Artificial Neural Network Based Self-Tuned PID Controller for Flight Control of Quadcopter

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***Abstract*—Proportional-Derivative-Integral (PID) controllers have been used for many kinds of systems in academia and industry. Multiple off-line approaches are available for PID tuning. However, physical systems which are subjected to continuous parametric changes and external disturbances require a robust PID controller with continuous auto-tuning. Quadcopter is the perfect example of such system which requires a robust control for stable flight operation. In this paper, a robust PID controller is presented for flight control of quadcopter. The proposed PID tuning algorithm continuously adjusts PID parameters which minimizes tracking error using artificial neural network consisting of a single hidden layer. Sigmoid function is used as activation function. Back-propagation algorithm is used to obtain optimized weights. Comparative analysis of three types of training algorithms (Bayesian regularization, Lavenberg-Marquardt and scaled conjugate gradient) against different number of neurons of hidden layer is performed to obtain minimized Mean Square Error (MSE). The effectiveness of proposed control scheme is witnessed for roll, pitch, yaw and altitude control of quadcopter.**

***Index Terms*—Artificial Neural Network, Quadcopter Control, PID, Auto Tuning**

I. Introduction

Research and development activities related to quadcopters have observed a considerable surge from past few years. Today, quaddcopters are widely used in military and law enforcement, disaster monitoring, package delivery, monitoring, search and rescue operations etc. [1]–[3]. Quadcopters are also used by researchers in various fields of control theory and robotics for implementation and evaluation of new ideas. Quadcopter is highly non-linear system because of coupled dynamics and uncertainties due to environmental disturbances. Therefore, a robust control system is required for stable flight of quadcopter. Zulu et. al. analyzed different control algorithms for control of autonomous quadcopter [4]. No single type of control system provided the best features required. However, to get the best combinations of features like adaptability, optimal trajectory tracking, robustness and disturbance rejection hybrid control schemes produced best results.

Proportional-Derivative-Integral (PID) controller is mostly used for control of physical systems due to its simplicity and easy implementation. The accuracy of PID controller depends upon the gains, better the gains, better are the results. However, highly non-linear systems subjected to system parameters variations and environmental disturbances mitigate the performance of PID controller. For such non linear systems conventional off-line PID tuning techniques are not very effective [5]. Online tuning of PID parameter is required for better performance of such nonlinear systems. Several studies highlight the use of different algorithms for tuning of PID gains such as fuzzy logic, internal model control method, Artificial Neural Network (ANN) etc. [6]–[9]. An advantage of using ANN over other methods is its ability to solve non trivial problems [9]. Alvarado et.al. discussed the online tuning of PID parameters using Neural Network (NN) for control of underwater vehicles [7]. Remotely operated vehicle is placed 1 meter underwater and data is collected for 3 minutes. Conventional gains of PID was calculated using NN and then programmed. Once PID controller is tuned the gains remain constant for the experiment. The results show that the gain obtained from NN consumed 3.03% of less energy as compared to conventional PID gains. In [6], feed forward multi-layer perceptron were used to fine tune the PID controller parameters for air conditioner. Genetic algorithm is used to train the neural network and results are compared with back propagation algorithm. By comparing results form both the methods genetic algorithm is found most effective for training ANN. In [8], Back Propagation Neural Network (BPNN) tuned PID controller is used to control the accurate position of pneumatic artificial muscle which is highly non-linear in nature. BPNN tuned PID controller display better position control, less overshoot and fast response in comparison to conventional PID controller. In [10], for a quadcopter, a robust control technique based on ANN with real time adjustment of PID parameters to deal with wind disturbance and payload is presented. Neural network is composed of a hidden layer. Input layer consists of two neurons. System output and controlled input is fed into the neural network as input while PID gains are output of the tuning algorithm. Several hovering experiments are performed to verify the proposed controller performance.

From the above discussion we can conclude that ANN

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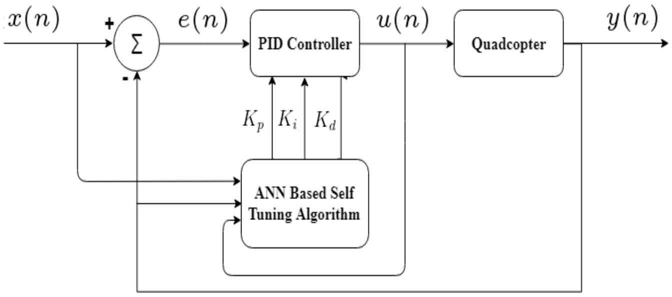

Fig. 1. Control system architecture

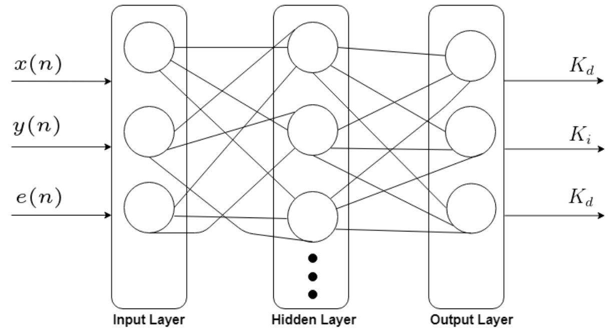

Fig. 2. Block diagram of neural network structure

can help us in improving the control system's performance. Similar approach is carried out in this paper. Quadcopter parameters such as altitude, roll, pitch and yaw is controlled using ANN based PID. PID gains are tuned online using NN based algorithm.

Remaining sections in this paper are arranged as follows: section II describes the proposed methodology, section III discusses simulation platform and results analysis, section IV provides conclusion and future recommendations.

II. PROPOSED METHODOLOGY

Exact mathematical model of quadcopter is difficult to comprehend mainly due to payload and wind disturbances. A robust control system is the possible solution to cater parametric variations and external disturbances. In this paper, the robustness of control system is achieved by continuous tuning of PID parameters (K_p, K_i and K_d). PID controller tuning depends on the adjustment of its gains. PID controller equation in time domain is expressed in equation 1.

$$\begin{aligned} u(n) = u(n-1) + K_p e(n) - e(n-1) + K_i e(n) \\ + K_d e(n) - 2e(n-1) + e(n-2) \end{aligned} \tag{1}$$

where $u(n)$ is control signal, $x(n)$ is input, $y(n)$ is output and $e(n) = y(n) - x(n)$ is tracking error. A block diagram of self-tuned PID control with artificial neural network is shown in Fig. 1. Error between output and input is fed into PID controller. ANN based self-tuning algorithm changes the values of K_p, K_i and K_d as the change in system parameters takes place. Our methodology differs with respect to conventional tuning approach due to continuous update of PID gains.

A. Tuning Algorithm

Artificial neural network architecture is inspired by the characteristic of biological neurons. Like synaptic connection in a normal neuron, each neuron in neural network is a function of weight. The processor has two parts, first part adds the weighted inputs and second part is a filter which is called active function of that neuron. The input in each neuron is multiplied by weight and is passed on the adjacent neuron through a activation function. Proposed artificial neural network has 3 inputs and 3 outputs as shown in Fig. 2. The inputs are reference signal, error and plant output. Where outputs are K_p, K_i and K_d. As the change in input parameters of NN takes place the output of NN also changes accordingly. Tuning algorithm proposed in this paper consists of three layers. A hidden layer, an input layer and an output layer. Sigmoid function is used as an activation function. The output of a hidden layer neuron j can be calculated as [10]:

$$O_j = f(x_j) \tag{2}$$

$$x_j = \sum_{i=1}^{n} \omega_{ji} O_i - \theta_j \tag{3}$$

where, ω is weight, x_j is input of hidden layer and θ_j is the threshold value of j neuron. Sigmoid function is presented in (4).

$$F = \frac{1}{1 + e^{-x}} \tag{4}$$

Similarly the output of an output layer of neural network can be written as:

$$O_k = f(y_j) \tag{5}$$

$$y_k = \sum_{j=1}^{n} \omega_{kj} O_i \tag{6}$$

where, y_k is the input of output layer of neural network. The Back-Propagation algorithm adjusts the weight of neurons. This is done by generating an error of desired output and actual output [10].

$$\omega_{ji}(n+1) = \omega_{ji}(n) + \alpha \delta_j O_i \tag{7}$$

$$\omega_{ki}(n+1) = \omega_{kj}(n) + \alpha \delta_k O_j \tag{8}$$

$$\theta_j(n+1) = \theta_j(n) + \beta \delta_j \tag{9}$$

where δ_j is error term of the hidden layer output. α and β are learning coefficients.

III. RESULTS AND DISCUSSION

Simulation is preformed using MATLAB®. Mathematical model of quadcopter presented in [11] is implemented in SIMULINK®. Artificial neural network toolbox is used for training and building neural network. Three types of training algorithms namely Bayesian regularization, Lavenberg-Marquardt and scaled conjugate gradient are tested for 3, 6

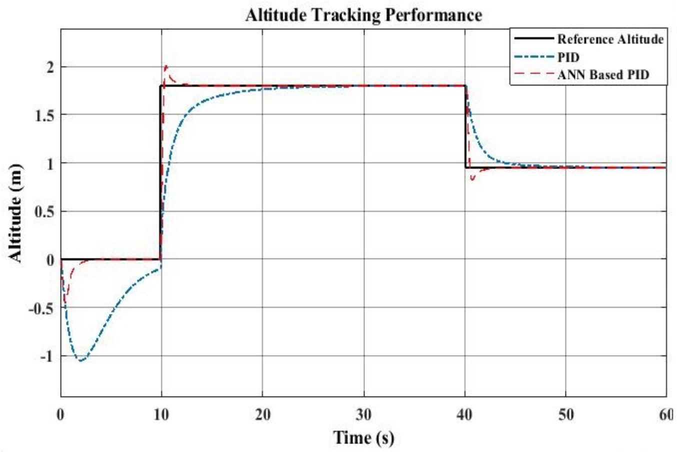

Fig. 4. Altitude tracking performance of ANN based PID

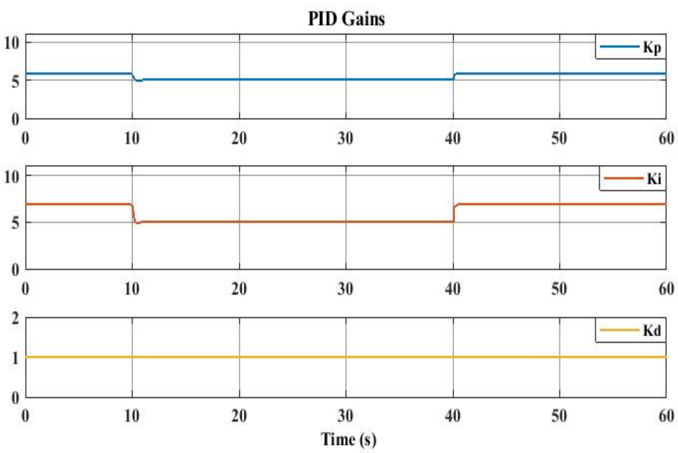

Fig. 3. PID gains in case of altitude tracking

and 9 number of neurons of hidden layer. Table I shows Mean Square Error (MSE) in each case of training method. For altitude control, Bayesian regularization algorithm with 9 neurons in hidden layer produces minimum MSE. In case of roll angle control, Lavenberg-Marquardt algorithm with 9 neurons in hidden layer generates minimum MSE. For pitch angle control, Lavenberg-Marquardt training algorithm having 6 neurons in hidden layer produces minimum MSE. Similarly, Lavenberg-Marquardt algorithm with 3 neurons in hidden layer generates minimum MSE for yaw angle control. The training algorithm and number of neurons of hidden layer which produces minimum MSE is selected for tuning purpose.

Fig. 4 shows the altitude tracking performance of ANN based PID. Transient response and settling time is much better in case of ANN based PID as compared to conventional offline tuned PID. Much improved tracking performance is due to continuous adjustment of PID gains as the change in reference altitude occurs. Change in PID gains can be observed in Fig. 3. K_d remains constant throughout the simulation analysis while K_p and K_i adjust accordingly by improving tracking performance of altitude.

TABLE I
MEAN SQUARE ERROR (MSE) IN EACH CASE OF TRAINING METHOD

Control Variable	Training Algorithem	No. of Neurons in Hidden Layer	MSE Value
Altitude	Lavenberg-Marquardt	3	2.58×10^{-15}
		6	4.44×10^{-16}
		9	9.04×10^{-19}
	Bayesian Regularization	3	3.37×10^{-16}
		6	1.24×10^{-17}
		9	5.93×10^{-21}
	Scaled Conjugate Gradient	3	7.91×10^{-15}
		6	8.83×10^{-13}
		9	5.83×10^{-14}
Roll	Lavenberg-Marquardt	3	5.70×10^{-17}
		6	8.69×10^{-13}
		9	2.33×10^{-18}
	Bayesian Regularization	3	5.54×10^{-16}
		6	5.02×10^{-13}
		9	3.85×10^{-13}
	Scaled Conjugate Gradient	3	3.94×10^{-08}
		6	1.15×10^{-08}
		9	3.70×10^{-09}
Pitch	Lavenberg-Marquardt	3	1.43×10^{-12}
		6	1.57×10^{-14}
		9	2.79×10^{-13}
	Bayesian Regularization	3	5.90×10^{-13}
		6	4.42×10^{-13}
		9	3.53×10^{-13}
	Scaled Conjugate Gradient	3	9.57×10^{-10}
		6	2.94×10^{-10}
		9	4.57×10^{-11}
Yaw	Lavenberg-Marquardt	3	2.85×10^{-25}
		6	1.77×10^{-20}
		9	1.54×10^{-21}
	Bayesian Regularization	3	2.10×10^{-16}
		6	4.02×10^{-21}
		9	3.36×10^{-24}
	Scaled Conjugate Gradient	3	1.40×10^{-14}
		6	4.38×10^{-14}
		9	1.18×10^{-13}

Roll angle tracking performance is represented in Fig. 5. Although, reference roll angle is constant but change in other parameters such as altitude induces deviation from tracking of constant roll angle. However, proposed control system efficiently caters this disturbance. Fig. 8 shows change in PID gains in case of roll angle control.

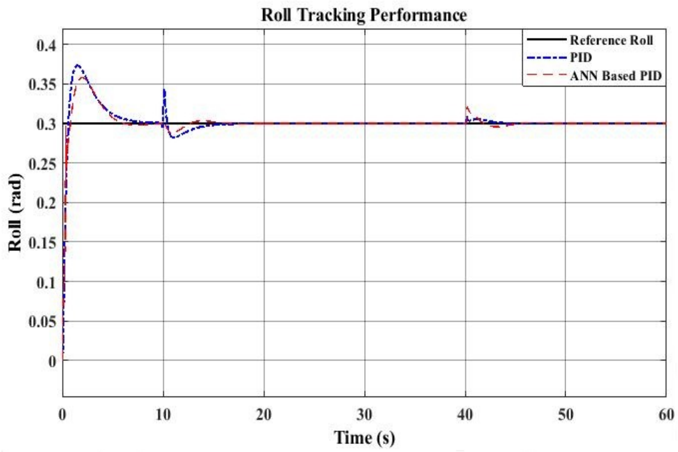

Fig. 5. Roll angle tracking performance of ANN based PID

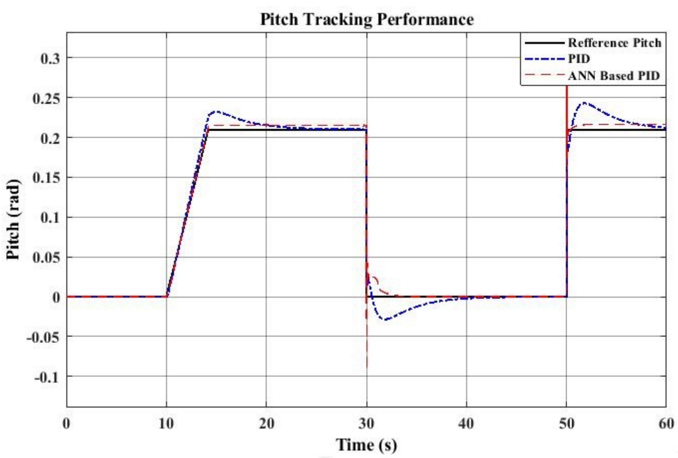

Fig. 6. Pitch tracking performance of ANN based PID

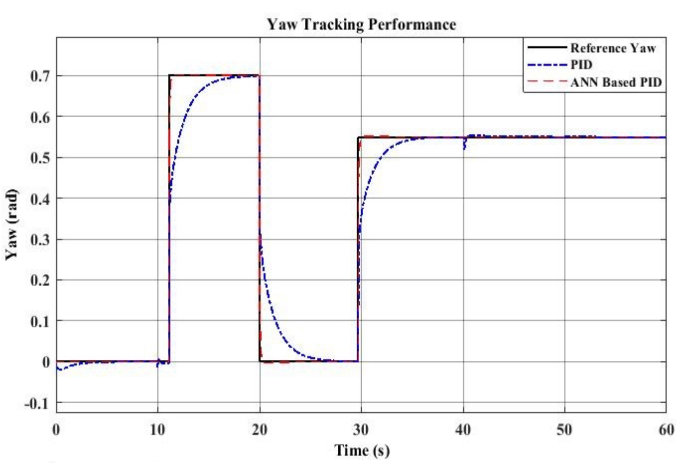

Fig. 7. Yaw angle tracking performance of ANN based PID

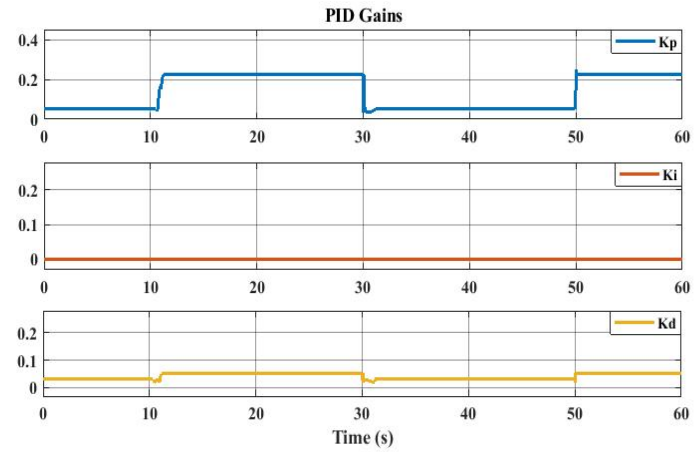

Fig. 8. PID gains in case of roll angle tracking

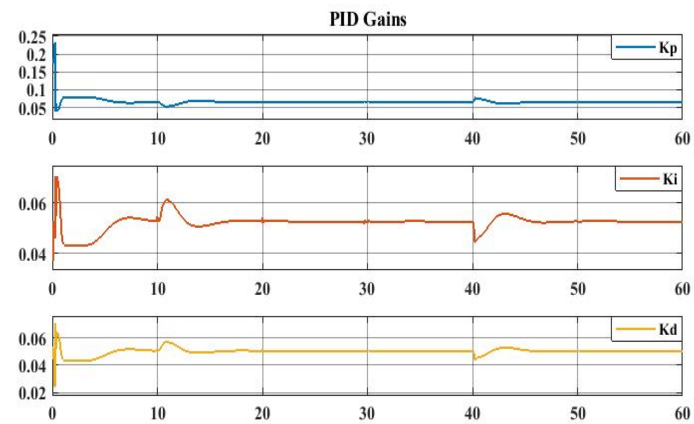

Fig. 9. PID gains in case of pitch angle tracking

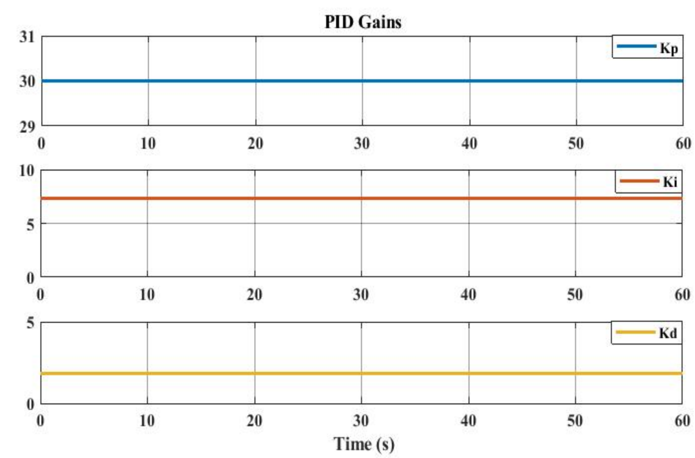

Fig. 10. PID gains in case of yaw angle tracking

Fig. 6 represents tracking performance of pitch angle. For certain portions of reference pitch angle, steady state response does not improve. However, this effect can be improved by increasing the number of samples of training data. Change in PID gains in this case is shown in Fig. 9. Fig. 7 shows tracking performance of yaw angle. Tracking performance is considerably improved in case of ANN based PID despite the fact that PID gains generated by ANN based tuning algorithm remain constant as represented in Fig. 10.

IV. CONCLUSION AND FUTURE RECOMMENDATION

Tracking performance of artificial neural network based PID controller is studied for altitude, roll, pitch and yaw angles control of a quadcopter. In proposed control scheme, PID gains are adjusted online using artificial neural network. Neural network having single hidden layer is developed to generate K_p, K_i and K_d online. A comparative analysis is performed to select suitable training algorithm and number of neurons of hidden layer to obtain minimized mean square error. Bayesian regularization, Lavenberg-Marquardt and scaled conjugate gradient training algorithms are tested along with 3, 6 and 9 number of neurons in hidden layer. For each control variable, training algorithm with minimum mean square error is selected to develop tuning algorithm. Performance of artificial neural network based tuning algorithm is tested for flight control of quadcopter. ANN based PID displays improvement in tracking performance.

More training algorithms with increased number of training samples can be studied to further improve tracking performance. Experimental study is being performed by same authors keeping in view more complex trajectories and environmental disturbances.

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