Flight Control System Design and Obstacles Avoidance for Quadcopter

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Abstract_Recently, unmanned aerial vehicle (e.g. quadcopter) has been used in many applications, e.g., search-and-rescue missions, because of its capabilities, e.g. vertical takeoff and landing. To achieve these missions, we need to design a suitable control system to stabilize and control quadcopter to track a desired flight trajectory. In this paper, we proposed a comparative simulation between a classical and optimal controllers implemented on a quadcopter model. Moreover, this paper discusses obstacles avoidance using path planning by Particle Swarm Optimization. Implementation of these linear controllers requires linearization the nonlinear quadcopter model around a steady state flight condition. The simulation results shows that the optimal controller LQR has an efficient performance compared to classical controller PID.

I. INTRODUCTION

In recent years, unmanned aerial vehicle (UAV) has grown significantly in popularity in many applications, e.g., surveillance, exploring unknown environments, weather forecast, meteorological monitoring, transportation, aerial photography, and crop assessments. Indeed, UAV (e.g., quadcopter) has the capabilities to efficiently perform highly risk tasks. Moreover, quadcopter have the ability of vertical take-off and landing which gives it advantages over a fixed wing aircraft. Moreover, quadcopter have more features, e.g., hovering, high maneuverability, and easy to control [1]. The UAV control system is designed to execute the guidance commands while stabilizing the UAV to guarantee achieving the desired mission objective. Many current literature on quadcopter control design pays particular attention to use classical control, e.g., proportional-integral-derivative (PID) control, as in [2]. The main advantages of PID controllers are ease of design and resistance to uncertainties. Self-Tuned PID controller confirm its performance effectiveness and robustness for UAV control under disturbances [3]. However, non-linearity in quadcopter dynamics put some limitations on using PID controller [4].

Another commonly used controller is the linear quadratic regulator (LQR), a type of optimal control that based on mathematical optimization of the dynamic system objective cost function, e.g. [5]. Many studies compared the performances of the PID and LQR controllers; some have explored how PID controllers give better stability as compared to LQR controllers [6]. On other hand, LQR controllers are more robust with a low steady state error based on experiment test results, e.g. in [7].

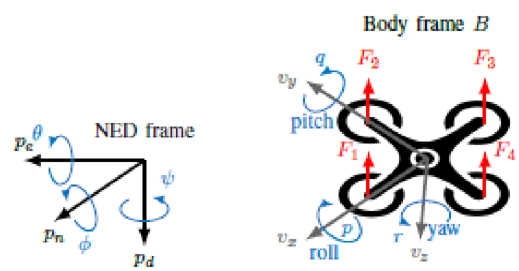

Fig. 1: Quadcopter variables (state and input) in different Coordinate systems (NED frame and body frame) [10].

PID and LQR controllers are both common in design simplicity and only applied to a linear dynamic system. Whereas the advantage of LQR compared to PID that it can deal with multi-variables systems but PID handles only single input single output systems (SISO). This work sets out to simulate the performance of quadcopter trajectory tracking by applying traditional and optimal control techniques. Implementation of these linear controllers requires to linearize the nonlinear dynamics. The simulation results compare the performances under some model uncertainties and external disturbance.
The paper is organized as follows. Section II outlines the problem formulation including the quadcopter nonlinear modelling and linearization. Section III presents the underlying PID and LQR controllers. Then, obstacles avoidance using path planning by Particle Swarm Optimization is proposed in Section

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IV. The analysis of the simulation results is discussed in Section V. Finally, the conclusion is presented.

II. UAV NONLINEAR DYNAMICS AND LINEARIZATION

Recently, the use of quadcopters for various purposes, e.g., surveillance, has received significant interest, since quadcopters are highly maneuverable and capable of diverse Tasks, e.g., hovering, vertical takeoff and landing. Quadcopter is an underactuated nonlinear system that has six degrees of freedom and four control variables. The movement of a quadcopter can be specified using two reference frames, NED (North-East-Down) coordinate system as inertial frame and the Body frame B, see Fig. 1.

The quadcopter dynamics are presented by non–linear equations, taken from [10]:

$$\dot{X} = A(x) + B(u) \qquad (1a)$$
$$y = C(x) + D(u) \qquad (1b)$$

Where x and u are the states and control vectors:

$$X = [\, p_n \;\; p_e \;\; p_d \;\; V_x \;\; V_y \;\; V_z \;\; \Phi \;\; \theta \;\; \Psi \;\; p \;\; q \;\; r \,]^{\top}$$
$$U = [f_t \;\; T_{\Phi} \;\; T_{\theta} \;\; T_{\Psi} \;\;]^{\top}$$

pn, pe, pd define the UAV position in NED coordinates, ϕ, θ, Ψ are the vehicle Euler angles, vx, vy, vz and p, q, r are translational and rotational velocities in the body frame, see also Fig. 1. For quadcopters, the vertical lift force Ft, roll, pitch and yaw moments Tϕ, T θ, Tψ are controlled properly to achieve a robust and stable flight response.

This paper propose a comparative synthesis between two control approaches, such as PID control as a type for classical controller and LQR as a type of optimal controller. These controllers are based on linear models even if the actual system behaves in a nonlinear way. For this reason, the quadcopter nonlinear dynamics is linearized around a stable operating condition (trim point), e.g., stable hovering.

A. Model Linearization

Using small signal theory, we assume steady quadcopter flight under small perturbations Δx as

$$x = \dot{x} + \Delta x \quad (2)$$

Where $\dot{x}$ represent a hovering condition at a constant altitude, while attitude angles and velocity components are zero.

$$\dot{p}_e = \dot{p}_n = \dot{v}_x = \dot{v}_y = \dot{v}_z = \dot{\theta} = \dot{\phi} = \dot{r} = \dot{q} = \dot{p} \; (3)$$

Substituting (3) into (2), and then substitute the result to (1) using the following assumptions, e.g., sine of small values is the value itself, cosine of a small value equals to one, **and** product of two small values can be neglected. That will lead to the simplified linear quadcopter model

$$\dot{X} = A(x) + B(u) \qquad (4a)$$
$$y = C(x) + D(u) \qquad (4b)$$

Where A ∈ $R^{12\times12}$, B ∈ $R^{12\times4}$ are state and input matrices, and C ∈ $R^{12\times12}$, D ∈ $R^{12\times4}$ are output matrices. Once the state space equations are obtained, the controller is designed for the quadcopter system.

$$A = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -g & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & g & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -\frac{1}{m_t} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \frac{1}{I_x} & 0 & 0 \\ 0 & 0 & \frac{1}{I_y} & 0 \\ 0 & 0 & 0 & \frac{1}{I_z} \end{bmatrix}$$

III. CONTROL TECHNIQUES OVERVIEW

In this paper, two control approaches, classical control (PID) and optimal control (LQR) controllers have been implemented to stabilize a quadcopter and to track a desired trajectory.

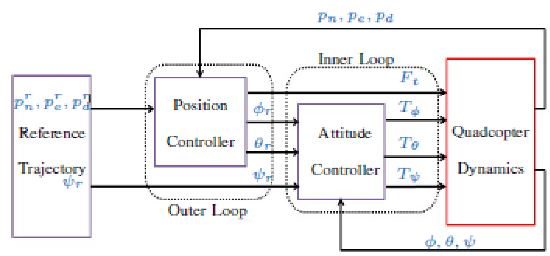

Fig. 2: Quadcopter control loops.

A. Proportional Integral Derivative (PID)

The general form of PID controller is given as follow:

$$u(t) = K_p e(t) + K_I \int_0^t e(t)dt + K_D \frac{de(t)}{dt} \quad (5a)$$
$$e(t) = y_r(t) - y(t) \qquad (5b)$$

Where e (t) is the error signal, K_P, KI, KD are the coefficients of the PID controller [2].

The aim is to minimize the error, i.e., the difference between the reference and the system output, that achieved by tuning the PID gains. The proportional term K_P has the main effect in changing the output value. The integral term K_I sums up all the past error value and controls the speed by which the system steady state error reduced. The derivative term KD estimates the controller future response depending on the error rate over time, this leads to enhance the stability and obtain a smooth response. Thus, all three coefficients are tuned using genetic algorithm (GA) optimization toolbox of MATLAB software to force the system output to track the desired state. In this work, six PID controllers for thrust, roll, pitch, and yaw motion control, see Fig 2. Two PID loops (inner and outer) are designed for each roll and pitch motion. For controller efficient response, the inner loop is mainly designed faster than the outer loop. However, one of the main drawback of PID is its limitation to handle multi-variables systems in the presences of the system uncertainties [9]. For this reason, we proposed a full state feedback controller, e.g., LQR.

B. Linear Quadratic Regulator (LQR)

LQR controller optimizes the objective cost function (J), e.g., the power consumption and tracking error, which depends on the system state and input, as follows:

$$J = \int_0^{inf} (X^T Q X + U^T R U) dt \qquad (6)$$

Where, $Q \in R^{12\times12}$ and $R \in R^{4\times4}$ are the state and input Weighting matrices, respectively, which are tunned to achieve the desired response. A, B, Q, R matrices are used to solve the Algebraic Riccati Equation (ARE)

$$(A^T S + SA - SBR^{-1}B^T S + Q = 0) \qquad (7)$$

To obtain the state feedback gain (K)

$$u = -k * x \ , \ k = R^{-1}B^T S \qquad (8)$$

To achieve the desired performance, both state and input weighting matrices are tuned based on firstly, set $Q = C^T.C$ where C is linear state space model output matrix and R is an identity matrix to be considered as the initial weighting matrices, then using trial-and-error method to fine-tune the entries elements of both Q and R matrices to achieve better controller performance.

IV.PARTICLE SWARM OPTIMIZATION

PSO algorithm simulates the movement of a swarm of particles in a multidimensional search space progressing towards an optimal solution (min-cost). Each particle represents a candidate solution randomly initiated. In every step the velocity of each particle is updated based on the previous velocity, the best position occupied by the particle, and the best position occupied by any particle. The best position is depend on the size of swarm and the number of iterations. Fig.3 shows PSO using (swarm size = 150 and no.of iterations = 50) and show the best path with optimal solution (min- cost) [12].

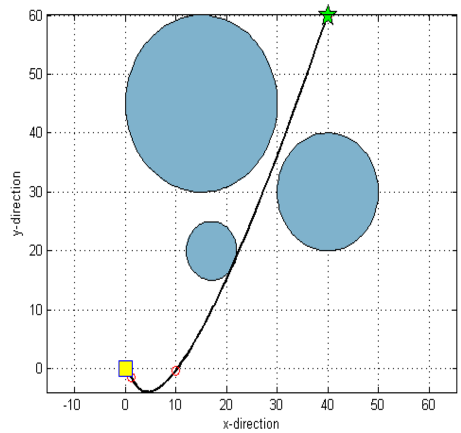

Fig.3a: Optimal Path.

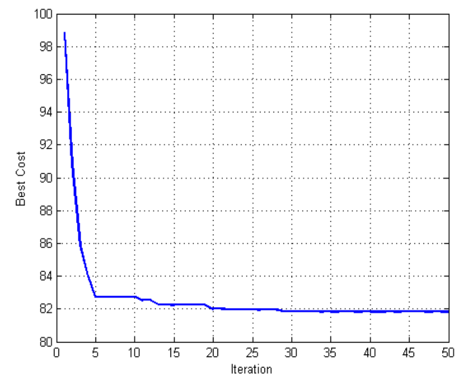

Fig.3b: Cost Function for Optimal Path.

V. RESULTS AND DISCUSSION

This work presents a comparative synthesis between classical PID and optimal LQR controllers implemented for quadcopter. The simulation performed in MATLAB/ Simulink environment using quadcopter linear dynamics, Quadcopter parameters considered for simulation are given in table.1.

Sr. No.	Parameter	Value
1.	Quadrotor mass (m)	1 Kg
2.	Arm length (l)	22.5cm
3.	Thrust Factor (K_f)	9.8×10^{-6}
4.	Drag Factor (K_m)	1.6×10^{-7}
5.	I_{xx}	0.0035
6.	I_{yy}	0.0035
7.	I_{zz}	0.005

Table.1 Quadcopter parameters

The simulation results for the performance of PID and LQR controllers shows each controller functionality and robustness to follow a predetermined trajectory under different flight simulation scenarios:

1. Trajectory tracking of step reference with zero initial condition.
2. Altitude tracking under the effect of varying time step reference.
3. Path tracking in presence of some obstacles at constant altitude.

In the first scenario, Fig. 4a, Fig. 4b, Fig. 4c and Fig. 4d show the response of PID, LQR controllers for x, y, z and

Ψ step reference commands, and Fig.4e clarifies 3D trajectory generated for both controllers due to these commands. The results showed that LQR gives a satisfactory response without any overshoots about its desired setpoints with minimum tracking error which provide a stable output response compared to PID. In the second scenario, Fig. 5 shows the quadcopter response for both PID and LQR altitude controllers to a time varying step commands; the graph clarifies the LQR robustness and smoothness response with small rising time and minimum error that vanish rapidly. In the third scenario, quadcopter is tested for achieving accurate path tracking with obstacles avoidance at constant altitude, the best path for quadcopter to avoid the obstacles is generated using PSO algorithm as shown in Fig.3a. This optimal path is considered as the reference input for both controllers. Fig.6a and Fig.6b show that PID and LQR achieve efficient tracking with small error to avoid obstacles.

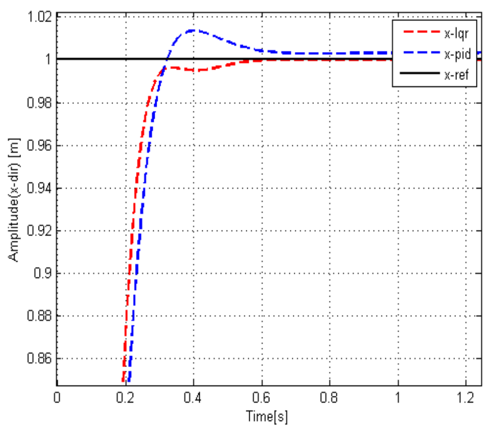

Fig.4a: Response in x-direction

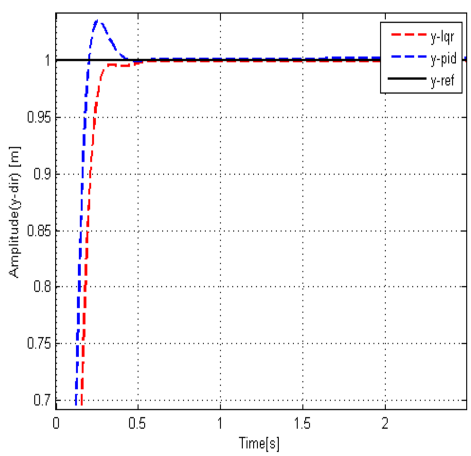

Fig.4b: Response in y-direction

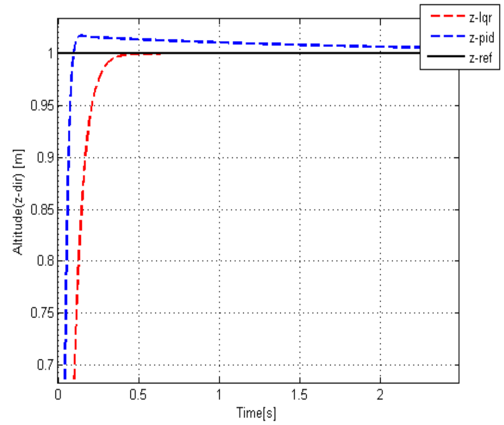

Fig.4c: Response in z-direction

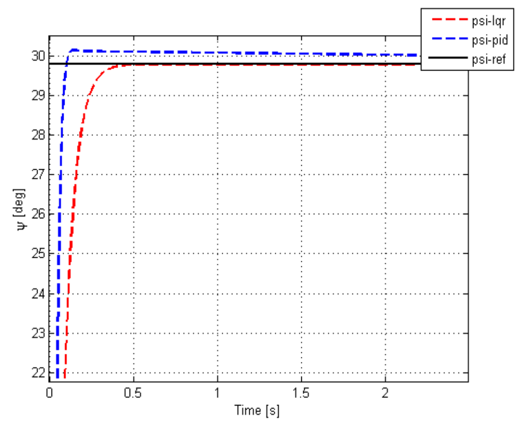

Fig.4d: Response of yaw angle (Ψ).

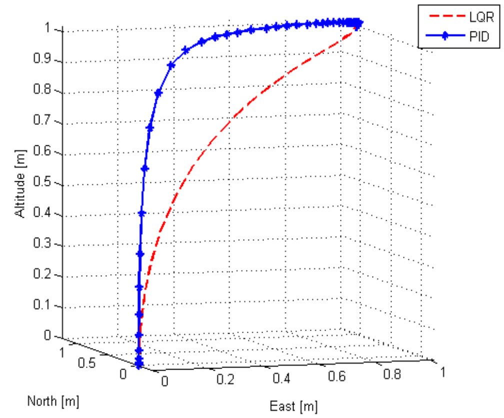

Fig.4e: 3-D Trajectory

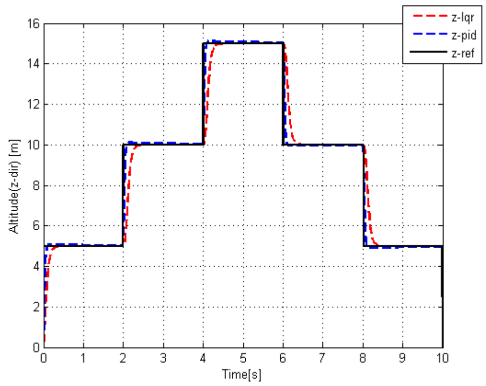

Fig.5: Response of altitude controller to a time varying step reference.

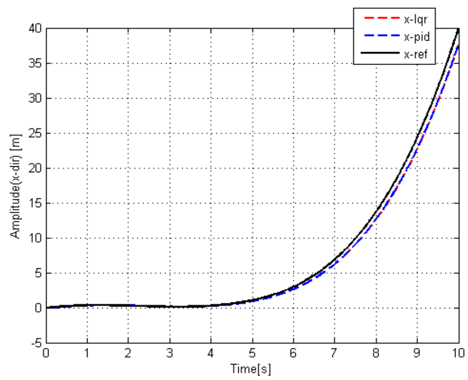

Fig.6a: response in x-direction.

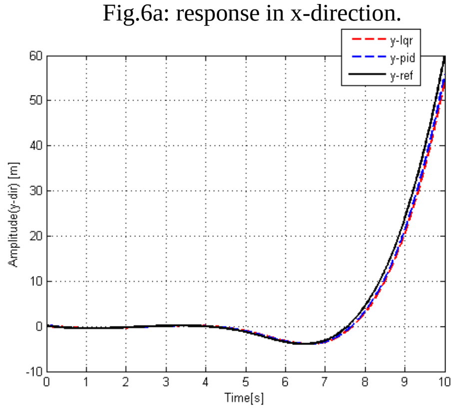

Fig.6b: response in y-direction.

VI. CONCLUSIONS

This paper has argued a comparative synthesis of both classical and optimal controllers implemented on a quadcopter platform. Moreover, this paper discusses obstacles avoidance using path planning by Particle Swarm Optimization. A linear state space model is derived at hovering flight condition from nonlinear dynamics using small signal theory. The simulation results shows that the optimal controller LQR has a robust and efficient performance compared to classical PID controller.

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