The manufactured soft glove and control system was used for collect the train and test dataset. The soft glove data, position and pressure data of each PNBA actuator of the glove, were collected by the pneumatic control board and Leap Motion sensor. The PWM generated for driving the PNBA actuator was used to operate within the pressure range of 0 (0 kPa) to 13 psi (89.63 kPa) considering actuator bending motion, and the position and pressure data of the soft glove was gathered at a speed of 20 Hz. Data were collected using glove worn in the subjects' hands, and worn gloves were driven only by the applied pressure. For the train data, the PWM values for the ten grasp motion were performed and the joint position data of soft glove were gathered using Leap motion sensor, and the size was 2,950. The test data were produced for two grasp motions in the same pressure range as the train data and 400 data were generated. Table 1 shows the summaries of the train and test data.

Table 1 Summary of dataset

	Pressure range (psi)	Number of grasp motion	Data size
Train data	0∼13	10	2,950 per each finger joint
Test data	0∼13	2	400 per each finger joint

3.2 Soft Glove Position Network

Unlike tendon-driven soft robots in which the actuator space and joint space are linearly related, pneumatic-driven soft robots require nonlinear mapping to define the relationship between two spaces [7]. One way to model nonlinear relationships is to use a deep neural network model. Our proposed soft glove position network (SGPN) was based on feed-forward neural network (FFNN) which can make nonlinear relations between the pressure sensor data of the control board and each actuator positions of soft pneumatic glove.

The FFNN is a type of typical deep neural network model that can map the nonlinear relationship between input and output due to multiple hidden layers between input and output layers [13]. In this network, learning proceeds while conveying information in one direction without a cycle, and it is possible to learn nonlinear relations by using several hidden layers. So, we developed SGPN that can estimate each joint position of soft glove using pressure of the actuator based on FFNN. The model we developed is shown in Fig. 4.

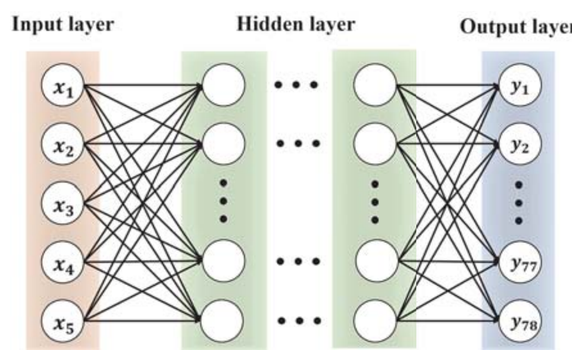


Fig. 4 The structure of the Soft Glove Position Network (SGPN) for position estimation of soft glove.

Our model was consists of six hidden layers composed of 128 hidden units and the Rectified Linear Unit (ReLU) was used in each hidden layer as the activation function [14]. For the input of our model, the pressure data of the soft glove were used. There were five actuators of our soft glove, so the input x is set to $x \in \mathbf{R^5}$. For guess the soft glove positions, we use five 3-D points of each finger and the center position of the palm are required.

So, the output y is $y \in \mathbf{R^{78}}$. After the define out model, we learned our SGPN model using the train data to map the relationship between the pressure data and glove position. As a loss function for learning, mean squared error (MSE) function was used to calculate the error between the predicted value and the true value position of the soft glove. We implemented the stochastic gradient descent (SGD) method to our SGPN model for learning, set the batch size to 32, and trained 100 epochs of train data using the Adam optimizer [15] to optimize the mode with a base learning rate of 0.001. The SGPN model was implemented using a deep learning framework, PyTorch [16].

4. RESULT

We evaluated our model through 400 test data generated by two grasp operations. Because the length of each finger is different, the positions of soft glove varies, even with the same control input, and may affect the position error of soft glove. Therefore, we used two evaluation metric: root mean square error (RMSE) and normalized root mean square error (NRMSE) as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_i - y_i)^2}, \quad (1)$$

$$NRMSE = \frac{RMSE}{\|p_{max} - p_{min}\|} \times 100\%. \quad (2)$$

where $\hat{y}$ is predicted value and y is true value. p_{max} and p_{min} are the points which have maximum distance within trajectory of each soft glove position. We defined that the distance $\|p_{max} - p_{min}\|$ to euclidean distance of trajectory in the position moving range of the glove. As shown in Eq. (2), the NRMSE is obtained by dividing the RMSE by the maximum distance of the region where the position of the soft glove is changed. By using the metric, it is possible to know how much error occurs due to the movement of the finger, even though the position of soft glove varies depending on the finger length.

We calculated the fingertip position error of the soft glove to accurately evaluate the performance of our SGPN model. The reason for this evaluation is that it is better to use the fingertip data instead of comparing all the joints of the hand in order to understand the relationship between the movement range of the hand and the two evaluation metrics. So, we extracted the end point data of each soft glove finger from the result of test data and calculated the max error, RMSE, euclidean distance of the trajectory, and NRMSE, and the results summarized in Table 2.

As shown in the Table 2, the maximum error of each finger does not exceed 23 mm and the average maximum error of the fingertips is also within 17 mm. In the case of RMSE, each finger does not exceed 5 mm, and NRMSE can be operated with an error within 8% of finger movement on average. The thumb had the largest RMSE (4.91) and the smallest distance of trajectory (34.13), resulting in NRMSE of 14.38%, which resulted in higher error rate rather than other fingers because of the relatively small range of movement. This result shows that our algorithm can be operated within 8% error based on the trajectory of each end soft glove finger except thumb.

Table 2 Experimental results of fingertip position estimation of soft glove

Test error	Thumb	Index	Middle	Ring	Pinky	Average
Max error [mm]	15.84	21.90	22.84	15.15	8.05	16.76
RMSE [mm]	4.91	4.41	3.95	4.00	3.62	4.18
Euclidean distance [mm]	34.13	73.12	69.82	69.30	46.32	58.54
NRMSE	14.38%	6.03%	5.72%	5.23%	7.44%	7.76%

We plotted the data that occurred during the test to figure out how the pressure applied to the soft glove affected the position estimation. The error of each fingertip generated during the test were shown in Fig. 5. The upper and below plot show the error of the fingertips of the soft glove and the target pressure on the glove for grasping motion over time, respectively. As shown in the figure, the each position error of the soft glove finger are reduced at 5 seconds and 16 seconds when the pressure is applied. On the other hand, the position error increases at 0 seconds, 10 seconds, and 20 seconds when there is no pressure. This is because the glove do not support the hand when pressure is not applied, and therefore the position changes variably due to gravity and the weight of the hand. The results indicate that our algorithm reduces the error of position estimation as the pressure acting on soft glove increases.

5. DISCUSSION AND FUTURE WORK

Our contribution is to propose a deep neural network that can estimate and control the position of the soft glove without prior knowledge such as wearer's hand size and the characteristic of a soft glove, which is required for modeling the analytical model of robots and control it. Using our model, it is possible to estimate the position of the soft glove using its pressure data. Also, we can control the glove endpoint position with the error within 8% based on the range.

Our model was able to estimate the position without previous information, but there was no sensor to feedback the error, so there was no way to reduce the error. One of the ways to improve the performance of our algorithms is to attach additional soft sensors to the soft glove and estimate current state algorithm [17] to enable feedback-control. We are interested in further research to develop soft wearable robot control algorithms capable of feedback control by applying a deep neural network model. In this way, more precise control results will be obtained.

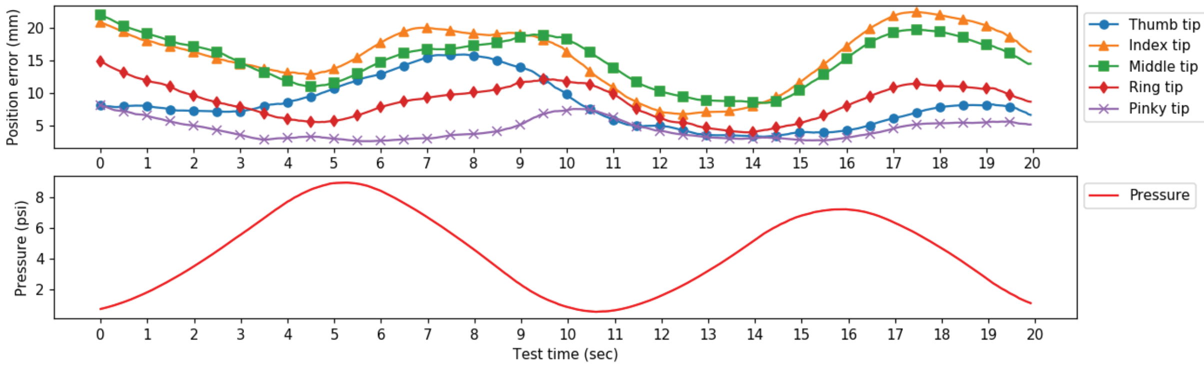


Fig. 5 Position errors of soft glove tips and the change of target pressure for grasping motion over time

6. CONCLUSION

We propose a learning-based control method for position control of soft wearable gloves without knowledge of the predefined model such as wearer's hand size or glove model, and it can be used as a method to solve the difficulty of mathematical modeling of a soft wearable robot. Our deep neural network method trained using pressure and position data of soft pneumatic glove, and test the models performance. According to the results, our model can control the position of soft glove using its pressure, and the error upon the trajectory were within 8%. It is possible to control complex robot systems such as wearable gloves without complex mathematical modeling.

REFERENCES

[1] D. Rus and M. T. Tolley, "Design, fabrication and control of soft robots," *Nature*, vol. 521, no. 7553, p. 467, 2015.

[2] C. Laschi, B. Mazzolai, and M. Cianchetti, "Soft robotics: Technologies and systems pushing the boundaries of robot abilities," *Sci. Robot.*, vol. 1, no. 1, p. eaah3690, 2016.

[3] P. Polygerinos, Z. Wang, K. C. Galloway, R. J. Wood, and C. J. Walsh, "Soft robotic glove for combined assistance and at-home rehabilitation," *Robotics and Autonomous Systems*, vol. 73, pp. 135–143, 2015.

[4] H. In, B. B. Kang, M. Sin, and K.-J. Cho, "Exo-glove: a wearable robot for the hand with a soft tendon routing system," *IEEE Robotics & Automation Magazine*, vol. 22, no. 1, pp. 97–105, 2015.

[5] S.-S. Yun, B. B. Kang, and K.-J. Cho, "Exo-glove pm: an easily customizable modularized pneumatic assistive glove," *IEEE Robotics and Automation Letters*, vol. 2, no. 3, pp. 1725–1732, 2017.

[6] A. T. Asbeck, R. J. Dyer, A. F. Larusson, and C. J. Walsh, "Biologically-inspired soft exosuit," in *Rehabilitation robotics (ICORR), 2013 IEEE international conference on*. IEEE, 2013, pp. 1–8.

[7] T. G. Thuruthel, Y. Ansari, E. Falotico, and C. Laschi, "Control strategies for soft robotic manipulators: A survey."

[8] H. K. Yap, J. H. Lim, F. Nasrallah, J. C. Goh, and R. C. Yeow, "A soft exoskeleton for hand assistive and rehabilitation application using pneumatic actuators with variable stiffness," in *Robotics and Automation (ICRA), 2015 IEEE International Conference on*. IEEE, 2015, pp. 4967–4972.

[9] D. P. Holland, E. J. Park, P. Polygerinos, G. J. Bennett, and C. J. Walsh, "The soft robotics toolkit: Shared resources for research and design," *Soft Robotics*, vol. 1, no. 3, pp. 224–230, 2014.

[10] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, and A. Y. Ng, "Ros: an open-source robot operating system," in *ICRA workshop on open source software*, vol. 3, no. 3.2. Kobe, Japan, 2009, p. 5.

[11] F. Weichert, D. Bachmann, B. Rudak, and D. Fisseler, "Analysis of the accuracy and robustness of the leap motion controller," *Sensors*, vol. 13, no. 5, pp. 6380–6393, 2013.

[12] L. Motion, "Leap motion controller," *URl: https://www. leapmotion. com*, 2015.

[13] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, *Deep learning*. MIT press Cambridge, 2016, vol. 1.

[14] V. Nair and G. E. Hinton, "Rectified linear units improve restricted boltzmann machines," in *Proceedings of the 27th international conference on machine learning (ICML-10)*, 2010, pp. 807–814.

[15] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[16] A. Paszke, S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer, "Automatic differentiation in pytorch," 2017.

[17] S. Han, T. Kim, D. Kim, Y.-L. Park, and S. Jo, "Use of deep learning for characterization of microfluidic soft sensors," *IEEE Robotics and Automation Letters*, 2018.