A New Method for Precision of a Serpentine Snake-like Robot

Siavash Sarrafan^{1,a}, Alireza Akbarzadeh^{2,b}

^{1,2}Center of Excellence on Soft Computing and Intelligent Information Processing, Mechanical Engineering Department, Ferdowsi University of Mashhad, Mashhad, Iran

^{a,b} ali_akbarzadeh@um.ac.ir

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Abstract. In this paper, a planar snake-like robot travelling in serpentine locomotion is considered. A method is presented where structural and gait control parameters are used to obtain the minimum snake-robot positional error, geometrical error. Two structural parameters, length and mass of each link as well as two control parameters, initial winding angle (α_0) and arc length (*s*) are considered. Each of the four input parameters is examined at five different levels. The method uses Taguchi experimental techniques and analyzes effects of uncertainties by means of adding *noise* to the robot parameters. Significance of the input parameters is also determined using Analysis of Variance.

Introduction

Many studies are presented on snake-like robots. However, to the best of authors' knowledge, no study does exist where precision of locomotion is investigated in it. In this paper, locomotion precision is defined as the error between desired and actual destination of the snake-like robot. In many applications such as search or rescue, the robot is directed to reach a certain point. Commonly, aside from the local sensors on the actuators, the robot does not benefit from having additional sensors from the outside to help with its navigation. Therefore, a snake-like robot that reaches its destination with minimum positional error is desirable. Moreover, presence of tolerances in manufacturing processes and uncertainties in control systems can alter structural characteristics and controlling variables of robots. This fact may lead the performance to change significantly from being satisfactory. The difference between the desired and actual position of a robot is called positional error and the average precision by which a robot performs tasks is termed positional accuracy [1]. Various researches are done in the field of statistics analysis of positional error. For example Whitney et al. suggested an approach to improve orientation and position accuracy of a robot [2]. Benhabib et al. also introduced direct and inverse error analysis [3]. Manoochehri and Seireg invented a computer program that chooses optimal parameters of a robot [4]. Rout and Mittal utilized Taguchi method to obtain optimum parameters in a 2 DOF manipulator [5, 6]. Liou determined tolerance of a robot using Taguchi method [7]. Burkan and Uzmay added robustness conception into robot's pathway [8] and Rout and Mittal employed design of experiment techniques to specify tolerance of manipulator parameters [9, 10].

In any design there are uncertainties which can change desired outcome; In other words, you can never be assured that after production, values like mass and length be exactly the same as the ones specified in the design stage. Furthermore, a control system employed has its own uncertainties. These uncertainties can cause a deviation in output and are undesirable. One of the main characteristics of a proper design is insensitivity to potential uncertainties, also called a *robust* design. Generally, after the construction, one can measure the differences between desired and actual values of robot physical components. This evaluation can lead to an optimum setting of parameters. Clearly, experimental assessment by means of actual construction is not economical both in terms of time and cost. In this paper, we propose an evaluation method in which design of experiment techniques are used to analyze effects of uncertainties in the output of snake-like robots. The proposed method applies deviation, also called *noise*, to selected robot structural and control parameters. Simulation of the robot with noises applied to its parameters is our touchstone to find the optimum conditions, leading to improved locomotion positional accuracy and repeatability. See Fig 2.

Dynamics Model

The snake-like robot considered in this study has five links and moves in serpentine gait. Serpenoid curve introduced by Hirose [11] is used to generate the serpentine locomotion. This curve best resembles curvature of a real snake. Relative angles in a snake-like robot for i^{th} link can be calculated by

$$\varphi_i(s) = -2\alpha_0 \sin\left(\frac{K_n \pi}{L}\right) \times \sin\left(\frac{2K_n \pi s}{L} + \frac{2K_n \pi i}{L} - \frac{K_n \pi}{n}\right),\tag{1}$$

where *n* is the number of links, *L* is the total length, K_n is the number of waves in the robot's body and *s* is body arc [12]. Relationship between absolute angles can be computed as

$$\theta_i = \theta_1 + \sum_{k=1}^{i-1} \varphi_k, \tag{2}$$

Where θ_i is absolute angle of i^{in} link and θ_1 is absolute angle of the first link (head of the snake).

Consider the snake-like robot shown in Fig. 1. To simulate serpentine locomotion, dynamics equations written in MATLAB software are used. The Lagrangian formulation is utilized to obtain the dynamics equations of the robot. Because planar motion is considered, potential energy remains unchanged. Therefore

$$\frac{d}{dt}\left(\frac{\partial K}{\partial \dot{q}_i}\right) + \frac{\partial K}{\partial q_i} - Q_i = 0, \quad (i = 1, 2, ..., 5), \tag{3}$$

Where q_i is generalized coordinates. *K* is also kinetic energy that can be calculated from Eq. 4 and Q_i is virtual work done by nonconservative forces that are obtained from Eq. 5, Eq. 6 and Eq. 7.

$$K = \sum_{i=1}^{5} \left[\frac{1}{2} I_i \dot{\theta}_i^2 + \frac{1}{2} m_i \left(\dot{x}_c^2 + \dot{y}_c^2 \right) \right].$$
(4)

In Eq. 4, I_i is moment of inertia and m_i is mass of each link. \dot{x}_c and \dot{y}_c are absolute velocities of mass center of each link in two perpendicular directions.

$$Q_{\theta j} = d_j \left(f_{yi} \cos \theta_i - f_{xi} \sin \theta_j \right) + l_j \left[\cos \theta_j \sum_{i=j+1}^5 (f_{yi}) - \sin \theta_j \sum_{i=j+1}^5 (f_{xi}) \right] + T_{j-1} - T_j,$$
(5)

$$Q_{xb} = \sum_{i=1}^{5} (f_{xi}),$$
(6)

$$Q_{yb} = \sum_{i=1}^{5} (f_{yi}).$$
⁽⁷⁾

Where $Q_{\theta j}$ are generalized forces in regard to θ_j coordinates. Additionally, Q_{xb} and Q_{yb} are generalized forces with regard to x_b and y_b coordinates respectively. The variable f_{xi} and f_{yi} represent friction forces in different directions. T_j is applied torque by motors in joint *j*. In this paper Coulomb coefficients of friction in normal and tangential directions are set to 0.6 and 0.05.



Figure 1. Schema of the snake-like robot

Figure 2. repeatability versus accuracy

Input and Output of the Problem

In this paper, the two input parameters affecting the dynamic behavior of the robot are link length and link mass. These two parameters are referred to as the robot structural parameters. Additionally, as it can be seen from Eq. 1, the variables *s* and α_0 also influence robot performance. These two variables can be used by robot controller to affect its locomotion. In this study we chose *l* and *m* as structural parameters as well as *s* and α_0 as control parameters. These four input variables are used in an optimization problem. For each of these four variables five different levels are considered which are shown in Table 1. It should be noted that length and mass are for properties of each link where as α_0 and *s* are used for the entire robot. The selected range for each of the four input variables represents reasonable and practical value for the snake-like robot.

Table 1. Input parameters and their corresponding levels

Parameter	Level 1	Level 2	Level 3	Level 4	Level 5
Length [cm]	20	25	30	35	40
Mass [gr]	100	200	300	400	500
s [sec]	0.01t	0.02t	0.03t	0.04t	0.05t
α_0 [rad]	$\pi/6$	$\pi/6 + \pi/24$	$\pi/6+2\pi/24$	$\pi/6+3\pi/24$	$\pi/6+4\pi/24$

In this study horizontal displacement of robot's center of mass after 20seconds is measured. Dynamic equation, Eq. 3, is solved and simulated 24 times with 24 different noises implemented on each of the four input variables. These noises are ± 0.0002 , ± 0.0003 , ± 0.0005 , ± 0.001 , ± 0.0015 , ± 0.002 , ± 0.0025 , ± 0.003 , ± 0.005 , ± 0.0075 , ± 0.01 and ± 0.02 . Note, the values of *s* and α_0 are considerably less than *m* and *l*. Therefore, to create a normalization effect, we multiply the noises by a factor of 0.1 for variables *s* and α_0 and by a factor of 10 for the variable *m*. Notice that noise values that are closer to the mean value of zero are repeated more than the ones that are further away from it. This pattern roughly resembles normal distribution for precision of the machine or equipment that is used for construction or control of the respected variables. Fig 3. illustrates this distribution.

To minimize performance variation of the robot in the presence of noise, robustness, two different approaches are considered. Therefore two different goal functions, outputs, are used. One goal is to minimize absolute mean of differences between final horizontal positions the robot reaches with noise and its final position without inclusion of the noises. This approach can lead into *accuracy* for horizontal position for the snake-like robot. The other goal is minimizing standard deviation of the final position for the 24 noisy states. The second approach can lead into obtaining the *repeatability* for the robot horizontal position. Depending on the requirements, one may choose either or both of these two approaches when designing and controlling the snake-like robot [13]. The concept of accuracy and repeatability are shown in Fig. 2. All this means that we do not focus on the values of mass or length of the robot; we also do not focus on how the robot reaches its final destination, its body shape or speed. The only thing that is important is the precision with which the final position is reached.



Figure 3. Selection of noise values based on a normal distribution

Design of Experiments

To find the best possible design, due to number of parameters and their respective levels, a full factorial design will require 5^4 =625 experiments. Furthermore, to implement the noise values, we require an additional 24 iterations for each of the 625 original experiments. This means the dynamics equations needs to be simulated 626×25=15,625 times. Clearly, this large number of experiment is not realistic to perform.

Taguchi method, developed at the beginning of 1950 by Genichi Taguchi, is a powerful tool for characterization, design and performance optimization. Taguchi method reduces cost of experiments by significantly reducing the number of needed experiments. In this method, a loss function is being used to calculate variations between results and desired values. This function is referred to as "signal to noise ratio". Various values of the loss function (L_{LB}, L_{HB}, L_{NB}) may be computed depending on conditions of the problem. Therefore, for the goal function 'LB=lower is better' Eq. 8, for 'HB=higher is better' Eq. 9 and for 'NB=nominal is the best' Eq. 10 will apply as

$$L_{LB} = \frac{1}{n} \sum_{i=1}^{n} y_i^2,$$
(8)

$$L_{HB} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2},$$
(9)

$$L_{NB} = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_0)^2.$$
⁽¹⁰⁾

In these formulae *n* is number of repeats and y_i is the measured output. After calculation of the loss function each output, signal to noise ratio can be obtained using Eq. 11 as [14]

$$\eta_{ij} = -10 Log(L_{ij}). \tag{11}$$

In the present study, our goal is to minimize the positional error; hence, the Taguchi loss function L_{LB} is used. Using Taguchi method and choosing L_{25} orthogonal array, the required number of experiments decreases from 625 to 25. Upon completing the experiments, Analysis of Variance (ANOVA) is performed to assess the effect of each parameter on the design and choose the best parameters leading to a robust design.

Results

The S/N ratio for both mean of the positional error as well as standard deviation of actual positions are calculated and shown in Fig. 4 and Fig. 5, respectively. The x-axis of these two figures represents the 5 levels for each of the four input factors. The factor setting with the highest S/N values is most desired. Referring to Fig. 4 and Fig. 5, for positional error and standard deviation, the best settings are $l_{2-m1-s4-\alpha_05}$ and $l_{2-m1-s4-\alpha_01}$, respectively.





Figure 4. S/N ratios for mean of errors



Therefore, the optimum levels in which noises have the least effect on robot performance are tabulated as follows.

Table 2. Optimum parameters for corresponding goal functions

<i>l</i> [cm]	m [gr]	s [sec]	α_{θ} [rad]	Goal Function
25	100	0.04t	$\pi/3$	Mean of Errors
25	100	0.04t	π/6	Standard Deviation of Noisy States

Significance of each parameter is also determined using ANOVA technique in Minitab software. Table 3 shows the importance of each parameter based on their effect on the outcome. It should be noted that as significance level increases the importance of the corresponding variable decreases.

Table 3. Order of Significance for each parameter for the goal functions

	l	т	S	α_{θ}	Goal Function	
Order of Significance For Each	4	r	1	3	Mean of Errors	
Parameter		4	1	5	Ivical of Ellois	
Order of Significance For Each Parameter		3	1	2	Standard Deviation of Noisy	
					States	

Therefore, depending on the goal, accuracy or repeatability, one should focus on its related significant parameters. For example, in case of accuracy, we note that parameter s is most important followed by parameter m. Hence, we should put more of the overall budget on controlling the variable, s, followed by the variable m, followed by the remaining variables.

Summary

In this paper a novel method is introduced to increase robustness of design by implementing *noise* using computer simulation. Taguchi method is also utilized to design the experiments for four parameters each having five levels. Dynamics equations of a five-link robot are solved and simulated with both noisy and noiseless states using MATLAB software. Two different goal functions, leading to accuracy and repeatability, are proposed. For each goal function, the optimum value for each parameter as well as relative significance of them is identified.

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