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Research Article

Tuning of Linear Active Disturbance Rejection Controller Parameters Using SOS Algorithm

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Abstract

In this study, it has proposed to adjust the parameters of the Linear Effective Distortion Prevention Controller (LADRC) with the Symbiotic Organism Search (SOS) algorithm. The parameters of LADRC were determined by both traditional methods and Symbiotic Organism Search (SOS) algorithm, and comparative analyzes were performed on the speed control performances of permanent magnet direct current motor (PMDCM). Two different reference signals have applied to both systems and monitoring performances were presented graphically and also in the form of a table containing the mean of the squared errors. Simulation-based results have shown that LADRC, which already has a powerfull control performance, can create a faster system response, especially in steep transitions and deterioration points in the reference mark, by adjusting its parameters offline with the SOS algorithm. This situation has caused a decrease in total tracking error and revealed that SOS optimized LADRC has a better tracking performance.

Keywords: Active Disturbance Rejection Control, Symbiotic Organism Search Algorithm, optimization.

Doğrusal Etkin Bozucu Engellemeli Denetleyici Parametrelerinin SOS Algoritması ile Ayarlanması

Özet

Bu çalışmada, Doğrusal Etkin Bozulma Engellemeli Kontrolörün (LADRC) parametrelerinin Simbiyotik Organizma Araması (SOS) algoritması ile ayarlanması önerilmiştir. LADRC'nin parametreleri hem geleneksel yöntemler hem de Simbiyotik Organizma Araması (SOS) algoritması ile belirlenerek sabit mıknatıslı doğru akım motorunun (PMDCM) hız kontrol performansları üzerinde karşılaştırmalı analizler yapılmıştır. İki farklı referans işareti her iki sisteme de uygulanmış ve izleme performansları grafiksel olarak ve ayrıca karesel hatalarının ortalamasını içeren tablo biçiminde sunulmuştur. Benzetim temelli sonuçlar zaten oldukça güçlü bir kontrol performansına sahip olan LADRC'nin parametrelerinin SOS algoritması ile çevrim-dışı olarak ayarlanması sonucunda özellikle referans işaretindeki dik geçişler ve bozulma noktalarında daha hızlı bir sistem cevabı oluşturabildiğini göstermiştir. Bu durum toplam izleme hatasının azalmasına neden olmuş ve SOS ile optimize edilmiş LADRC'nin daha iyi bir izleme performansına sahip olduğunu ortaya koymuştur.

Anahtar Kelimeler: ADRC, SOS, optimizasyon.

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1. 1. Introduction

Active disturbance rejection control (ADRC) was first proposed in Chinese by [Han, 1998], but became more popular after the English version [Gao et al., 2001] was introduced. Even with little knowledge of the system to be controlled, ADRC can be implemented easily and provides great transient response and control performance. For this reason, it has been used frequently by researchers especially in applied studies and has been applied to almost all control engineering fields. Some of these are: DC brushless servo motor speed control [Gao et al., 2001], Web Tension Regulation, alternative MEMS Gyroscope design, temperature control [Zheng and Gao, 2010], PMSM speed control [Su, 2011, Li et al., 2016, Yi 2018, Qu et al., 2020], DC-DC power converter [Sun and Gao, 2005], aerodynamical system control [Madonski and Herman, 2011], gun control system [Gao et al., 2013], industrial pressure control [Li, 2016], power plant furnace regulation [Sun et al., 2019], active suspension system [Wang et al., 2019], magnetic bearing control [Wang et al., 2020], ship steering control [Cao et al., 2019].

The original ADRC was presented in a non-linear form. The linear state of ADRC (LADRC) is equivalent to a custom model-based classical state-space control that includes a state observer based on disturbance estimation. While a traditional model predictive control requires a precise model of the system to be controlled, it is sufficient to have a rough knowledge of the model to design the LADRC. From this point of view, LADRC has a structure that combines the easy applicability of PID type methods with the powerful features of model-based approaches [Herbst, 2013]. Also, LADRC contains fewer control parameters than the original non-linear ADRC (NADRC). In addition, easy-to-apply methods for tuning these parameters are presented, depending on the controller's bandwidth or settling time [Gao, 2003, Chen et al., 2011]. Thus, the parameters of both the disturbance estimation based state observer and the controller can be easily tuned.

Although bandwidth-based controllers can easily find the controller parameters, they should be optimized for better control performance and transient response while tracking a reference signal containing steep changes or encountering a peak disturbance. Also researchers have studied on optimization to determine NADRC parameters, where parameter selection is more difficult and complex. A Chaotic Cloud Cloning Selection Algorithm (CCCSA) is proposed to overcome the difficulty on the parameter choosing of NADRC [Zang et al., 2014]. Beside in [Chao et al. 2019] Adaptive Particle Swarm Optimization (APSO), is proposed to to tune the parameters of the LADRC for ship steering. In this paper, Symbiotic Organism Search Algorithm (SOS) is proposed to tune the parameters of LADRC to control a permanent magnet DC motor. The tracking performance results have compared in each other and with conventional LADRC.

The remainder of this article is organized as follows. In Section 2, the LADRC structure and parameter adjustment depending on the controller bandwidth are explained. Then, SOS algorithm and BB-BC optimization algorithms are given respectively. Then, in the third Section, simulation-based control of a permanent magnet DC motor with LADRC whose parameters were adjusted in 3 different ways was performed. Also its performance is presented graphically and as an MSE and compared. Finally, in Section 4, the paper has been concluded.

2. LADRC and Parameter Tuning

2.1. LADRC

The linear ADRC is a special type of the original ADRC introduced in [Han, 1998, Gao et al., 2001] and includes an extended state observer leading Proportional-Derivative (PD) controller [Gao, 2003], as shown in Figure 1.

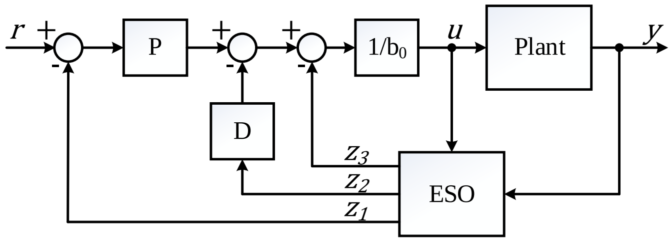


Figure 1: The block diagram of LADRC.

Consider the plant dynamics as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= f(x_1, x_2, t) + bu(t) + d(t) \\ y(t) &= x_1(t). \end{aligned} \tag{1}$$

where $x_1(t)$, $x_2(t)$ are states, $u(t)$ is the input, $y(t)$ is the output of the system and $d(t)$ is the external disturbance. It is assumed that the internal dynamics of the system $f(x_1, x_2, t)$ and a system parameter b are unknown.

Considering the uncertainties in the mathematical model, we can express the parameter b in Equation (1) as $b = b_0 + \Delta b_0$. b_0 represents the known part of b and Δb_0 represents an (unknown) modeling error. If Equation (1) is rearranged accordingly, we get Equation (2).

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= f(x_1, x_2, t) + b_0 u(t) + \Delta b_0 u(t) + d(t) \\ y(t) &= x_1(t). \end{aligned} \tag{2}$$

Assuming only approximate value of b_0 is known about the system to be controlled, Equation (1) can be shown as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= D(x_1, x_2, u, d, t) + b_0 u(t) \\ y(t) &= x_1(t). \end{aligned} \tag{3}$$

where

$$D(x_1, x_2, u, d, t) = f(x_1, x_2, t) + \Delta b_0 u(t) + d(t) \tag{4}$$

Here $D(x_1, x_2, u, d, t)$ is called the total disturbance. Finally, taking D as an augmented state, Equation (1) is represented as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= \dot{x}_3(t) + b_0 u(t) \\ \dot{x}_3(t) &= \dot{D}(x_1, x_2, u, d, t) \\ y(t) &= x_1(t). \end{aligned} \tag{5}$$

Since it is assumed that only approximate value of b_0 is known, an Extended State Observer (ESO) has been proposed as follows to estimate the values of states of augmented state space model of a plant in Figure 1.

$$\begin{bmatrix}\dot{z}_1(t)\\ \dot{z}_2(t)\\ \dot{z}_3(t)\end{bmatrix} = \begin{bmatrix}0 & 1 & 0\\ 0 & 0 & 1\\ 0 & 0 & 0\end{bmatrix}\begin{bmatrix}z_1(t)\\ z_2(t)\\ z_3(t)\end{bmatrix} + \begin{bmatrix}0\\ b_0\\ 0\end{bmatrix}u(t) + \begin{bmatrix}l_1\\ l_2\\ l_3\end{bmatrix}(r(t) - z_1(t)) \tag{6}$$

where z_1, z_2, z_3 are estimations of $x_1,\ x_2, x_3$ in Equation (5) and l_1, l_2, l_3 are gains of the observer. Then the control signal can be expressed as

$$u(t) = \frac{K_p(r(t) - z_1(t)) - K_d z_2 - z_3}{b_0} \tag{7}$$

where K_p is the proportional gain and K_d is the derivative gain of the PD controller. Thus the plant, the dynamics of which are assumed unknown except aproximate value of b_0, can be controlled by LADRC, by choosing appropriate observer gains in Equation (6) and controller gains in Equation (7).

The difficulty in selecting these gain values can be easily overcome with the method suggested in [Gao, 2003] and improved in [Herbst, 2013]. According to this design process, bandwidth of the controller w_c is determined first and then the parameters of the controller can be obtain as

$$\begin{aligned} K_p &= w_c^2 \\ K_d &= 2w_c \end{aligned} \tag{8}$$

Then, the bandwidth of the observer (w_o) is chosen 3-10 times of w_c, and finally observers gains can be obtain as

$$\begin{aligned} l_1 &= 3w_0 \\ l_2 &= 3w_o^2 \\ l_3 &= w_o^3 \end{aligned} \tag{9}$$

2.2 Symbiotic Organism Search Algorithm

The aim of SOS is to find the most suitable organism by simulating symbiotic interactions within a paired organism relationship to solve continuous time numerical optimization [Cheng and Prayogo, 2014].

SOS starts with the first population of randomly produced organisms called ecosystems. Each of these organisms is a candidate solution for the problem being addressed, and they are handled according to the amount of error they produce when used in the problem. In each iteration while reaching the optimum solution, the biological interaction between two organisms in the ecosystem is imitated. Each iteration consists of 3 phases:

i. the mutualism phase,
ii. the commensalism phase and
iii. the parasitism phase.

The mutualism phase mimics the effects of two interacting organisms in nature on each other. Both organisms interact to increase their mutual survival advantage in the ecosystem. The new candidate solutions X_{inew} and X_{jnew} they produce are calculated as

$$\begin{aligned} X_{inew} &= X_i + rand(0,1) * (X_{best} - MV * BF_1) \\ X_{jnew} &= X_j + rand(0,1) * (X_{best} - MV * BF_2) \\ MV &= (X_{inew} + X_{jnew})/2 \end{aligned} \tag{10}$$

where X_i is the i^{th} member of the ecosystem while X_j is the member of the ecosystem that is chosen randomly and interacts with X_i. MV is the mutual vector presents relationship between X_i and X_j. The mutual symbiosis between these two organisms is modeled $rand(0,1)$ that is a vector of random numbers. BF_1 and BF_2 are the beneficial advantage of the X_i and X_j, respectively. Finally, X_{best} is the highest degree of survival adaptation. If the fitness value calculated with X_{inew} and $X_{jnew}$is better than the previous ones, the candidate solutions are updated and this phase is completed.

In phase commensalism, while X_i tries to exploit the interaction of X_i and X_j organisms, the organism X_j does not try to benefit from the association but does not suffer from it. At this stage, according to the symbiosis between X_i and X_j organisms, X_i's new candidate solution is calculated as follows. If the fitness produced by this new candidate solution is better than the previous fitness, the X_i organism is updated.

$$X_{inew} = X_i + rand(-1,1) * (X_{best} - X_j) \tag{11}$$

In the last stage of SOS, Parasitism phase, a noise vector is created using X_i. If the fitness produced by this vector is better than the previous fitness, it replaces X_j.

3. Case Study

In this study, the angular velocity of the PMDCM, given in Equation (12) [Stankovich et al.,2014], has controlled by LADRC to track two different reference signals.

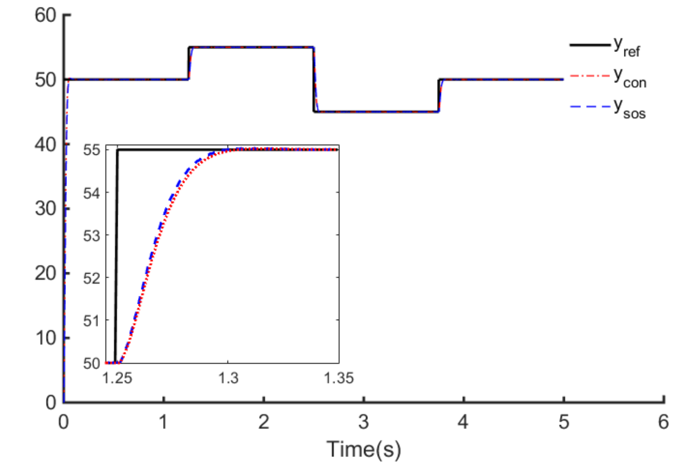
$$\ddot{y} + 204.21\dot{y} + 8.93 \times 10^3 y = 7.89 \times 10^4 u + w \tag{12}$$

The first signal is a staircase-type reference signal without external disturbance, and it was used to obtain optimized LADRC parameters and then for comparison. The second signal is a constant reference signal containing an external disturbance has used for only comparison between both optimized and non-optimized LADRC performances when there exists a disturbance.

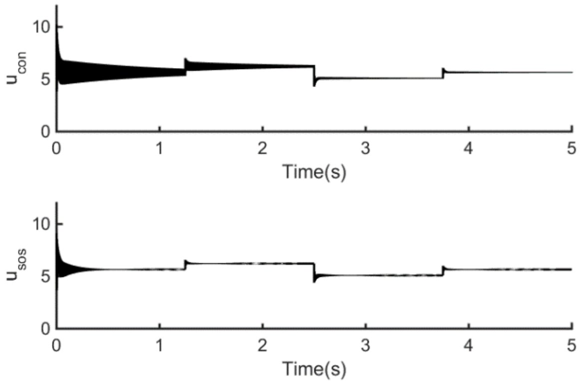
The controller bandwidth has chosen as $w_c = 120rad/sec$ in the conventional LADRC design, therefore the controller parameters in Equation (7) have obtained as $K_p = 14400$ and $K_d = 240$. The ESO bandwidth has formed as $w_o = 10 \times w_c$, so the ESO gains in Equation (6) have obtained as $l_1 = 3600$, $l_2 = 4320000$, $l_3 = 1.728 \times 10^9$.

In order to find the optimized parameters of LADRC, the optimized bandwidth of the controller is obtained first by using the SOS algorithm. For this purpose, the SOS algorithm was run for an ecosize with 20 members whose limit values have determined as [0,200]. Each member in the ecosize can be considered to be a candidate solution that expresses the best controller bandwidth and thus determines the optimized LADRC parameters. For this reason, in each iteration, LADRC has used in order to ensure that the first reference signal is followed by the angular velocity of the PMDCM given by Equation (12). Then a fitness calculation has performed on the obtained off-line tracking errors to determine the best solution.

Optimized LADRC versus conventional LADRC have first compared their performance in tracking the first reference signal. The tracking performances of two systems have given in MSE in Table 1 and illustrated graphically in Figure 1. Although the steady state performances are same, the optimized LADRC by SOS is faster than conventional one in all transition periods in Figure 2. This situation is clearly seen from the small graph showing the focused part in the time period between 1.25-1.35 seconds in Figure 2. On the other hand, the control signal of the conventional LADRC is smoother than the optimize one especially for 2.5 seconds from the start.



a) Tracking Performances



b) Control Signals

Figure 2: Tracking Results for First Reference Signal.

After the SOS Optimized LADRC was successfully tested on the first reference signal, it has used for the second reference signal containing a disturbance. At $t = 2s$, a disturbance has manually added to the reference signal with an amplitude of $10 rad/s$ for $10 ms$. The responses of the two systems to this effect on the reference signal are shown in Figure 3. Although both systems are quite successful in eliminating the disturbance effect, the optimized system has better tracking performance with a faster response. This situation can also be seen on the MSE values given in Table 1.

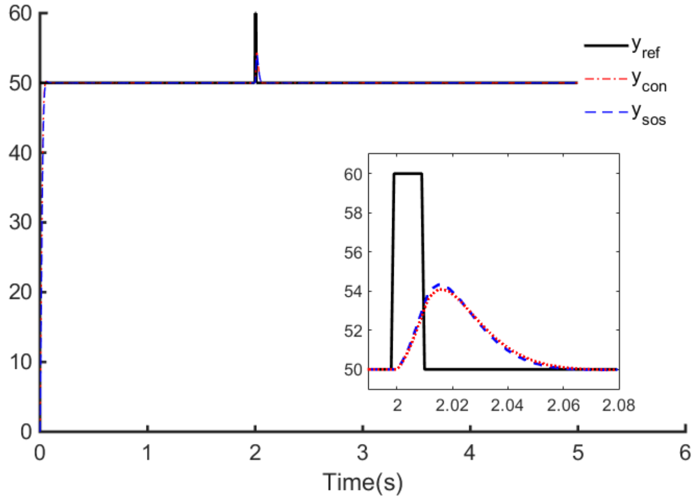


Figure 3: Tracking Results for Second Reference Signal.

These results indicated that LADRC, whose parameters have determined by conventional method in [Gao, 2003, Herbst, 2013, Stankovich et al., 2014] has a powerful tracking performance for steady state period. However, optimized LADRC is faster especially for transient period. This shows that the successful performance of the LADRC can be increased by optimization of its parameters off-line by SOS algorithm.

Table 1: *Tracking Errors in MSE.*

Methods	**Reference 1**	**Reference 2**
Conventional LADRC	6.5	6.4
SOS Optimized LADRC	6.2	6.1

5. Conclusions and Recommendations

In this study, the SOS algorithm has been proposed to adjust the parameters of LADRC used for the control of a permanent magnet DC motor. The parameters of LADRC used to enable the angular velocity of the DC motor to track a stair-case reference signal have optimized off-line with the SOS algorithm. This optimized LADRC has compared with conventional LADRC in their performance in tracking both the stair-case reference that not contains a disturbance and a step reference containing a disturbance. The comparative results, which have shown graphically and in the table of MSE values of the tracking errors, revealed that the LADRC optimized with the SOS algorithm shows a better control performance by providing a faster system response, especially in transition periods.

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