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CHARACTERISTICS ANALYSIS AND MODELING OF A MINIATURE PNEUMATIC CURLING RUBBER ACTUATOR

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Abstract. *Soft actuators driven by pneumatic pressure have been shown to have many potential applications as actuators for mechanical systems in medical, biological, agriculture, welfare fields and so on, for they can ensure high safety for fragile objects from their low mechanical impedance. In this paper, a miniature pneumatic bending soft actuator is reviewed, and a nonlinear model of which is identified using nonlinear model based on support vector regression (SVR). That is, first, characteristic of miniature pneumatic bending soft actuator is analyzed, a new output variable is defined based on characteristic analysis, and a nonlinear input output model is presented. Second, motion characteristics of miniature pneumatic bending soft actuator are studied by experiment. Finally, based on experimental data, the present nonlinear model of miniature pneumatic bending soft actuator is identified using data-based SVR model, where a generalized Gaussian function is used as the kernel function.*
Keywords: Miniature pneumatic bending soft actuator, Support vector regression, Nonlinear model, Characteristic analysis and modeling

1. **Introduction.** Pneumatic rubber actuator holds typical advantages over the more common electric actuators because of simple structures, high compliance, high-efficiency, and high power/weight ratio. Flexible Microactuator is bending-type actuator, it belongs to the category of pneumatic rubber actuators and has been expected to be one of the most promising new bending type pneumatic actuator for soft mechanisms and soft handling robots, and shown to have many potential applications as actuators for mechanical systems in medical, human-support/human-care robots, micromanipulation, and inspection in narrow space [1-3]. Despite its high expectation and interests, the field of pneumatic soft actuators is still in a nascent stage, and it requires radically new approaches for significant breakthroughs of morphological computation, nonlinear analysis and modeling, precise position and force control, etc.

A type of typical miniature pneumatic bending soft actuator made from silicone rubber has been developed by Wakimoto et al. [4,5]. It bends like FMA motion, but the structure is simpler than FMA. It consists of one chamber and one air-supply tube and can generate

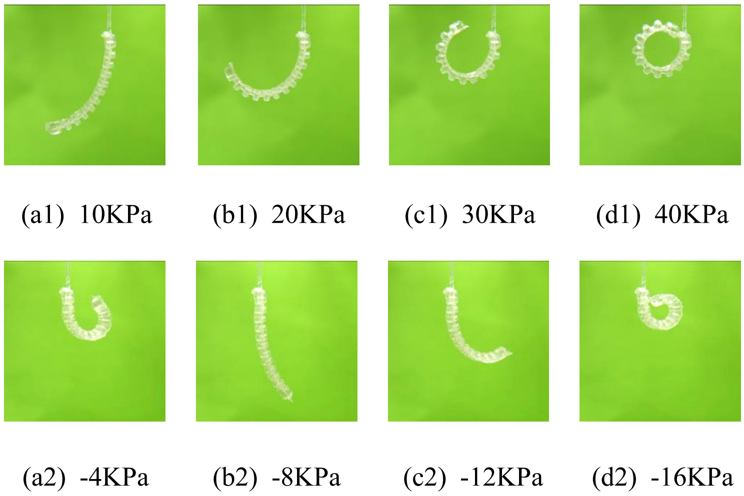


Figure 1. Bidirectional motion in different positive and negative pressures

curling motion in two directions under different positive and negative pressures. Figure 1 shows bidirectional motion of a miniature pneumatic bending soft actuator in different positive and negative pressures. Consider applications of miniature pneumatic bending soft actuator like a robotic manipulator, which has to move from one specified position to another, and has to maintain the position constant. As we all know, it needs an accurate mathematical model. However, because rubber has a highly nonlinear property in this type miniature pneumatic curling rubber actuator, it is difficult to analyze its accurate dynamic model, especially including large deformation [6]. As a result, in this paper, a nonlinear modeling technique based on statistical learning theory is considered to model the nonlinear property of the miniature pneumatic bending soft actuator.

For nonlinear modeling based on statistical learning theory, there exist several main kinds of methods: least square (LS) method, Bayesian method, neural network (NN) method, support vector regression (SVR) method extended by support vector machine (SVM) method and extended SVR method [7-16]. Least square modeling method and Bayesian method are the linear regression methods to model the relationship between a scalar variable y and one or more variables denoted $\mathbf{x}$, such that the models depend linearly on the unknown parameters to be estimated from the data. That is, least square method and Bayesian method are mainly used to fit the generalized linear models. Neural network method can be used as an arbitrary function approximation mechanism by learning from observed data. However, it is easy to lead to local minima and over-fitting caused by empirical risk minimization principle. SVR method, which is based on the principle of structural risk minimization, has been proposed to model for solving global optimization problems of model output. SVR is a new sparse kernel modeling technique, by which the identified nonlinear dynamic model can be seen as an approximation of a real phenomenon, and can capture the underlying systems dynamics. In order to control precise position or displacement, the relationship between position or displacement of miniature pneumatic curling rubber actuator and pressure should be obtained. Therefore, in this paper, SVR based on input output data is used to identify nonlinear dynamic model of this type miniature pneumatic bending soft actuator. To consider more generalized movement condition of the crane, a generalized Gaussian function is adopted as the kernel function. By using the built model, the relationship between position or displacement of miniature pneumatic curling rubber actuator and pressure can be estimated real time.

The outline of the paper is given as follows. SVR and problem statement are described in Section 2. Nonlinear model of miniature pneumatic bending soft actuator based on characteristic analysis is presented in Section 3. Motion characteristics and SVR-based modeling for miniature pneumatic bending soft actuator are proposed in Section 4, and Section 5 is the conclusion.

2. SVR and Problem Statement.

2.1. SVR.

SVM, as a novel type of machine learning method, is gaining popularity due to many attractive features and promising empirical performance. Initially developed for pattern classification problems, the SVM algorithm was extended by Vapnik for regression using a ε-insensitive loss function [9], which is often referred to as SVR. The goal of SVR is to identify a function $f(x)$ that has at most ε from the actually obtained targets y_i for all training data, and at the same time, is as flat as possible. Recently, the SVR has been extended to solve nonlinear system modeling. In the following, we briefly introduce soft margin SVR algorithm for nonlinear system modeling.

Consider regression in the following set of function,

$$f(\mathbf{x}) = \mathbf{w}^T\phi(\mathbf{x}) + b \tag{1}$$

where $b \in R$, $\mathbf{w} \in R^n$, $\phi(\mathbf{x})$ is a nonlinear function that maps the input space into a higher dimension feature space. Given training data (x_i, y_i), where $i = 1, 2, \ldots, n$ denotes the total number of exemplars, $\mathbf{x}_i \in R^n$ are the inputs and $y_i \in R$ are the target output data, and the soft margin SVR approach defines an optimization problem as follows

$$\min_{w,b,\xi} J = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{n}(\xi_i^+ + \xi_i^-) \tag{2}$$

subject to equality constraints,

$$\begin{cases} \mathbf{w}\cdot\phi(\mathbf{x}_i) + b - y_i \leq \varepsilon + \xi_i^+, \quad i = 1, \ldots, n \\ y_i - \mathbf{w}\cdot\phi(\mathbf{x}_i) - b \leq \varepsilon + \xi_i^-, \quad i = 1, \ldots, n \\ \xi_i^+, \ \ \xi_i^- \geq 0, \quad i = 1, \ldots, n \end{cases} \tag{3}$$

where ξ_i^+ and ξ_i^- are the slack variables corresponding to the size of the excess deviation for positive and negative direction, and $C > 0$ controls the penalty associated with deviations larger than ε.

Construct the Lagrangian

$$\begin{aligned} L_p = J &- \sum_{i=1}^{n}\lambda_i^+(\varepsilon + \xi_i^+ + y_i - \mathbf{w}\cdot\phi(\mathbf{x}_i) - b) \\ &- \sum_{i=1}^{n}\lambda_i^-(\varepsilon + \xi_i^- - y_i + \mathbf{w}\cdot\phi(\mathbf{x}_i) + b) - \sum_{i=1}^{n}(\mu_i^+\xi_i^+ + \mu_i^-\xi_i^-) \end{aligned} \tag{4}$$

where λ_i^+, λ_i^-, μ_i^+ and μ_i^- are the Lagrange multipliers.

Calculating the partial derivatives of L_p with respect to w, b, ξ_i^+, ξ_i^-, respectively, the optimal conditions are given by

$$\begin{cases} \frac{\partial L_p}{\partial w} = 0 \rightarrow \sum_{i=1}^{n}(\lambda_i^+ - \lambda_i^-) = 0 \\ \frac{\partial L_p}{\partial b} = 0 \rightarrow \mathbf{w} - \sum_{i=1}^{n}(\lambda_i^- - \lambda_i^+)\mathbf{x}_i \\ \frac{\partial L_p}{\partial \xi_i^+} = 0 \rightarrow C - \lambda_i^+ - \mu_i^+ = 0 \\ \frac{\partial L_p}{\partial \xi_i^-} = 0 \rightarrow C - \lambda_i^- - \mu_i^- = 0 \end{cases} \tag{5}$$

The dual optimization problem is obtained by substituting (5) into (4):

$$\max_{\lambda_i^+,\lambda_i^-} G = -\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\lambda_i^- - \lambda_i^+)(\lambda_j^- - \lambda_j^+)\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_j) + \sum_{i=1}^{n} y_i(\lambda_i^- - \lambda_i^+) - \sum_{i=1}^{n}\epsilon(\lambda_i^- + \lambda_i^+) \tag{6}$$

subject to constraints,

$$\begin{cases} \sum_{i=1}^{n}(\lambda_i^+ - \lambda_i^-) = 0 \\ \lambda_i^+, \ \ \lambda_i^- \in [0, C] \end{cases} \tag{7}$$

The vector $\mathbf{w}$ is obtained from (5) and (6),

$$w = \sum_{i=1}^{n}(\lambda_i^- - \lambda_i^+)\phi(\mathbf{x}_i) \tag{8}$$

which leads to the final expression for $f(\mathbf{x}_k)$,

$$f(\mathbf{x}_k) = \sum_{i=1}^{n}(\lambda_i^- - \lambda_i^+)\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_k) + b \tag{9}$$

Because a special class of functions, called kernels, allows the computation of the dot product $\phi(\mathbf{x}_i)\cdot\phi(\mathbf{x}_k)$ in the original space defined by the training patterns. Then, the resulting soft margin SVR model for dynamic estimation can be described by the following equation,

$$f(\mathbf{x}) = \sum_{k=1}^{N}(\lambda_i^- - \lambda_i^+)K(\mathbf{x}, \mathbf{x}_k) + b \tag{10}$$

where $K(\mathbf{x}, \mathbf{x}_k)$ is the kernel function, and it can be any symmetric function satisfying Mercers condition.

2.2. **Problem statement.** For precision position control, deformation of the miniature pneumatic curling rubber actuator can be controlled by regulating pressure. However, because highly nonlinear property of rubber, it is very difficult to predict deformation of the rubber in miniature pneumatic curling rubber actuator by pressure with high accuracy. How to obtain and identify a nonlinear model is a key to solve the problem. Therefore, in this paper, how to define a new nonlinear model of the miniature pneumatic curling rubber actuator is presented, and SVR based modeling for the miniature pneumatic curling rubber actuator is proposed, where a generalized Gaussian function is adopted as the kernel function.

3. Nonlinear Model of Miniature Penumatic Curling Rubber Actuator.

3.1. **Characteristic analysis.** The structure of the miniature pneumatic curling rubber actuator is shown in Figure 2. To obtain precise position or force using the miniature pneumatic bending soft actuator, deformation of the rubber in miniature pneumatic curling rubber actuator by pressure should be clear. However, it is very difficult to predict deformation of the rubber in miniature pneumatic curling rubber actuator by pressure with high accuracy. That is to say, all areas of rubber of miniature pneumatic actuator cannot maintain the same shape and state perfectly during actual operations like fabrication and driving. Addressing this phenomenon, in this paper, all areas of rubber are firstly assumed to maintain the same shape and state perfectly during motions.

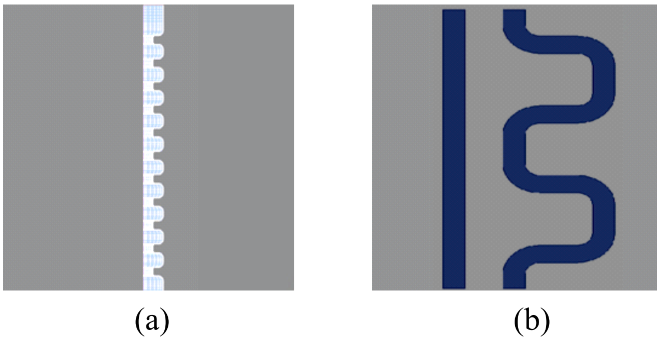


FIGURE 2. The structure of a miniature pneumatic curling rubber actuator

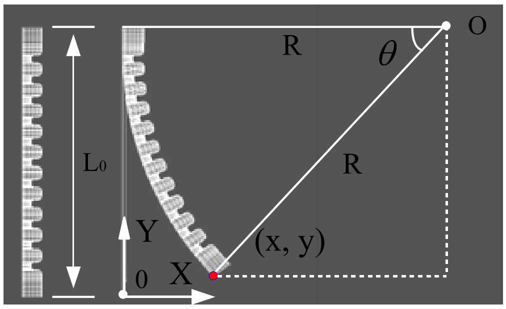


FIGURE 3. Calculation of the position based on bending grade and arc length

According to above assumption (see Figure 3), we define two new variables $\rho \in [0, 1]$ called bending grade and L called time-varying arc length corresponding to the bended miniature pneumatic curling rubber actuator, which can be described by

$$\rho \equiv \frac{\theta}{2\pi} = \frac{L}{2\pi R} \tag{11}$$

where, $\theta \in [0, 2\pi]$ is central angle corresponding to bending arc, R is radius of arc, and L_0 represents the original length of miniature pneumatic curling rubber actuator.

Based on bending grade ρ and time-varying arc length L, any position (x, y) can be obtained,

$$\begin{cases} x = \dfrac{L}{\theta}(1 - \cos\theta) = \dfrac{L}{2\pi\rho}(1 - \cos(2\pi\rho)) \\ y = L_0 - \dfrac{L}{\theta}\sin\theta = L_0 - \dfrac{L}{2\pi\rho}\sin(2\pi\rho) \end{cases} \tag{12}$$

and the displacement d can also be calculated,

$$d = \sqrt{x^2 + y^2} = \sqrt{L_0^2 + \frac{2L}{(2\pi\rho)^2}(L - L\cos(2\pi\rho) - 2\pi\rho L_0 \sin(2\pi\rho))} \tag{13}$$

3.2. **Nonlinear model.** For precise position or displacement control, the relationship between position or displacement of miniature pneumatic curling rubber actuator and pressure should be obtained. According to above analysis, we can find that the precise position or displacement can be calculated using bending grade ρ. Therefore, in this paper, a nonlinear model is proposed.

$$\rho = f(u) \tag{14}$$
$$L = g(u) \tag{15}$$

where, u is input pressure, $f(u)$ and $g(u)$ are nonlinear functions. If we can identify $f(u)$ and $g(u)$, the position (x, y) or displacement d can be obtained using the nonlinear model. In the following section, how to identify the proposed nonlinear model using SVR method will be discussed.

4. SVR-Based Modeling for Miniature Penumatic Curling Rubber Actuator.

4.1. Experimental system. The experimental system of position or displacement measurement has four major parts (see Figure 4): 1) computer and DSP (TMS320C6713); 2) high speed camera (CV-M40); 3) regulator of pressure; 4) a miniature pneumatic curling rubber actuator ($L_0 = 15.25$mm). High speed camera and image input board record image information, which is processed by commercial image processing software. Regulator of pressure consists of air compressor and vacuum pump, by which positive and negative pneumatic pressure can be obtained.

4.2. Motion characteristics. For the miniature pneumatic curling rubber actuator ($L_0 = 15.25$mm), the position (x, y) is measured by experimental system. The experimental position in different positive pressures and different negative pressures are shown in Figure 5(a) and Figure 5(b), respectively. From Figures 5(a) and 5(b), we can find that the miniature pneumatic curling rubber actuator not only can bend in different pressures, but also the length of which can elongate in positive pressures or shrink in negative pressures.

According to Equations (11) and (12), the following relationship can be obtained,

$$\rho = \frac{\arccos\left(\dfrac{L_0 - y}{\sqrt{x^2 + (L_0 - y)^2}}\right)}{\pi} \tag{16}$$

$$L = \frac{(x^2 + (L_0 - y)^2)\arccos\left(\dfrac{L_0 - y}{\sqrt{x^2 + (L_0 - y)^2}}\right)}{x} \tag{17}$$

Based on the measured position (x, y), the bending grade ρ and arc length L can be calculated in different positive pressures and negative pressures, and are shown in Figures 6(a)-7(b), respectively. From Figures 6(a)-7(b), we can find the bending grade ρ and

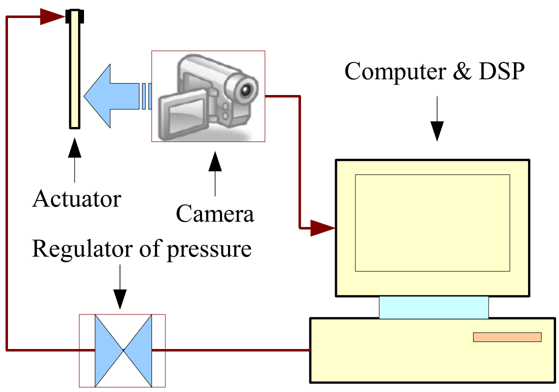
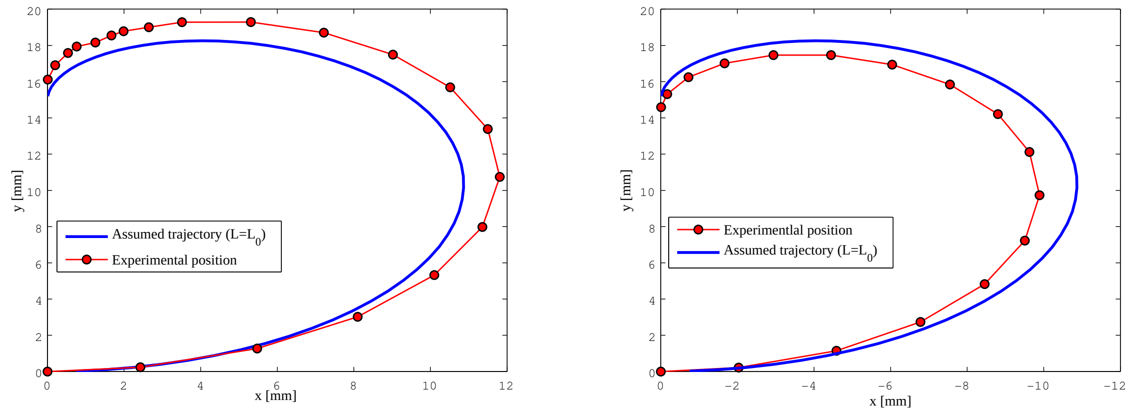
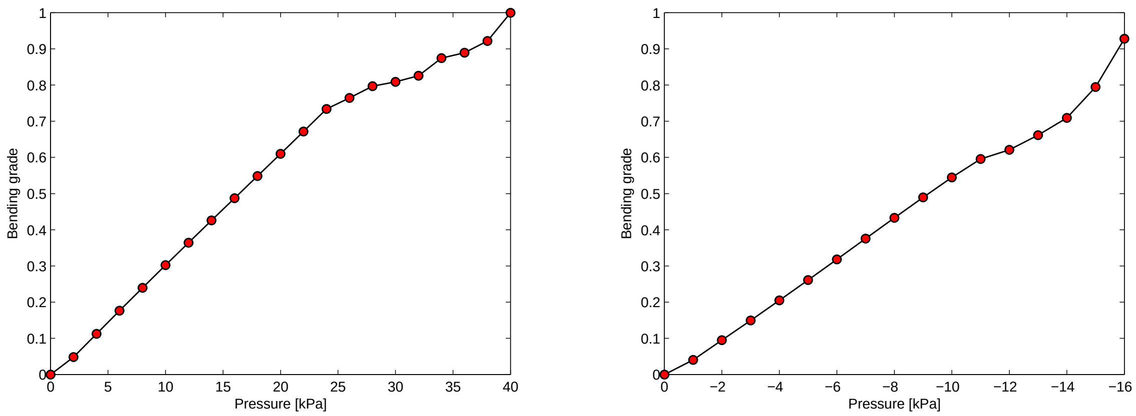


FIGURE 4. Experimental system schematic illustration



(a) (b)

FIGURE 5. (a) The measured position (x, y) in different positive pressures; (b) the measured position (x, y) in different negative pressures



(a) (b)

FIGURE 6. (a) The calculated bending grade ρ in different positive pressures; (b) the calculated bending grade ρ in different negative pressures

arc length L can be assumed to nonlinear functions of input pressures u. We also can calculate maximum elongation ratio,

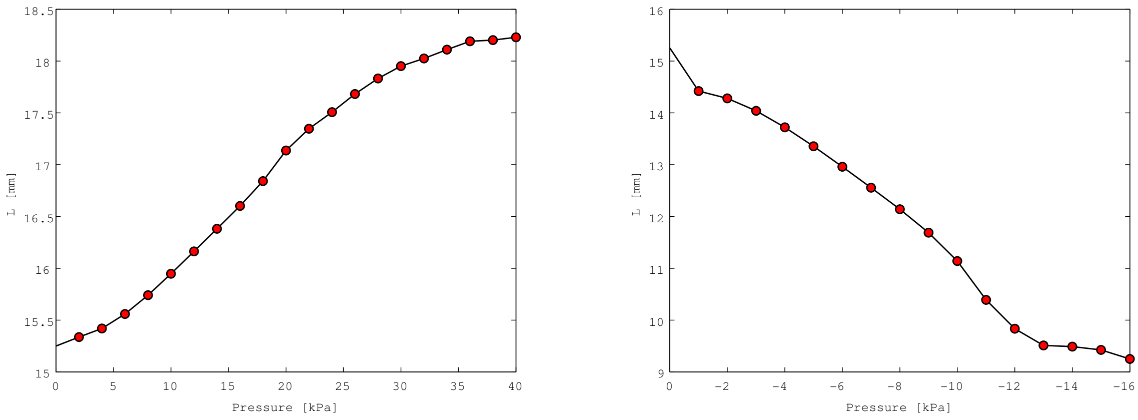
$$\frac{\Delta L}{L_0} \times 100\% = \frac{18.25 - 15.25}{15.25} \times 100\% = 19.67\% \tag{18}$$

and maximum shrink ratio

$$\frac{\Delta L}{L_0} \times 100\% = \frac{15.25 - 9.25}{15.25} \times 100\% = 39.34\% \tag{19}$$

It is very obvious that the capability of shrink in different negative pressures is more strong than the capability of elongation in different positive pressures.

4.3. **SVM-based modeling.** An appropriate kernel function is a key issue in using SVR, there are many kernel functions used in SVR, such as polynomial function, Gaussian function and hyperbolic tangent [17-19]. The Gaussian function is used extensively in numerous applications in engineering, physics, and many other fields, where real-valued



(a) (b)

FIGURE 7. (a) The calculated arc length L in different positive pressures; (b) the calculated arc length L in different negative pressures

random variables often tend to cluster around a single mean value. However, during the movement of the miniature pneumatic curling rubber actuator, the Gaussian distribution may be either inadequate or inappropriate such that a generalized Gaussian distribution is adopted as the kernel function, which includes all normal and Laplace distributions, and all continuous uniform distributions on bounded intervals of the real line. The probability density function (pdf) of a generalized Gaussian distribution with zero mean, variance σ^2 and shape parameter γ is given by

$$K(\tilde{x}_i;\sigma,\gamma) = \frac{g(\gamma)\gamma}{2\sigma\Gamma(1/\gamma)} \exp\left[-\left(\frac{g(\gamma)|\tilde{x}_i|}{2\sigma^2}\right)^{\gamma}\right] \tag{20}$$

$$g(\gamma) = \sqrt{\frac{\Gamma(3/\gamma)}{\Gamma(1/\gamma)}} \tag{21}$$

where $\Gamma(\cdot)$ is Gamma function [20,21]. As we notice above, when $\gamma = 1$, the K distribution corresponds to a Laplacian or double exponential distribution, when $\gamma = 2$ corresponds to a Gaussian distribution, whereas in the limiting cases when $\gamma \to +\infty$ the pdf in Equation (20) converges to a uniform distribution in $(-\sqrt{3}\sigma, \sqrt{3}\sigma)$, and when $\gamma \to 0+$ the distribution becomes a degenerate one in $\tilde{x}_i = 0$, shown in Figure 8.

The K distribution is symmetric, hence the odd central moments are zero, i.e., $E(\tilde{x}_i)^{2m-1} = 0$, $m = 1, 2, 3, \ldots$. The even central moments can be obtained from the absolute central moments, which are given by

$$E(\tilde{x}_i)^{2m} = \left\{\frac{\sigma^2\Gamma(1/\gamma)}{\Gamma(3/\gamma)}\right\}^m \frac{\Gamma((2m+1)/\gamma)}{\Gamma(1/\gamma)} \tag{22}$$

In particular, the variance of $\tilde{x}_i (m = 1)$ is

$$E(\tilde{x}_i)^2 = \sigma^2 \tag{23}$$

In order to use the generalized Gaussian function, parameters γ and σ need to be known. Variance σ can be calculated by (23), but the calculation of the shape parameter γ is difficult. As a result, we will be focused on estimating the shape parameter using the method of moments in the following part. In order to estimate the shape parameter, the fourth-order or higher even moment needs to be used. The method of the fourth-order

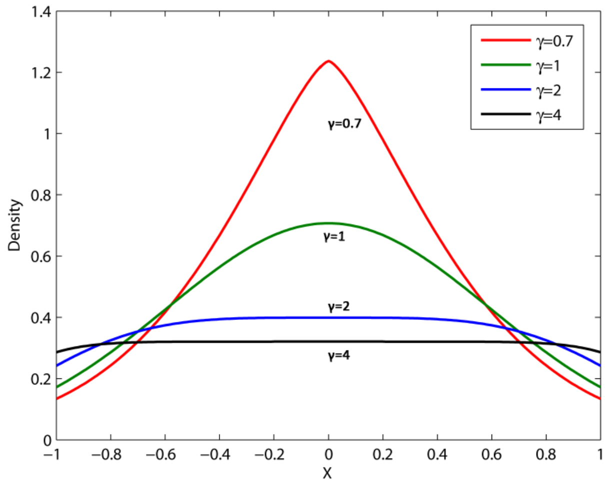


FIGURE 8. The pdf of generalized Gaussian distribution

even moments estimation of γ is given by the value satisfying the following equation,

$$\phi(\gamma) = \frac{\Gamma(5/\gamma)\Gamma(1/\gamma)}{\Gamma^2(3/\gamma)} \tag{24}$$

where $\phi(\gamma)$ is defined as generalized Gaussian function ratio, which can be calculated as follows,

$$\phi(\gamma) = \frac{E(\tilde{x}_i)^4}{(E(\tilde{x}_i)^2)^2} \tag{25}$$

where $E(\tilde{x}_i)^2 = \sigma^2$. Then, by solving the following equations, we can obtain the estimations $\phi(\gamma)$ and σ,

$$E(\tilde{x}_i)^4 = \frac{1}{N_x}\sum_{i=1}^{N_x}(\tilde{x}_i)^4, \quad E(\tilde{x}_i)^2 = \frac{1}{N_x}\sum_{i=1}^{N_x}(\tilde{x}_i)^2 \tag{26}$$

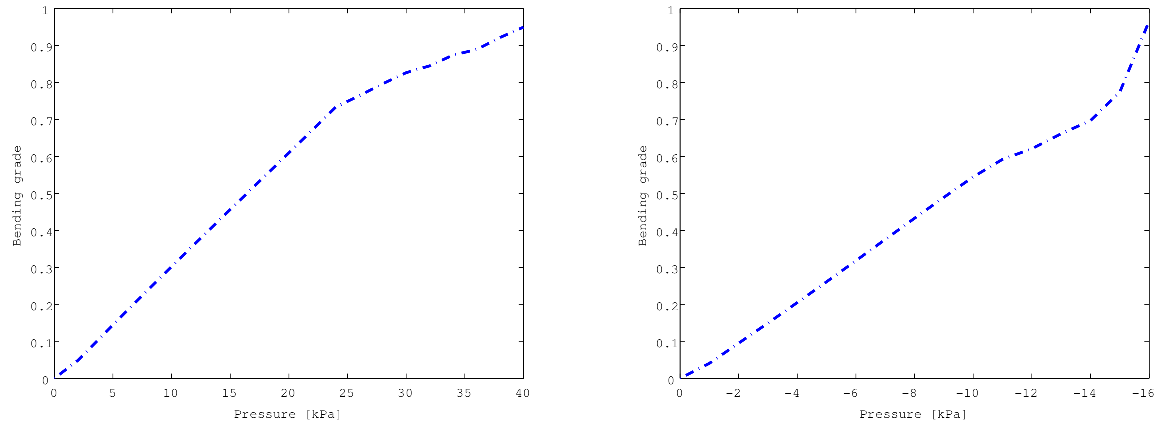
where N_x is the current sample number. Then, a cyclic numerical method can be used to calculate the shape parameter in (24).

In summary, the variance and shape parameter estimation algorithm is implemented by following steps:
1) Sampling data $X = \tilde{x}_i$, $i = 1, 2, 3, \ldots$.
2) Calculate EX^4 and EX^2 $(X = \tilde{x}_i,\ i = 1, 2, 3, \ldots)$.
3) Calculate σ and $\phi(\gamma)$ by (23) and (25).
4) Calculate the shape parameter γ by (24).

In the present nonlinear black-box dynamical system, the input $u(t)$ represents air pressure, and the output $y(t)$ is bending grade ρ or arc length L of miniature pneumatic curling rubber actuator, which can determine the actuator position or displacement. To set up this nonlinear model using SVR technique, we use the following repressor,

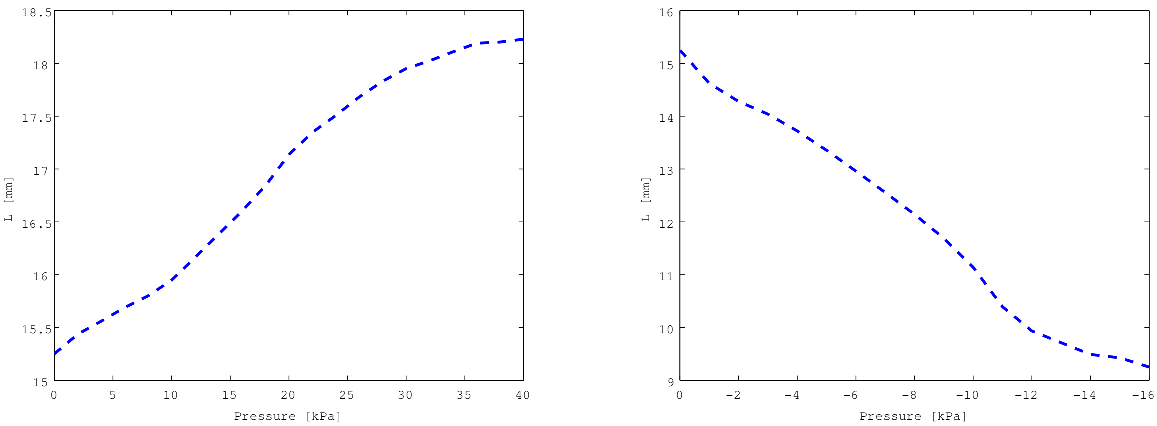
$$\phi(\mathbf{x}) = [y(t-1), y(t-2), u(t), u(t-1)]^T \tag{27}$$

That is, the dimension of input vector is 4. In training, we use 6×512 data pairs, where penalizing constant $\gamma = 100$, error-accuracy parameter $\epsilon = 0.1$. The estimated results of the bending grade ρ and arc length L in positive pressures and negative pressures are shown in Figures 9(a)-10(b), respectively. In the real application, the difference between the SVM-based estimation value and real value of the relationship between position or displacement of miniature pneumatic curling rubber actuator and pressure will lead some



(a) (b)

Figure 9. (a) The identified bending grade ρ in different positive pressures; (b) the identified bending grade ρ in different negative pressures



(a) (b)

Figure 10. (a) The identified arc length L in different positive pressures; (b) the identified arc length L in different negative pressures

uncertainties. Also, there exist some unmodelled uncertainties in the position or displacement control system. In the future, operator-based robust right coprime factorization approach will be further used to deal with this issue.

5. **Conclusion.** In this paper, for a new miniature pneumatic bending soft actuator, based on characteristic analysis of which a new nonlinear model is presented. Motion characteristics are studied using experimental results, and the nonlinear model is identified based on SVR method, where a generalized Gaussian function is used as the kernel function.

REFERENCES

[1] K. Suzumori, S. Iikura and H. Tanaka, Applying a flexible microactuator to robotic mechanism, *IEEE Control Systems*, vol.12, no.1, pp.2122-2127, 1992.

[2] K. Kawashima, T. Sasaki, T. Miyata, N. Nakamura, M. Sekiguchi and T. Kagawa, Development of robot using pneumatic artificial rubber muscles to operate construction machinery, *Journal of Robotics and Mechatronics*, vol.16, no.1, pp.8-16, 2004.

[3] K. Hosoda, T. Takuma, A. Nakamoto and S. Hayashi, Biped robot design powered by antagonistic pneumatic actuators for multi-modal locomotion, *Robotics and Autonomous Systems*, vol.56, pp.46-53, 2008.

[4] S. Wakimoto, K. Suzumori and K. Ogura, A miniature pneumatic curling rubber actuator generating bidirectional motion with one air-supply tube, *Advanced Robotics*, vol.25, no.9-10, pp.1311-1330, 2011.

[5] S. Wakimoto, K. Ogura, K. Suzumori and Y. Nishioka, Miniature soft hand with curling rubber pneumatic actuators, *Proc. of IEEE International Conference on Robotics and Automation*, pp.556-561, 2009.

[6] C. P. Chou and B. Hannaford, Measurement and modeling of mckibben pneumatic artificial muscles, *Transactions on Robotics and Automation*, vol.12, no.1, pp.90-102, 1996.

[7] V. Vapnik, *The Nature of Statistical Learning Theory*, Springer, New York, 1995.

[8] B. Nasution and A. Khan, A hierarchical graph neuron scheme for real-time pattern recognition, *IEEE Trans. Neural Networks*, vol.19, no.2, pp.212-229, 2008.

[9] F. Liang, C. Liu and N. Wang, A robust sequential Bayesian method for identification of differentially expressed genes, *Statistica Sinica*, vol.17, no.2, pp.571-597, 2007

[10] M. Cabrerizo, M. Ayala, P. Jayakar and M. Adjouadi, Classification and medical diagnosis of scalp EEG using artificial neural networks, *International Journal of Innovative Computing, Information and Control*, vol.7, no.12, pp.6905-6918, 2011.

[11] Z. Cui, X. Cai and J. Zeng, Chaotic performance-dependent particle swarm optimization, *International Journal of Innovative Computing, Information and Control*, vol.5, no.4, pp.951-960, 2009.

[12] W. Chan, C. Chan, K. Cheung and C. Harris, On the modeling of nonlinear dynamic systems using support vector neural networks, *Engineering Applications of Artificial Intelligence*, vol.14, no.2, pp.105-113, 2001.

[13] B. Scholkopf and A. Smola, *Learning with Kernels-Support Vector Machines, Regularization, Optimation, and Beyond*, The MIT Press, London, 2005.

[14] L. Jiang, M. Deng and A. Inoue, Support vector machine-based two wheeled mobile robot motion control in noisy environment, *Journal of Systems and Control Engineering*, vol.222, no.7, pp.733-743, 2008.

[15] S.-C. Huang and C.-H. Hsieh, Wavelet-based relevance vector regression model coupled with phase space reconstruction for exchange rate forecasting, *International Journal of Innovative Computing, Information and Control*, vol.8, no.3(A), pp.1917-1930, 2012.

[16] P. Zhong and L. Wang, Support vector regression with input data uncertainty, *International Journal of Innovative Computing, Information and Control*, vol.4, no.9, pp.2325-2332, 2008.

[17] Z. Lu and J. Sun, Non-Mercer hybrid kernel for linear programming support vector regression in nonlinear systems identification, *Applied Soft Computing*, vol.9, no.1, pp.94-99, 2009.

[18] N. Cristianini and J. Shawe-Talor, *An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods*, Cambridge University Press, London, 2005.

[19] B. Scholkopf, C. J. C. Burges and A. J. Smola, *Advances in Kernel Methods-Support Vector Learning*, The MIT Press, Cambridge, 1999.

[20] M. Deng, Y. Teramura, A. Wang and A. Yanou, Particle filter-based viscoelasticity estimation of human multi-joint arm, *Proc. of the 18th World Congress of IFAC*, pp.14312-14317, 2011.

[21] M. Deng, A. Inoue and Q. Zhu, An integrated study procedure on real time estimation of time varying multijoint human arm viscoelasticity, *Transactions of the Institute of Measurement and Control*, vol.33, no.8, pp.919-941, 2011.