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Araştırma Makalesi / Research Article

Intelligent Quadcopter Control Using Artificial Neural Networks

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Keywords
Quadcopter control; PSO; single layer neural network; PID Controller.

Abstract

An advanced controller architecture and design for quadcopter control implementation is proposed in this study. Instead of using only the error information as input to the controller, reference and measured outputs are used separately independent from each other. This enhances the performance of the controller of quadcopter being a highly non-linear platform. In this study single layer neural network is directly used as a controller. A complex controller is grown from an initially simple PID controller. This elevates the need for time consuming search in huge parameter space due to very high dimensions. About ten percent improvement over state-of-the-art controllers is observed and results are reported both numerically and graphically. Promising results encourage to use the type of controller proposed for various real applications.

Yapay Sinir Ağları Kullanarak Akıllı Kuadkopter Kontrolü

Anahtar kelimeler
Kuadkopter kontrolü; PSO; tek katmanlı sinir ağı; PID Kontrolör.

Öz

Bu çalışmada ileri seviyede bir kontrolör mimarisi tasarlanmış ve geliştirilmiştir. Kontrolöre girdi olarak sadece hata sinyali yerine referans ve ölçüm sinyalleri ayrı ayrı girilmiştir. Bu yaklaşım doğrusallıktan yüksek derecede farklı olan kuadkopterin kontrol performansını artırmıştır. Bu çalışmada tek katmanlı sinir ağı doğrudan kontrolör olarak kullanılmıştır. Basitten başlayarak daha karmaşık bir kontrolörü tasarlayarak bir bakıma kontrolör büyütme yapılmıştır. Bu sayede son derece yüksek boyutlu olan parametre uzayında arama zamanı oldukça azaltılmıştır. Literatürdeki mevcut başarılı kontrolörlere göre yüzde on civarında bir performans artışı gözlemlenmiştir. Sonuçlar hem numerik olarak hem de grafiksel olarak verilmiştir. Elde edilen cesaret verici sonuçlar önerilen kontrolör algoritmasının yeni platformlarda da denenmesinin yolunu açacaktır.

1. Introduction

Quadcopters are the most versatile type of drone used in various types of applications. In unmanned aerial vehicle type of applications, current state-of-the-art controllers have enough reliability for safe operation. But for carrying humans, much more reliability under harsh conditions is required in order to guarantee safe flight since the life of humans is of ultimate importance. Quadcopter controllers must exhibit robust disturbance rejection capability in order to operate even under strong wind conditions.

There are several studies for quadcopter control in the literature which are based on various controller designs. Several controller types are reviewed as a survey study by (Idrissi *et al*. 2022). Park *et al*. (2019) used a PID controller for attitude control of the quadcopter. Parameters of the PID controller are found using neural network-based reinforcement learning. The PID controller is used to control the attitude of the quadcopter while the reinforcement learning-based adaptive controller is used to control the altitude in (Barzegar *et al*. 2022). Adaptive sliding mode control is used to actively reject disturbances in the attitude and altitude control of quadcopters by (Suhail *et al*. 2022). El Gmili *et al*. (2022) used an optimal PD controller to control the orientation and position of quadcopters in their study. Parameters are found using the cuckoo search algorithm. Deep reinforcement learning is

used to control the attitude of quadcopters by (Agarwal and Tewari 2021). Energy efficiency is also considered in controlling the attitude with both stable and low energy-consuming controller designs. Karakaya *et al*. (2022) used two types of controllers, PID and neural network based, are used for controlling the attitude of quadcopters. They have done performance comparisons and reported results accordingly. Position and attitude tracking of quadcopters is done using a neural network-based adaptive controller by (Jin *et al*. 2020). In the study, a numerical simulation is run and results are reported. Quadcopter attitude stabilization and altitude tracking are done using an adaptive sliding mode control strategy by (Bouadi *et al*. 2011). Attitude and altitude dynamics are used for parameter adaptation of the controllers. Numerical simulations are done and results are reported. Long short-term memory (LSTM) was used to evaluate the flight motions of quadcopters controlled with optimal PID controller by (Yoon and Doh 2022). Attitude disturbance is applied and quick stabilization with the optimal controller is observed. It is reported that simulation results agreed with real quadcopter experimental values. PSO-optimized PID control of quadcopter is implemented and tested for various disturbances by (Sonugur *et al*. 2021).
The studies in the literature are mostly based on classical controller architecture where the error signal which is the difference between reference and measured output is fed into the controller. One importance of the proposed approach is that the reference and measured output signals are fed separately to the controller independent from each other. Another importance is a new type of controller design, namely intelligent controller growing, is used in this study.

2. Material and Method

Mathematical Model of Quadcopter

Quadcopter is a four-rotor aerial vehicle as shown in Figure 1.

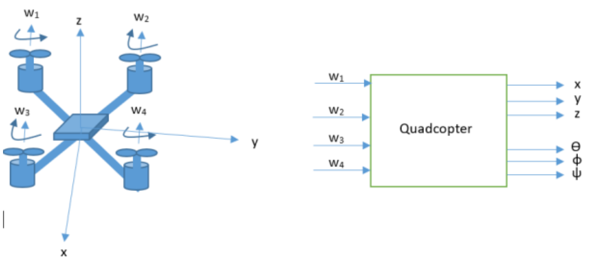

Figure 1. Quadcopter as a four-rotor aerial vehicle.

The quadcopter has four inputs and six outputs. Inputs are four rotor velocities. Three of the outputs are position variables x, y and z, other three of the outputs are orientation variables Θ, ϕ and ψ. The mathematical model of the quadcopter is as follows (Sonugur *et al*. 2021):
The state-space model of the quadcopter can be found as

$$\dot{X} = f(X, U) \qquad (1)$$

where the state variables are defined as:

$$x_1 = \phi, x_2 = \dot{\phi}, x_3 = \theta, x_4 = \dot{\theta}, x_5 = \psi, x_6 = \dot{\psi},$$
$$x_7 = x, x_8 = \dot{x}, x_9 = y, x_{10} = \dot{y}, x_{11} = z, x_{12} = \dot{z}$$

Here, x, y and z are 3D position coordinates of the center of the quadcopter. ϕ, θ and ψ are rotational roll, pitch and yaw angles which represent the orientation of the quadcopter with respect to a fixed orientation earth frame. The equations below can be derived using either of two methods: Newton-Euler or Euler-Lagrange. Newton-Euler method is used in this paper.

$$\dot{x}_1 = x_2 \to \dot{x}_2 = \left[\frac{I_{yy}-I_{zz}}{I_{xx}}\right] x_4 x_6 - \left(\frac{J_r}{I_{xx}}\right) x_4 \Omega_d + \left(\frac{l}{I_{xx}}\right) U_2 \qquad (2)$$

$$\dot{x}_3 = x_4 \to \dot{x}_4 = \left[\frac{I_{zz}-I_{xx}}{I_{yy}}\right] x_2 x_6 - \left(\frac{J_r}{I_{yy}}\right) x_2 \Omega_d + \left(\frac{l}{I_{yy}}\right) U_3 \qquad (3)$$

$$\dot{x}_5 = x_6 \to \dot{x}_6 = \left[\frac{I_{xx}-I_{yy}}{I_{zz}}\right] x_2 x_4 - \left(\frac{1}{I_{zz}}\right) U_4 \qquad (4)$$

$$\dot{x}_7 = x_8 \to \dot{x}_8 = (cos\phi sin\theta cos\psi + sin\phi sin\psi)\left(\frac{1}{m}\right) U_1 \qquad (5)$$

$$\dot{x}_9 = x_{10} \to \dot{x}_{10} = (cos\phi sin\theta sin\psi + sin\theta cos\psi)\left(\frac{1}{m}\right) U_1 \qquad (6)$$

$$\dot{x}_{11} = x_{12} \to \dot{x}_{12} = -g + (cos\phi cos\theta)\left(\frac{1}{m}\right) U_1 \qquad (7)$$

where,

$$U_1 = b(\omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2), \quad U_2 = b(\omega_4^2 - \omega_2^2),$$
$$U_3 = b(\omega_3^2 - \omega_1^2), \quad U_4 = d(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2)$$
$$\text{and } \Omega_d = \omega_1 - \omega_2 + \omega_3 - \omega_4$$

I_{xx}, I_{yy} and I_{zz} are rotational inertias with respect to principal axes of rotation of the quadcopter. J_r is the rotational inertia of motor rotors. m is total mass of the quadcopter and l is distance between two reciprocal motor centers. g is gravity constant and b is the force to rotational speed of each propeller.

Closed-loop Control

Note that quadcopter plant is highly non-linear and inherently unstable. In order to achieve an acceptable performance closed-loop control must be utilized appropriately. In most of the current closed-loop controllers, error signal which is the difference between reference and measured signals is fed into the controller. In this study, we propose a completely different approach to closed-loop control where we use reference and measured signals separately as two independent sets of variables to be entered to the controller. This is illustrated in the Figure 2 below.

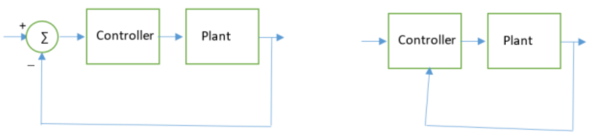

Figure 2. Two broad types of closed-loop control strategies: On the left is classical closed-loop control, on the right is proposed closed-loop control.

Disturbance Generation

The ideal structure given in Figure 2 above is valid only theoretically. In reality, there is always some kind of external disturbance to the system which can not be modeled during the design stage. Disturbance rejection capability is very crucial in the overall performance of the system and should be considered separately. In this study, an external disturbance is modeled using additive noise to input rotor velocities which can model very general types of disturbances. Four different and independent disturbance sources are used in experiments in order to validate the disturbance rejection capability of the system.

PID control

PID control is the most popular control technique in industry and intelligent machines. It is simple to implement and has shown satisfying performance in most applications. In PID control, the control signal is generated using three components: the proportional part, consisting of multiplying the error signal with a constant, the integral part, consisting of multiplying the integral of the error signal with a constant and the derivative part, consisting of multiplying the derivative of the error signal with a constant. There are three parameters for each output to be determined in a PID control system, Kp, Ki, and Kd.

Optimization with PSO

For finding the optimal parameters of the PID controller, the parameters are initialized randomly within acceptable limits and iteratively optimized by computing the updated points. Optimization is done using the PSO algorithm and satisfying results are obtained.

In the PSO algorithm, there are several particles used to search the parameter space for the optimum point. The position of each particle is updated in each iteration with three pieces of information. The first piece depends on the previous velocity of the particle. The second piece is about the particle's known optimum point. Third and the last piece of information is about the known global optimum of the swarm.

Neural control

The proposed controller structure consists of a single layer neural network. Input to the controller is the past and current values of measured outputs and past, current, and future values of reference values. A past window and a future window are maintained to form the input to the controller. Outputs of the controller are the reference rotor velocities. In between the inputs and outputs are the weights of the single-layer network. For each output, the following single-layer network is implemented.

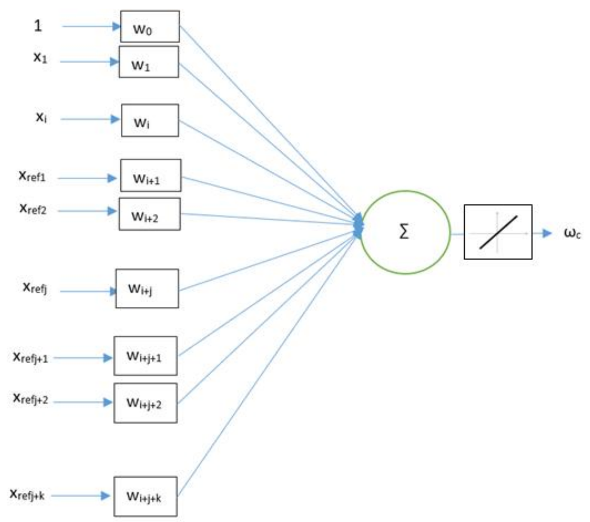

Figure 3. Structure of single layer neural network controller.

Since there are too many parameters to be found, classical PSO is not feasible for single layer neural network controller tuning. A novel solution is proposed in this study for this problem. Initially, a network equivalent to PID controller is designed. So, the parameters of the network are initialized in such a way that input-output relation is equivalent to PID controller tuned by PSO algorithm. After this coarse initialization, several particles are started from nearby points using random number generation. The performance of each particle is calculated and next point of each particle is computed using standard PSO technique. The results are given in the following section.

3. Results

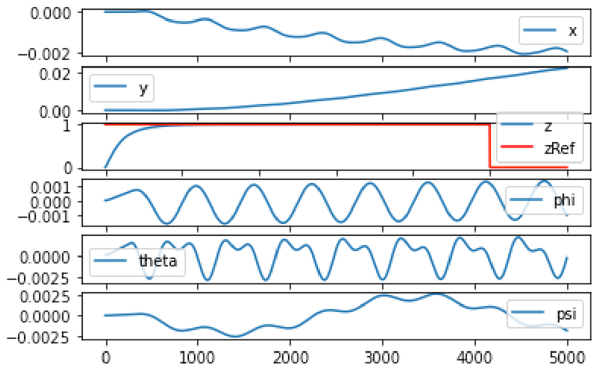

Figure 4. Initial performance of initial pattern vector= 2603.802279047071

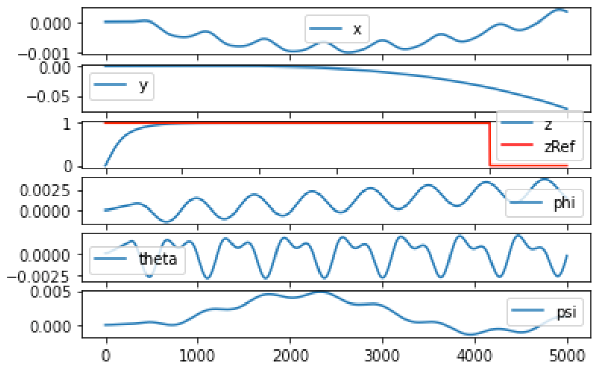

Figure 5. Final performance of optimized LR controller= 2880.3898498702433.

There is more than 10% improvement in performance. Note that this improvement is essential for stability and reliability of the quadcopter. Especially for complex disturbances of high magnitude, this improvement means more flight safety of the quadcopter.

4. Conclusion and Comments

It is clearly seen that the neural controller having more parameters and being more complex than the PID controller shows better performance for complex disturbances. This can be explained by the increased complexity of the controller compensating for complex disturbances which make the system effectively more complex. So, for complex disturbances, the PID controller becomes an underfit. With increased complexity and a much greater number of parameters, learning becomes a more difficult task requiring a search in parameter space with a much higher dimension. Randomly initializing the parameters results in inhibiting the amount of learning time so starting from a known point of acceptable performance works well as expected.
Starting from a known point of acceptable performance, the controller is grown up to a certain level of complexity to compensate for complex disturbances that cannot be coped enough with a simple PID controller. In further future studies, multilayer neural networks with more than one layer of weights will be designed and tested with more complex disturbances.

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