Morphological Computation using a Soft Robot: A Nonlinear Oscillator Network Model

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Abstract. Morphological Computation (MC) is based on the intriguing idea that a physical body can itself serve as a computational device. Specifically, given their strongly nonlinear dynamics, soft robots are considered ideal candidates for MC. Here we propose a novel nonlinear oscillator network model for a soft manipulator and use it to study MC. The results primarily indicate that the soft robot, as represented by the model, can serve as an effective computational resource. Moreover, it is found that the computational efficiency is enhanced when the number of elements in the model is increased from two to three. The results highlight that the complex nonlinear dynamics, characteristic of soft robots, can be exploited for MC. Interestingly, they also suggest that a model with larger number of elements better illuminates its computational capabilities, which also provides a more accurate representation of the dynamics for a soft manipulator.

Introduction

Morphological Computation (MC) refers to using physical bodies (e.g. coupled nonlinear oscillators) as reservoirs for computing [2]. The complex nonlinear dynamics of soft robots could potentially be exploited for MC via computation of a desired output function [1]. Here we propose using a *triple* element nonlinear coupled oscillator network, with predefined damping and stiffness parameters, as a computational reservoir. This nonlinear network extends a *single* element model which comprises a spring-mass damper coupled to a bob. Referring to our other Abstract in this Conference, the EOM are given in Eqn. (1):

$$\ddot{X} + 2\zeta_1\dot{X} + X - \frac{6R}{5\epsilon}\left[\dot{\theta}^2 cos\left(\theta\right) + \ddot{\theta} sin\left(\theta\right)\right] = f\left(t\right); \ddot{\theta} + 2\zeta_2 r\dot{\theta} + r^2\theta - \frac{5\epsilon}{6}\ddot{X} sin\left(\theta\right) = \tau\left(t\right) \quad (1)$$

$$\begin{aligned} I(t) &= 0.2 sin(2\pi f_1 t) sin(2\pi f_2 t) sin(2\pi f_3 t);\ u(t) = scale * I(t) \\ y(t+1) &= 0.4y(t) + 0.4y(t)y(t-1) + 0.6I^3(t) + 0.1 \end{aligned} \quad (2)$$

where ζ_1 and ζ_2 are damping ratios, R is the mass ratio, r is the ratio of the undamped natural frequencies, ϵ is a coupling parameter, and $f(t)$ and $\tau(t)$ are the external force and torque. For MC, the sinusoidal input ($I(t)$), the scaled input to the system nodes ($u(t)$) and second order nonlinear dynamic system used as the output target function ($y(t)$) are given by the following expressions, where input frequencies are f_1 = 2.11, f_2 = 3.73, f_3 = 4.33 [3]:

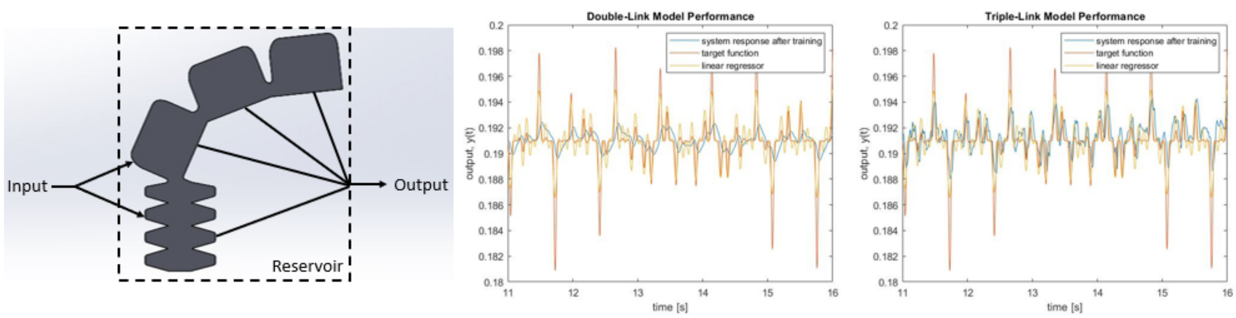

Figure 1: Performance of the morphological devices: Physical System (left), Double Link results (middle), Triple Link results (right)

Results and Discussion

The model is used as the MC device to emulate a second-order nonlinear target function. While maintaining similar system parameters, performance comparisons are made between the linear regressor, double element, and triple element models in how well their morphologies are exploited during MC. Upon training and evaluation, the triple element model provides more effective computational abilities over the double element model, which suggests that a system beholding more complexity and nonlinearity serves as a better computational device; a visual is provided in the figure. For system parameters of $\zeta_1 = \zeta_2 = \zeta_3 = \zeta_4$ = 0.035, $r_1 = r_2 = r_3$ = 1, ϵ = 0.02, R_1 = 0.02, R_2 = 0.0199, R_3 = 0.0198, and $scale$ = 0.01 for the triple element model, the MSE is 2.4980e-06, compared to the linear regressor which has MSE of 9.7357e-07.

References

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[3] Nakajima, K. et al. (2015) Information processing via physical soft body. *Scientific Reports* **5**, 10487.