Modified inverse neural controller using adaptive gain factor for DC motor

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Abstract. Disturbances and input changes effects lead to condition of error in the action integrity of control systems especially when the system is nonlinear. Adaptive controllers are being used to solve this problem. However they may add cost and complexity to the system design, and may not give the required action. This paper presents a DC motor speed controller using Inverse Neural controller and adaptive gain factor. The adaptive gain factor designed to be a function of the error signal (will be used to cancel the error in the controller signal), also a positive feedback from the output (to overcome the error of the plant) will be added to the adaptive gain factor signal to create a new input to the plant. Simulation results proved that the proposed method excellently controls the DC motor speed and evicts the steady-state response error thus; makes the output correctly tracking the desired input with minimum rising time, reduced peak time and settling time, and minimum peak overshoot, with average enhancement of 50% for each versus the results of PID controller for the same plant and same inputs. MATLAB R2015b, SIMULINK simulation has been used to simulate the system and obtain the results.

Keywords: Inverse Neural Control, Adaptive gain factor, PID controller, Speed Control, DC Motor.

1. Introduction

In the recent years, adaptive control made a significant attention. There has been an increasing of adaptive control settings in a wide range of applications such as robotics, aerospace, process control, etc. Adaptive control research receives attention from industry, government agencies, and academia. Many investigations have been done and led to the propose of various methods of adaptive control during the past many years. Most of these methods can be classified as indirect, direct, or a combination of both. Indirect methods of adaptive control are stem from identifying the unknown parameters of the plant and control schemes as certainty-equivalence gained by parameter estimating that are assumed to be the true values. Indirect adaptive control methods use techniques for parameter identification like Neural Networks and Recursive-Least-Squares. In the other hand, the methods of direct adaptive control, adjust control parameters directly for accounting the system uncertainties and no need for identifying the unknown parameters of the plant explicitly [1]. The concern in designing the adaptive controllers rather than the conventional controllers have increased because of some reasons like [2]:

- System changes unpredictability.
- Internal and external unforeseen disturbances.
- Possibility of the abrupt faults.
- Nonlinear attitudes in complex systems cases.
- Unidentified system parameters.
The following, are some of related works with different types of control methods:

In 2013, Arundhati, and Febin Daya Presented a research paper of brushless DC motor speed control by using PI controller. Troubles such as roll-over could be happened when using conventional PI controller because of the effect of saturation. To overcome Troubles like this, anti-wind-up techniques are proposed. Also, a fuzzy controller had been designed for controlling the speed of BLDC-motor [3]. In the same year Walaa M. and, et al. Aimed to design a DC motor speed controller by parameters selection of a PID controller through the use of Genetic Algorithm (GA) and an Inference System of Adaptive Neuro-Fuzzy (ANFIS). These proposed methods can be applied to the systems of higher order. They found that Artificial-Intelligence methods provide better results if compared to the conventional controlling methods [4]. While in 2015, Mohamed Amine and et al. Introduced the use of soft computing for Investigating the modeling and control of DC motor price-setting of Fuzzy Logic controller and Neural Networks. Direct and, Inverse Neural models have been used for the position and speed response. Simulations showed a good compatibility between the developed neural model and responses of the simulation signal [5]. After two years in 2017, Muhammad Aftab, and Fakhra Aftab Investigated the achievement of smooth control of DC motor speed by applying, Neuro-Adaptive-Inverse controller that will minimize the effect of nonlinearities. The presented controller has a unique mechanism weight updating that guarantees the closed-loop system stability, by the basis of Lyapunov stability theory [6]. And in the same year, Didi Susilo, and et al. used Artificial Neural Network (ANN) to obtain the DC motor inverse model. Then it is used as a controller. For the purpose of obtaining control schemes of well dynamic-response, a Model Reference Adaptive Controller (MRAC) approach is applied. The results showed that their proposed controller response matches the response of the reference model [7]. In 2019, Trong-Thang Nguyen, aimed to propose a neural adaptive controller for controlling the DC motor. The control system composed of two Neural Networks: the first is used for estimating the DC motor speed and the second used as a controller. The author proposed his control system based on Neural Network for controlling the plant to reach high quality in the task of unknowing parameters of the plant [8].

The aim of this paper is to modify the Inverse Neural controller by using Adaptive Gain Factor in series with the Inverse Neural controller in order to overcome the error in the output response without using negative feedback to the controller.

This paper composed of six sections, the first is the introduction and related works, the second is to explain the basic concept of the Inverse Neural Network controller, the third explains DC motor modeling (the plant to be controlled), section four the proposed controller method, the simulations and results in section five, and the last section is the conclusions.

2. Inverse Neural Network Controller

The decupling inverse system method is a feedback linearization method for nonlinear complex systems. It faces a major problem in practical control, that is the generation of the inverse system. If the original nonlinear system mathematical model is known, then it will be used to solve the analytic expressions. However, it is a complicated solution process. In some cases, the generation of inverse system is very difficult to identify even if the original system mathematical model is known [9].

Applying the Artificial Neural Networks (ANN), is very beneficial in system-identification and control because of its learning ability, fast adaptation, massive parallelism, and approximation capability [9].

If the method of inverse system has been integrated with the Neural Network capability of nonlinear approximation and creating inverse system by utilizing neural network. It will be possible to avoid the algorithmic troubles of the inverse systems method. Hence there will be possibility for utilizing inverse control method for non-linear-complicated system. By the series connection of the original system and the Neural Network (inverse system) a unity gain transfer function will be formed and linear systems could be acquired thus, the control of original nonlinear system is turned into straightforward control of two integral-linear subsystems [10].

3. DC Motor Modeling

Depending on torque and back-electromotive force equations, the DC motor mathematical-model has been derived. The generated torque of the DC motor is directly proportional to the armature current by
a constant factor $K_t$. While the magnetic field is constant as explained in equation (1). This is called ‘Armature-Controlled DC motor’. ‘Figure 1’ shows the rotor and armature free-body diagram (electric circuit) [11-12]:

\[
    T = K_t i 
\]

(1)

\[\text{Figure 1. Equivalent Circuit of the DC motor [12].}\]

The speed $\omega(s)$ and the position $\Theta(s)$ transfer functions with respect to the input $V(s)$, are depicted in equation (2) and equation (3) respectively [12]:

\[
    \frac{\omega(s)}{V(s)} = \frac{K}{(Ls + R)(Js + b) + K^2} 
\]

(2)

and

\[
    \frac{\Theta(s)}{V(s)} = \frac{K}{(Ls + R)(Js + b) + K^2} 
\]

(3)

Where:
- J: Rotor-Moments of inertia, (Kg.m).
- b: Mechanical system -Damping, (N.m.sec).
- L: Inductance, (H).
- R: Resistance, (Ω).
- V: Voltage-Source, (v).

Equations (2) and (3) are used to simulate the model as indicated in Figure 2.

\[\text{Figure 2. Block diagram of DC motor model.}\]

4. Proposed Control Method
Researchers had been proposed many adaptive control techniques like the MRAC method that define the desired closed loop response by incorporating a reference model to the control system, also the Gain Scheduling control method that controls a nonlinear system by providing a family of linear gains each of these gains will be the controller for a specific operation point from the plant. These methods will add cost and complexity to the control systems and may requires a too much work (as in the case of gain scheduling), and programming difficulties.
The goal of this research is to present and prove the idea of using an adaptive gain factor (single adaptive gain instead of multiple gains or model referencing) side by side with Inverse Neural controller. The proposed control method shown in Figure 3, will try to let the output (motor speed) matches the desired input and the adaptive gain factor will try to cancel both of the error generated from the controller as well as the error generated by the plant. The idea of adding the adaptive gain factor can be explained as follows:

According to the inverse control approach, the controller should be the reciprocal of the plant in other words;

If we let the system transfer function is \( G(s) \) then, the transfer function of the inverse system (the controller) will be \( \frac{1}{G(s)} \). Also, if the plant produces error signal = \( e \) then, the controller error will produce error signal = \( \frac{e}{e} \).

Consider \( U \) is the input, \( Y \) is the output.

Now according to the inverse control technique the complete system transfer function (that defines the output relationship to the input) will be as shown in equation (4):

\[
\frac{Y}{U} = G(s) \times \frac{1}{G(s)} = 1
\]  

(4)

The inverse open-loop control block diagram shown in Figure 4.

![Figure 3. Proposed control method.](image)

Equation (4) will be true if \( \frac{1}{G(s)} \) is the exact (typical) inverse of \( G(s) \), but it is not the exact inverse because of the training error of the Neural Network (the Mean Square of Error will never reach 0 value), also the practical plants may suffer from some kind of nonlinearities (the error generated by the plant), so a steady state error will appear in the system output response. In other words, equation (4) will not be equal to 1 \( (\frac{Y}{U} \neq 1) \).

To solve this problem, the adaptive gain factor \( (K_{ad}) \) will be added in series with the controller \( \frac{1}{G(s)} \). The factor is a function of the input and output error which is the reciprocal of the controller error, therefore the two errors is supposed to be canceled and an error free control signal will be generated. Also a unity positive feedback \( (U - e = Y) \) will be added to the generated control signal so if the input changed or a case of a disturbance happened, \( (K_{ad}) \) will continually adapt its value and eliminate the steady state error between the desired input, and the output response. The adaptive gain factor expression is shown in equation (5):

\[
K_{ad} = [U \times (\frac{1}{G(s)}) \times e] + (U - e)
\]

(5)

The system block diagram is shown in Figure 5.
The use of the proposed control method led to contributions these are, the steady state error elimination and the enhancements in the output response accomplished without using a feedback returned to the input of the controller and that will improve the stability of the controller. Also, the proposed method could be applied for both linear and nonlinear systems. And the most important contribution is that; the adaptation process has been achieved without adding a model reference or multiple gains as usually used in MRAC and Gain scheduling techniques.

5. Simulations and Results
Simulations and results had been obtained by using MATLAB R2015b, including the DC motor modeling, and the data obtained from it to train the Inverse Neural controller. The Neural Network is trained using error back propagation technique, and consisted of two layers; the first layer of three neurons with log-sigmoid activation function and the second layer of five neurons with tan-sigmoid activation function. Also, the complete designs of the DC motor controlled system using PID controller and using the proposed control method has been designed. The parameters of the plant (DC motor) used in the simulation are shown in table (1).

Table 1. DC-Motor Parameters [13]

| Motor parameters             | Abbreviation | Value          |
|------------------------------|--------------|----------------|
| Resistance                   | (R)          | 5.61 Ω         |
| Inductance                   | (L)          | 2.29 mH        |
| Constant of motor torque     | (K)          | 0.16 N.m/A     |
| Damping factor               | (b)          | 5.0526*10^{-2} N.m.s |
| The rotor moments of inertia | (I)          | 0.4366 kg.m^2  |

5.1 Step Response of the System Using PID Controller
The system here is controlled only by a PID controller. It has been tested by a step input of 5 volts, as shown in Figure 6. Also, the output response shown in Figure 7.

Figure 6. Controlled system by PID controller.
Figure 7. System response with PID controller

As shown in Figure 7, the output of the system is approximately the same as the step input but with a steady state error, high rise time, and a peak overshoot.

5.2 Step Response of the System Using the Proposed Method (Adaptive gain Factor)
In this subsection, the same system in subsection 5.1 will be tested using the same input step of 5 volts but now it will be controlled using the proposed method instead of the PID controller the simulation and the step response are shown in Figure 8 and Figure 9 Simulink block diagram of the system.

Figure 8. System with adaptive gain

Figure 9. Step response of the system controlled by the proposed method.

The step response of the system using both the PID controller and the proposed control method is shown in Figure 10.

Figure 10. PID and proposed method responses.

As can be seen from Figure 10, utilizing the proposed method is greatly improved the system response since all of; the rising time, the peak time, the percent over shot, and the settling time are reduced by 50%. That means the system output tracked the input in fast and very efficient way.
Table (2) illustrates the calculations of the percent overshoot, rising time, peak time, and settling time for the step responses shown in Figure 10. Also, table (2) lists the enhancement percentage when the proposed control method is used.

|                  | PID      | Adaptive Gain Factor | Enhancement by Proposed Method |
|------------------|----------|-----------------------|---------------------------------|
| Rising Time      | 0.4 sec  | 0.2 sec               | 50 %                            |
| Peak Time        | 0.855 sec| 0.405 sec             | 52.63 %                         |
| Percent Overshoot| 1.244 %  | 0.725 %               | 41.72 %                         |
| Settling Time    | 1.975 sec| 0.725 sec             | 63.29 %                         |

5.3 Robustness analysis
To prove the robustness of the proposed control method, a performance test has been done by using variable input types, also test in the presence of load has been done. The results of these tests is compared to the PID controller results submitted to same tests. The results of all the tests showed that the proposed control method made the system output response follows the desired input efficiently with less overshoot, and decreased rising time, peak time, and settling time. The tests results shown in the following:

1. The repeated sequence input, and the test result are shown in Figure 11.

![Figure 11. Repeated sequence test.](image)

As shown in Figure (11), the green line represents the input, the red line is the response of the system controlled by the PID controller and the blue line is the system response when using the adaptive gain factor (proposed method). It is obviously shown that the Blue line (system with proposed control method) tracked the input much better than the red line (system with PID controller) with no overshoot, less rising time, and the most important the steady state error $\approx 0$.

2. The disturbance load test, the system has been tested by applying a positive and negative load (increasing and decreasing load). The results showed that the system using the proposed method is very efficient in tracking the input and overcomes the effect of the added load in comparison with the system controlled by PID controller. Also, the output reaches the reference input value at less settling time, minimum overshoot, and steady state error $\approx 0$. The output response of the system with the added load is shown in Figure 12.
6. Conclusions

This paper is an attempt to propose a modified and adaptive control method that will enhance the system response and evicts the steady state error. The results proved that the added adaptive gain factor with the Inverse Neural controller excellently improved the system output response by eliminating the input-output steady state error, decreasing the percent overshoot by 41.72%, and reducing the; rising time by 50%, peak time by 52.63%, and settling time by 63.29% in comparison to the PID response. In addition to that, the testing results approved that the proposed design is reliable for various types of inputs and robust in handling the addition of load. In few words, if it is compared with the system controlled by the PID controller, the proposed method has less transient time, and no oscillation in the steady state response with high stability. In addition to these advantages, our proposed design have a lowest complexity, less programming requirements, and lower cost if compared with other controllers mentioned in the related works.

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