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Particle Swarm Optimization Based Parameter Identification Applied to a Target Tracker Robot with Flexible Joint

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P A P E R I N F O	*A B S T R A C T*
	This paper focuses on parameter identification of a target tracker robot possessing flexible joints using particle swarm optimization (PSO) algorithm. Since, belt and pulley mechanisms are known as flexible joints in robotic systems, their elastic behavior affecting a tracker robot is investigated in this work. First, dynamic equations governing the robot behavior are extracted taking into account the effects of considered flexible joints. Thus, a flexible joint is modeled by a non-linear spring and damper system connecting the motor to the link. It is found that the governing dynamic equations include some unknown parameters, which must be identified in order to design the robot system. Consequently, a PSO-based identification scheme is proposed to achieve the unknown variables based on the experimental data of the open-loop system. Lastly, for validating the proposed identification scheme, the obtained results are compared to the experimental measurements as well as the results of another similar work in which the robot is modeled with rigid joints. The consequences reveal that the mathematical model of the robot with flexible joint can describe the elastic behavior of the tracker robot. Thus, a better agreement between the simulation and experimental data are found in comparison with outcomes of the robot model with rigid joints.

1. INTRODUCTION

One of the most widely used methods for power transmission in the robots is the belt and pulley system called the flexible joint. Flexible joints have several advantages compared to rigid joints such as lower cost, light weight, smaller dimension, and better maneuverability. Considering the flexibility of the joints in the robot model provides a more accurate prediction, which results in a better performance of the robot controller. For an *n*-link robot, 2*n* generalized coordinates are needed to describe the overall dynamic behavior when the joints are considered flexible. Accordingly, modeling a robot with flexible joints is more complex than the rigid joints. Researchers utilized different configuration for modeling the flexible joints. A linear spring is the simplest model that is employed for a flexible joint [1–4]. Chaoui et al. [5] modeled a

flexible joint with a spring associated with the friction of motors. Furthermore, the dynamic equations of electric motors can be taken into account in the modeling of robots with flexible joints [6]. To achieve more accurate modeling the flexible joints can be modeled by a pair of spring and damper [7]. Moberg and Hanssen [8] used a model consisting of a pair of spring and damper along with the friction of motor. Indeed, there are various types of dampers. In this regard, Daniel et al. [9] conducted a comprehensive review work on magnetorheological fluid and dampers. Moberg [10] proposed a complete model for a robot with a flexible joint that included the coupling of links and motors. Another issue that has a significant effect on the systems and controllers performance, is the estimated value of parameters versus their real values. Therefore, accurately estimating the value of parameters is an important issue. Wu et al. [11] conducted a review on

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the estimation of the parameters of parallel and series robots. Accordingly, they categorized the identification methods into two parts, i.e. traditional and intelligence methods. The traditional parameters estimation methods include the least-squares method, the maximum probability method, and so on. Because of simplicity in concept and deployment, the least square method is a common method for parameter estimation. In [12–14], the least-square method is used for parameter estimation of a linear system and an electromechanical system with one-degree of freedom. Maximum likelihood is another method for parameter estimation, which is an important method for system identification and has been used in many works [14, 15]. However, in complex nonlinear systems, traditional methods do not provide accurate and effective results. Hence, intelligent algorithms such as particle swarm algorithm, genetic algorithm, ant colony algorithm, and so on are usually used to estimate parameters of complex systems. Particle swarm optimization and genetic algorithm are the most well-known optimization algorithm and many works can be found in which the PSO and GA are compared [16]. Correspondingly, because of the benefits of the PSO, this algorithm is adopted to use in this work. Eberhart and Shi [17] performed a complete study on the particle swarm algorithm and its performance. Particle swarm optimization can be used in different applications such as identifications of magnetorheological fluid dampers [18], chaotic dynamic systems [19], permanent magnet synchronous motors [20], and enhancing the performance of a nonlinear free piston Stirling engine [21]. Another intelligent algorithms like genetic [22–24], gray wolf [25], ant colony [26], and bee colony [27] algorithms can also be employed for identification purpose each of which contains some advantages and drawbacks.

The flexible joints have different behavior compared to the rigid joints, so when a robot is equipped with the flexible joints (e.g. belt and pulley mechanism), it would be better to consider the dynamics of flexible joints in the overall dynamic model of the robotic system. Consequently, this paper is devoted to study a 2-degree-of-freedom target tracker robot equipped with the flexible joints. Thus, an identification scheme based on PSO is applied to an open-loop test rig in order to obtain a more accurate model of the prototype robot. Firstly, the dynamic equation of the target tracker robot with the flexible joint is presented in Section 2. Next, Section 3 describes the parameter identification process of the mathematical model of the robot based on the PSO algorithm. The particle swarm algorithm and the procedure of collecting data are explained in this section respectively. Afterwards, the results of parameter identification and model validation are discussed in Section 4. Finally, the main conclusions of this research work are given in Section 5.

2. ROBOT DYNAMICS

In this section, first, the configuration of a flexible joint is described and the dynamic equations of a flexible joint are extracted. Then, the working principle of the prototype robot is explained and the dynamic equations of the robot with rigid joints are presented. Finally, the section ends up with the extraction of the dynamic equations of the tracker robot with the flexible joint by combining the dynamic equations of the tracker robot with the flexible joint dynamics.

2. 1. Dynamic of Flexible Joint
Figure 1 shows the general structure of a simple robot with a flexible joint. The links are considered rigid and the motors are connected to the links elastically. If the flexible joint is considered as a pair of linear spring and damper, the dynamic equations of the robot will be obtained as Equation (1) and (2):

$$I_a\ddot{q}_a + C(q_a, \dot{q}_a)\dot{q}_a + g(q_a) = T_{spring} + T_{damper} \tag{1}$$

$$I_m\ddot{q}_m + B\dot{q}_m + f(\dot{q}_m) + \frac{1}{r}T_{spring} + \frac{1}{r}T_{damper} = T \tag{2}$$

where the link and motor angular positions are indicated as $q_a \epsilon \Re^N$ and $q_m \epsilon \Re^N$, respectively. $I_a \epsilon \Re^{N \times N}$ and $I_m \epsilon \Re^{N \times N}$ are the inertia matrix of the link and the motor. $C(q_a, \dot{q}_a)\epsilon \Re^N$ denotes the Coriolis matrix, $B \epsilon \Re^{N \times N}$ is the motor damping matrix and $g(q_a)\epsilon \Re^N$ the gravitational acceleration vector. A vector of friction torques is introduced for this model and is shown by $f(\dot{q}_m)\epsilon \Re^N$. r is the joint reduction ratio and the control input $T \epsilon \Re^N$ used as the torque input at each motor. $T_{spring} \epsilon \Re^N$ and $T_{damper} \epsilon \Re^N$ are also the torque vector of the spring and the damper respectively.

2. 2. Target Tracker Robot Dynamics
The target tracker robot consists of a barrel and a base resulting in a 2-DOF dynamic system. The base and the barrel rotations are done in such a way to track a target in the horizontal and vertical directions, respectively. The dynamic equations of the robot without considering the flexibility of joints can be writte as Equations (3)
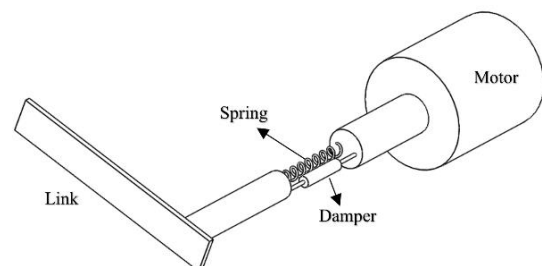

Figure 1. General structure of flexible joint

and (4) ([28]):

$$T_{Base} = (J_\theta + (m + \acute{m})R^2 - (m + 2\acute{m}u)R\cos\alpha + J_\alpha \cos^2\alpha)\ddot{\theta} + ((ml + 2\acute{m}u)R\dot{\alpha}\sin\alpha - -2J_\alpha\dot{\alpha}\cos\alpha\sin\alpha + b_\theta)\dot{\theta} \qquad (3)$$

$$T_{Barrel} = J_\alpha\ddot{\alpha} - \left(\frac{1}{2}(ml + 2\acute{m}u)R\sin\alpha - J_\alpha\cos\alpha\sin\alpha\right)\dot{\theta}^2 + b_\alpha\dot{\alpha} + mg\frac{l}{2}\cos\alpha + \acute{m}gu\cos\alpha \qquad (4)$$

2. 3. Dynamics of Target Tracker Robot with Flexible Joints
The target tracker robot is designed as shown in Figure 2 according to the required performance.

In this prototype robot, the belt and pulley mechanism is used for power transmission from the motors to the base and the barrel. In this study, the belt and pulley system is considered as a flexible joint and is modeled by a pair of nonlinear spring and linear damper.

The nonlinear behavior of the power transmission system (i.e. belt and pulley) can have a great impact on the robot performance. For this reason, the models of springs and friction are considered nonlinear. The following nonlinear equations are chosen as the friction model [9].

$$f_\theta(\dot{\theta}_m) = f_{v\theta}\dot{\theta}_m + f_{c\theta}\,sign(\dot{\theta}_m) \qquad (5)$$

$$f_\alpha(\dot{\alpha}_\alpha) = f_{v\alpha}\dot{\alpha}_\alpha + f_{c\alpha}\,sign(\dot{\alpha}_\alpha) \qquad (6)$$

In these equations, f_v is viscous friction and f_c is the Coulomb friction. As mention earlier, the flexible joint is modeled as a nonlinear spring and a linear damper. Therefore, the springs and the dampers connected to the base and the barrel are modeled as:

$$T_{spring-\theta} = K_{\theta 1}\left(\frac{\theta_m}{r} - \theta\right) + K_{\theta 2}\left(\frac{\theta_m}{r} - \theta\right)^3 \qquad (7)$$

$$T_{spring-\alpha} = K_{\alpha 1}\left(\frac{\alpha_m}{r} - \alpha\right) + K_{\alpha 2}\left(\frac{\alpha_m}{r} - \alpha\right)^3 \qquad (8)$$

$$T_{damper-\theta} = C_\theta\left(\frac{\dot{\theta}_m}{r} - \dot{\theta}\right) \qquad (9)$$

$$T_{damper-\alpha} = C_\alpha\left(\frac{\dot{\theta}_\alpha}{r} - \dot{\alpha}\right) \qquad (10)$$

Figure 2. 3-D solid model of the considered target tracker robot

$$(J_\theta + (m + \acute{m})R^2 - (ml + 2\acute{m}u)R\cos\alpha + J_\alpha\cos^2\alpha)\ddot{\theta} + ((ml + 2\acute{m}u)R\dot{\alpha}\sin\alpha - 2J_\alpha\dot{\alpha}\cos\alpha\sin\alpha + b_\theta)\dot{\theta} = K_{\theta 1}\left(\frac{\theta_m}{r} - \theta\right) + K_{\theta 2}\left(\frac{\theta_m}{r} - \theta\right)^3 + C_\theta\left(\frac{\dot{\theta}_m}{r} - \dot{\theta}\right) \qquad (11)$$

$$J_{m\theta}\ddot{\theta}_m + B_{m\theta}\dot{\theta}_m + f_{v\theta}\dot{\theta}_m + f_{c\theta}\,sign(\dot{\theta}_m + \frac{1}{r}K_{\theta 1}\left(\frac{\theta_m}{r} - \theta\right) + \frac{1}{r}K_{\theta 2}\left(\frac{\theta_m}{r} - \theta\right)^3) + \frac{1}{r}C_\theta\left(\frac{\dot{\theta}_m}{r} - \dot{\theta}\right) = T_{Base} \qquad (12)$$

$$J_\alpha\ddot{\alpha} - \left(\frac{1}{2}(ml + 2\acute{m}u)R\sin\alpha - J_\alpha\cos\alpha\sin\alpha\right)\dot{\theta}^2 + b_\alpha\dot{\alpha} + mg\frac{l}{2}\cos\alpha + \acute{m}gu\cos\alpha = K_{\alpha 1}\left(\frac{\alpha_m}{r} - \alpha\right) + K_{\alpha 2}\left(\frac{\alpha_m}{r} - \alpha\right)^3 + C_\alpha\left(\frac{\dot{\theta}_\alpha}{r} - \dot{\alpha}\right) \qquad (13)$$

$$J_{m\alpha}\ddot{\alpha}_m + B_{m\alpha}\dot{\theta}_m + f_{v\alpha}\dot{\theta}_m + f_{c\alpha}\,sign(\dot{\theta}_m) + \frac{1}{r}K_{\alpha 1}\left(\frac{\alpha_m}{r} - \alpha\right) + \frac{1}{r}K_{\alpha 2}\left(\frac{\alpha_m}{r} - \alpha\right)^3 + \frac{1}{r}C_\alpha\left(\frac{\dot{\theta}_\alpha}{r} - \dot{\alpha}\right) = T_{Barrel} \qquad (14)$$

The dynamic equations of the robot is obtained as Equations (11)-(14) by rewriting Equations (3) and (4) based on Equations (1) and (2) and combining them with Equations (5) - (10). As can be seen, there are some coefficients that there values are unknown. Thus, in the next section, a PSO-based identification scheme is presented for estimating them. At last, it is worth noting that Equations (11) and (12) are for the base and Equations (13) and (14) are for the barrel.

3. PARAMETER IDENTIFICATION SCHEME

The algorithm used for parameter identification in this study is the PSO algorithm. In this part, the parameter identification procedure is described within both experimental and simulation environments. Finally, it is accomplished with the introduction of an appropriate cost function for the PSO algorithm.

The parameter identification is implemented via some open-loop tests on both the mathematical model of the robot and the developed robot (Figure 3) in the laboratory. First, the open-loop test is done on the experimental rig so that the experimental robot is excited by an input signal (see [29]) and the experimental dynamic response (i.e. the output angles of the base and the barrel) of the robotic system is captured. Next, the open-loop test is carried out using the mathematical model of the robot. Therefore, the mathematical model of the robot is simulated in MATLAB/Simulink based on the Equations (11) - (14) and the input voltage is applied to the mathematical model of the robot and the dynamic response of the robot model is captured. Afterward, for the best

matching of the experimental and the simulation results (the output angles of the base and the barrel), the PSO algorithm is utilized for the calculation of the unknown parameters.

According to the designed procedure for parameters identification, the PSO algorithm is used to minimize the error between the angles of the base and the barrel in the experimental and simulation environments. Consequently, the proposed cost function is considered in this paper to meet the demand of this work.

$$J = \sum_{i=1}^{n}(|e_\theta^i| + |e_\alpha^i|) \qquad (15)$$

where e_θ^i is the error between simulation and experimental results of i-th data for the base, and e_α^i is the error between simulation and experimental results of i-th data for the barrel. n represents the number of data used for parameter identification.

4. RESULTS AND DISCUSSION

In this section, the results are presented and the performance of the proposed method is evaluated. For a better assessment, the results are compared to another similar work ([29]) done on the prototype robot with rigid joint. In the beginning, the experimental results for the base and the barrel sections were respectively measured and depicted in Figures 4 and 5.

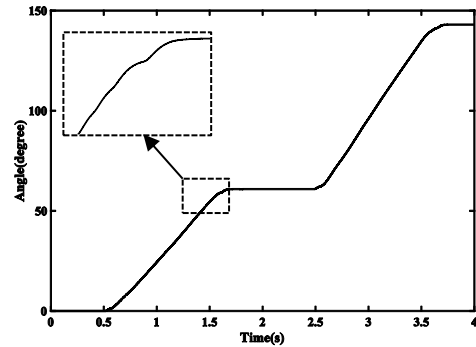**Figure 3.** Experimental model of the target tracker robot

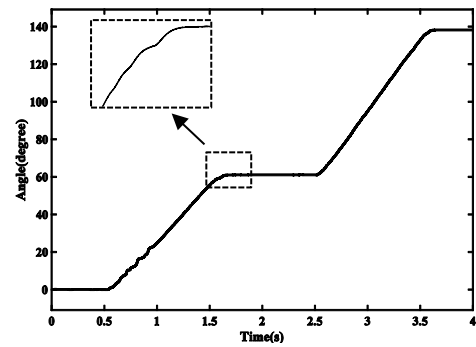**Figure 4.** The base angle in experimental test

**Figure 5.** The barrel angle in experimental test

According to the specified area in Figures 4 and 5, an elastic behavior can be observed in the robot. Indeed, this elastic behavior can be attributed to the existence of a flexible joint. That is why the paper has been focused on the flexible joints applied to the target tracker robot.

As discussed earlier, the target tracker robot is modeled by Equations (11) - (14) assuming that the joints are flexible (they modeled by a pair of nonlinear spring and linear damper). According to Equations (11) -(14), there are some unknown coefficients and in the previous section, a procedure was proposed to reach their values. Correspondingly, the unknown parameters are found by using the PSO toolbox in MATLAB, such that the proposed objective function is minimized. At last, the optimal values of considered parameters are acquired and given in Table 1.

TABLE 1. Values of unknown dynamic parameters

Parameter	Value	Parameter	Value	Parameter	Value
J_θ	0.095(kg m^2)	$K_{\theta 1}$	91.66(N.m/rad)	$B_{m\theta}$	0.0039(N.m.s/rad)
J_α	0.0254(kg m^2)	$K_{\theta 2}$	-261.30(N.m/rad^3)	$B_{m\alpha}$	0.0053(N.m.s/rad)
$J_{m\theta}$	0.0074(kg m^2)	$K_{\alpha 1}$	105.62(N.m/rad)	$f_{v\theta}$	0.1358(N.m.s/rad)
$J_{m\alpha}$	0.0136(kg m^2)	$K_{\alpha 2}$	-183.90(N.m/rad^3)	$f_{c\theta}$	0.1158(N.m)
b_θ	0.2598(N.m.s/rad)	C_θ	0.0016(N.m.s/rad)	$f_{v\alpha}$	0.1123(N.m.s/rad)
b_α	0.01504(N.m.s/rad)	C_α	0.0259(N.m.s/rad)	$f_{v\alpha}$	0.0653(N.m)

For validating the results, the dynamic response of the mathematical model of the robot with the flexible joints is compared to the dynamic response of the experimental robot and the dynamic response of the mathematical model of the robot with the rigid joints that done previously in another work. Figures 6 and 7 show this comparison respectively for the base and the barrel.
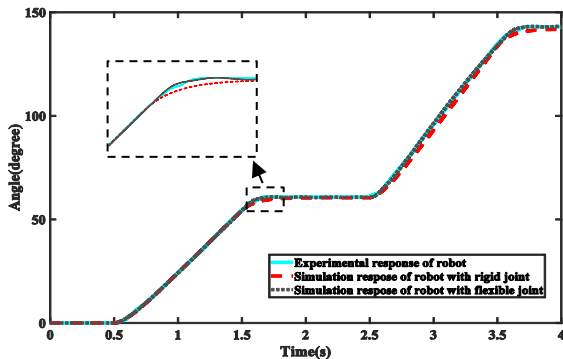
Figure 6. Comparison among simulation response of the robot with rigid and flexible joints and the experimental response (for the base angle)
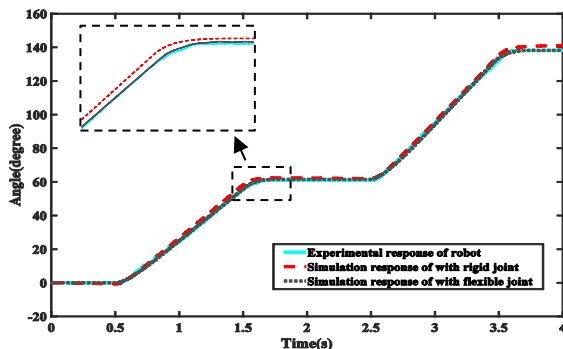
Figure 7. Comparison among simulation response of the robot with rigid and flexible joints and the experimental response (for the barrel angle)

5. CONCLUSION

The paper studied the joints flexibility in a target tracker robot and proposed a procedure for parameter identification of the prototype robot. Based on the experimental test, it was found that the joints had elastic behavior due to the employment of the belt and pulley mechanism as the power transmission system. After obtaining the dynamic equations governing the robot system it was found that some coefficients (inertia and damping coefficients, spring stiffness, viscous friction, Coulomb friction, …) were unknown. Hence, a PSO-based identification scheme is proposed to estimate

these parameters. The proposed method contained an open-loop test in both experimental and simulation platforms for collecting data and the particle swarm algorithm was used for obtaining the optimum values of unknown parameters as the first objective of the paper. After achieving the values of unknown parameters, the open-loop simulation results matched well with the experimental data in which the elastic behavior of the robot joint was seen. At the end, validating the obtained results was carried out by comparing the outcomes with the experimental data and the results of another similar work, in which the robot had been modeled with rigid joints. The consequences showed that the mathematical model of the robot with flexible joints possessed a better convergence to the experimental outcomes than that of the robot with rigid joints and thus, the second aim of the paper was fulfilled. Future works will be directed towards the designing of a control system for the prototype robot with the identified dynamic equations in this study to cope with the robot nonlinearities.

6. ACKNOWLEGEMENT

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Persian Abstract

چکیده

این مقاله به شناسایی پارامترهای یک ربات ردیاب هدف مجهز به اتصالات انعطاف‌پذیر به‌وسیله‌ی الگوریتم گروه ذرات می‌پردازد. با توجه به این که مکانیزم‌های تسمه و پولی در سیستم‌های رباتیکی به عنوان مفاصل انعطاف‌پذیر شناخته می‌شوند، در این مطالعه، تأثیر رفتار کش‌سان این نوع مفاصل بر ربات ردیاب بررسی می‌شود. ابتدا، معادلات دینامیکی ربات با توجه به مفاصل انعطاف‌پذیر استخراج شده‌اند. بدین گونه که یک مفصل منعطف به صورت یک سیستم فنر غیرخطی و دمپر مدل شده است که موتور را به لینک متصل کرده است. بعد از استخراج معادلات دینامیکی، مشخص شد که تعدادی پارامتر نامشخص وجود دارد که برای طراحی سیستم ربات باید شناسایی شوند. در نتیجه، یک روش برای شناسایی پارامترها برپایه الگوریتم گروه ذرات پیشنهاد شده است. در این روش از داده‌های آزمایشگاهی در تست حلقه‌باز سیستم استفاده می‌شود. در نهایت برای اعتبارسنجی روش پیشنهاد شده، نتایج به دست آمده با نتایج آزمایشگاهی و نتایج یک کار مشابه دیگر که در آن مفاصل صلب در نظر گرفته شده‌اند، مقایسه می‌شوند. نتایج به دست آمده نشان می‌دهند که مدل ریاضی ربات که در آن مفاصل انعطاف‌پذیر در نظر گرفته شده‌اند می‌تواند رفتار کش‌سان ربات ردیاب را توصیف کند. پس، در مقایسه با نتایج به دست آمده از مدل ربات با مفاصل صلب، هم‌گرایی خوبی بین داده‌های شبیه‌سازی و آزمایشگاهی حاصل شده است.