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Design of a Nonlinear Controller on Quadrotor Drone Using Combined Method of Gradient Particle Swarm Optimization

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ABSTRACT: In the paper a new method of optimal control in presented which is composed of policy gradient reinforcement learning and particle swarm optimization. This method has a lot of applications in the real world. The combined method is implemented on a quadrotor drone to control attitude and position of the drone. Inspired from reinforcement methods, the gradient of the policy is computed for a proportional-integral-derivative controller and used in particle swarm optimization to be used in optimization process in addition to the other factors. To study the performance of Optimal proportional-integral-derivative controller on attitude control of the system, a quadrotor is fixed to the design a test stand. The system consists of an accelerometer and a gyroscope sensors and a microcontroller which is used to design fuzzy proportional-integral-derivative attitude controller for the quadrotor. Considering that the experimental data has lots of errors and noises, Kalman filter is used to reduce the noises. Finally using Kalman filter leads to better estimation of the quadrotor angles and the optimized proportional-integral-derivative controller performs the desired motions successfully. The presented method is implemented and tested on the quadrotor test bench and compared with some old methods. To check the robustness of the proportional-integral-derivative controller to the external disturbances, random disturbances are applied to the quadrotor. The controller stabilized the quadrotor rapidly even with disturbance is applied.

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1- Introduction

Optimal control deals with the problem of finding a control law for a given system such that a specific optimality criterion is achieved. In this paper a new method is proposed to design an optimal controller for a Quadrotor drone. Quadrotor is a vehicle with 6 degrees of freedom that can fly via four rotors. These rotors can create a thrust force by pushing air downwards. The rotors are arranged at the corner of quadrotor's body. Quadrotor has four input forces and six output coordinators, the dynamic of quadrotor is highly coupled and unstable [1, 2]. Several linear controller has been designed and applied to quadrotor such as Proportional-Integral-Derivative (PID) or LQR controllers [3, 4]. Since quadrotors has nonlinear characteristic, so applying the classic controllers are not sufficient particularly in presence of disturbance. Therefor to get a better performance, nonlinear control methods have been used such as feedback linearization, back stepping and sliding mode control [5-7]. This paper presents the optimal PID controller applied to a quadrotor for stabilization and trajectory tracking. Various methods are reported for PID controller design. For instance a state-space method based on feedback poles placement is presented in [8]. PID design based on pole distribution of the characteristic equation has been proposed in Ref. [9].

2- Controller Design for a Quadrotor

Several methods can produce dynamic equations of quadrotor [10-12]. To design a new controller for this paper is used the basic dynamics of the quadrotor and a PD-controller. The PD-controller is optimizing during the control process to reach the best performance. In this controller the gains of PD-controller are k_{pz}, k_{dz}, k_{pt}, k_{dt}, k_{ps}, k_{ds}, k_{pp}, k_{dp} which can be determined by a new optimization process. To find these gains a stochastic Gaussian policy π_θ function can be defined for the control system:

$$\pi_\theta(x,u,y)=\frac{1}{\sigma\sqrt{2\pi}}exp\left(-\frac{1}{2}\left(y-g_\theta(x,\ u)\right)\right) \quad (1)$$

In this equation the parameterized policy corresponds the input state variables to the inputs and outputs of the system. Similar policy functions for control systems are defined in Refs. [13-16].

A reward function is also defined for the controller to train itself and achieves the best policy.

$$r(x,y)=(z_{desired}(x,u)-y)^2 \quad (2)$$

This reward function compares the output of the plant to the desired one to calculate the current error of the control. The value function for the controller is defined as:

$$V^\pi(x(t))=E\int_t^\infty e^{-\frac{s-t}{\tau}}r(x(s),y(s))ds] \quad (3)$$

Where E is the expected return of the total error for a control period. To complete the definition of the policy function we need to define g_θ *(x,u)* as:

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$$
\begin{aligned}
&g_\theta(x,u) = \\
&= \left\{ \begin{array}{l}
x(1)+dt.x(2) \\
x(2)+dt.\left((\cos\phi\sin\theta\cos\psi+\sin\phi\sin\psi)\left(\dfrac{\left(g+K_{pz}E_z+K_{dz}(-\dot{Z})\right)}{\cos\phi\cos\theta} \right) \right) \\
x(3)+dt.x(4) \\
x(4)+dt.\left((\cos\phi\sin\theta\sin\psi-\sin\phi\cos\psi)\left(\dfrac{\left(g+K_{pz}E_z+K_{dz}(-\dot{Z})\right)}{\cos\phi\cos\theta} \right) \right) \\
x(5)+dt.x(6) \\
x(6)+dt.\left(-g+\left(\dfrac{\left(g+K_{pz}E_z+K_{dz}(-\dot{Z})\right)}{\cos\phi\cos\theta} \right) \right) \\
x(7)+dt.x(8) \\
x(8)+dt.\left(\dot{\theta}\dot{\psi}\left[\dfrac{I_{yy}-I_{zz}}{I_{xx}}\right]+\dfrac{J_r}{I_{xx}}\dot{\theta}\Omega_d+\dfrac{1}{I_{xx}}\left(\left(K_{pp}E_p+K_{dp}(-\dot{\phi})\right)\right) \right) \\
x(9)+dt.x(10) \\
x(10)+dt.\left(\dot{\phi}\dot{\psi}\left[\dfrac{I_{zz}-I_{xx}}{I_{yy}}\right]-\dfrac{J_r}{I_{yy}}\dot{\phi}\Omega_d+\dfrac{1}{I_{yy}}\left(\left(K_{pt}E_t+K_{dt}(-\dot{\theta})\right)\right) \right) \\
x(11)+dt.x(12) \\
x(12)+dt.\left(\dot{\theta}\dot{\phi}\left[\dfrac{I_{xx}-I_{yy}}{I_{zz}}\right]+\dfrac{1}{I_{zz}}\left(\left(K_{ps}E_s+K_{ds}(-\dot{\psi})\right)\right) \right)
\end{array} \right\}
\end{aligned} \quad (4)
$$

The gradient of this term is calculated and used in the optimization process. Since the partial gradient of this term has a large description, a general description of that is presented in Eq.(5).

$$\nabla\left(g_\theta(x,u)\right)=dG_\theta=\left[dG1\ dG2\ dG3\ dG4 dG5\ dG6\ dG7\ dG8\right] \quad (5)$$

The gradient of g_θ (x,u) is used to calculate the total gradient of the cost function (J(θ)) calculated in Eq.(6).

$$\nabla J_\theta = 2.\sum_{i=1}^{m}\left(z_{desired}(x,u)-g_\theta(x,u)\right).\nabla\left(g_\theta(x,u)\right) \quad (6)$$

The combinational process of optimization is an iterative one which starts from a set of N initial values and searches for the best parameters in the parameter-space. This process is designed based on particle swarm optimization. The particles moves in each iteration with respect to the gbest (the best value found so far) and the pbest (individual particle's best position). In addition to these directions, the presented method uses the total gradient of the cost function. The new equation is presented in Eq.(7).

$$
\begin{aligned}
VG(i)^{it} &= VG(i)^{it-1}+\alpha.\left(BPos(it)-Pos(i)^{it-1}\right) \\
&+\beta.\nabla J\left(Pos(i)^{it-1}\right)
\end{aligned} \quad (7)
$$

3. Experimental Results

To have a secure and reliable verification, an experimental test stand is manufactured to evaluate the performance of the controllers in the quadrotor. To measure the inclination of the quadrotor for pitch and roll, the digital data will be combined. To prevent miscalculation which will affect the stability in quadrotor flight a suitable filter is needed for reducing the noise from sensor to get a near- real value. The filtered data will be used as feedback in the optimal PD-control system. Kalman Filter is used to reduce the noise from the sensor. The microcontroller produces four Pulses With Modulations (PWM) to control the brushless motor speed. These pulses will be sent to the Electronic Speed Controllers (ESC) which will control the brushless motors. The test stand allows the quadrotor to have roll and pitch motion up to ±20 and to have yaw motion freely. A quadrotor is installed in the stand and an IMU is used to obtain the acceleration and the velocity information of the system. An Arduino board is used as an onboard controller to control rotors speed and a GY-80 sensor is used for measuring the value of roll pitch and yaw. The presented method of Gradient Particle Swarm Optimization (Grad-PSO) is compared with some other well-known optimization method including formal PSO, Grey-PSO and SSM-PSO. A comparison of optimization curves of these methods is presented in Fig.1. It shows that Grad-PSO is the fastest and the best method among these methods. Table 1 contains the numerical comparison of different methods

4. Conclusions

The paper presented a model for optimal control of a flying robot. A stochastic optimization algorithm based on policy gradient learning is presented in the paper. The controller parameters are determined using a combined PSO with a special value function. The performance of the presented method is compared with some other optimization method on PD-controller. Generally Grad-PSO yields to a better results reducing the cost function. To check the performance and the effectiveness of PD controller a quadrotor is installed on the stand and an IMU is used to obtain the acceleration and the velocity information of the system. Various experiments were performed such as step input for roll and pitch angle control and Roll angle control while subjecting to disturbance. The quadrotor performs the desired motion successfully and the controller could stabilize the quadrotor rapidly even with disturbance is applied.

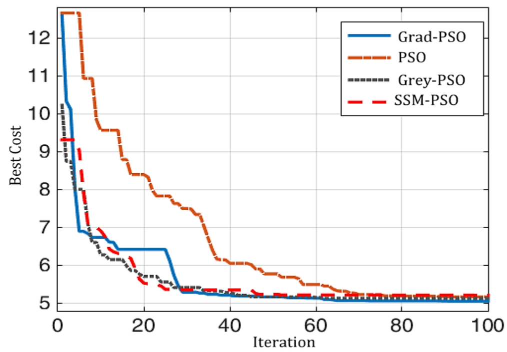

Fig. 1. Comparison of optimization curves of different methods

Table. 1. Comparison of different methods

Controller	K_p	K_d	$(\%)M_p$	t_r	t_s
Gradient PSO	0.98	0.16	01/0	0.5900	0.40
SSM PSO	0.74	0.15	02/0	0.83	0.48
Grey PSO	0.69	0.13	012/0	0.66	0.45
PSO	0.66	0.14	033/0	0.73	0.52

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