INTELLIGENT CONTROL OF NON-LINEAR DYNAMICAL SYSTEM BASED ON THE ADAPTIVE NEURO-CONTROLLER*

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Abstract. This paper presents an adaptive neuro-controller for intelligent control of non-linear dynamical system. The formed as the fuzzy selective neural net the adaptive neuro-controller on the base of system’s state, creates the effective control signal under random perturbations. The validity and advantages of the proposed adaptive neuro-controller are demonstrated by numerical simulations. The simulation results show that the proposed controller scheme achieves real-time control speed and the competitive performance, as compared to PID, fuzzy logic controllers.

1. Introduction
Non-linear dynamical systems are commonly suffering from restrictions imposed by the uncertainty of the environment and therefore unstable dynamics when designing control systems to provide stability, disturbance attenuation, and reference signal tracking. Within the research literature, a whole array of differing control strategies is proposed to deal with the control of the linearized system problem. One of the most common control strategies is Proportional-Integral-Derivative (PID) controller due to its simplicity and applicability [1]. But the PID controllers for non-linear dynamical system are often designed by hand, requiring extensive analysis of the system and dynamics. This process is generally difficult because it is hard to anticipate all operating conditions. The controller must coordinate the non-linear dynamical system properly, generating robust behavior to negotiate different terrains effectively while maintaining stability. Moreover, the non-linear dynamical system should be robust to different environmental conditions, wear and tear, and even failure to reliably complete its mission. Therefore, automatic design methods utilizing intelligent techniques such as neural network (NN) and fuzzy logic are a promising alternative [2]. Monitoring and fault detection play an important role for non-linear dynamical system due to the increasing demands on fault tolerant real-time applications. This fault tolerant behavior of non-linear dynamical system refers to the possibility to autonomously detect faults early before they result in catastrophic failures as well as to the capability to continue operating after a fault has occurred by switching to a safe state. However, fault detection for non-linear

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dynamical system is a complex problem because of the large space of possible faults (e.g. non-linear system’s sensors, actuators, the uncertainty of the environment). Non-linear dynamical object are best modeled as hybrid systems since their behaviors result from the interaction between continuous and discrete dynamics. Several methods have been developed to deal with the monitoring of such systems. The most important approaches are these that combine the basic model, which are differential equations, with the intelligent models, which are neural network and fuzzy logic. This paper presents an adaptive neuro-controller for intelligent control of non-linear dynamical system.

2. Adaptive neuro-controller on the base of the fuzzy selective neural net

A large body of literature on neuro-adaptive control exists on nonlinear systems of the form $\dot{x} = f(x) + g(x)u$, where the neural nets are used to approximate $f(x)$ and $g(x)$ [3]. Adaptive control methods such as linearization have been shown to be very effective for the control of a broad class of systems [3]. In contrast, in this paper, the function approximation capabilities of fuzzy selective neural net [4] are exploited to approximate a nonlinear control law. The adaptive neuro-controller is capable of handling uncertainties in both the system parameters and the environment. The formed as the fuzzy selective neural net the adaptive neuro-controller creates the effective control signal according identified system’s state under random perturbations (Fig. 1). The fuzzy selective neural net trained base on data

$$Z_i = (s_1^i, s_2^i, ..., s_r^i, u_1^i, u_2^i, ..., u_b^i, \Omega_1^i, \Omega_2^i, ..., \Omega_q^i, Y),$$  \hspace{1cm} (1)

where $i \in \{1, ..., m\}$ – time, $Y$ – response of the nonlinear system; $s$ – input signal of the nonlinear system; $u$ – control signal; $\Omega$ – influences of environment.

First, in order to obtain the dynamics of the system the fuzzy sets $A_j$ with membership function $\mu_j(X)$ are interpreted as the GNG’s clustering of the data (1). Second, for each $j$ an identifier is constructed by a two-layer feed forward neural network. These neural networks create the effective control signals $f_j(s)$

Formed as Simulink’s block if-then rules are defined as:

$\Pi_j$: IF $X$ is $A_j$ THEN $u$ is $f_j$ \hspace{1cm} (3)

Aggregation antecedents of the rules (3) maps input data into their membership functions and matches data with conditions of rules. These mappings are then activates the $k$ rule, which indicates the $k$ system’s state.

According the $k$ system’s state the adaptive neuro-controller creates the effective control signal $f_k$ under random perturbations

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{The adaptive neuro-controller.}
\end{figure}
Third, an adaptive neuro-controller is carefully designed to correctly tackle the control task under uncertainty of the nonlinear system and of the environment.

3. Dynamic modeling of the mobile robot
In this paper a mobile robot prototype with four DC motor actuators was considered as an example of non-linear dynamical system. The drive and steering subsystem is included two independent wheels and motor [6]. The robot navigates by changing the relative rate of rotation of its wheels motor. The physical parameters of the motors are shown in Table 1.

| Table 1. The physical parameters of the motors. |
|-----------------------------------------------|
| Parameters                  | values               |
| Moment of inertia of the rotor (J)           | 42.6e-6Kgm²          |
| Viscous friction coefficient (b)             | 47.3e-6Nms           |
| Torque constant (k_t)                      | 14.7e-3Nm/Amp        |
| Back emf (k_e)                             | 14.7e-3V.s/rad       |
| Terminal resistance (R)                    | 4.67ohm              |
| Electric inductance (L)                     | 170e -3 H            |

The behavior of the motor speed for a given voltage is derived from physics law described in Laplace domain by the open-loop transfer function

\[ \frac{\dot{\omega}(s)}{V(s)} = \frac{k_t}{s^2 + (J[R+bl]_s + bR+k_e k_t)} \]  

(2)

where voltage \( V(s) \) is input and shaft speed \( \omega=\dot{\omega}(s) \) is output [7]. The relation between the reference speed \( \dot{\omega}_{ref} \) and the output speed \( \dot{\omega}_{out} \) is given by the closed loop transfer function

\[ \frac{\dot{\omega}_{out}}{\dot{\omega}_{ref}} = \frac{k_t k_e}{s^2 + (J[R+bl]_s + bR+k_e k_t)} \]  

where \( K \) is a constant gain.

The state space representation of the robot’s dynamic as follows

\[ \begin{bmatrix} \dot{i} \\ \dot{i} \end{bmatrix} = \begin{bmatrix} -\frac{R}{L} & -\frac{k_t}{L} \\ k_t & -\frac{b}{J} \end{bmatrix} \begin{bmatrix} \dot{i} \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} V(t) \text{and } \dot{\theta} = \left[ \begin{array}{c} \dot{1} \\ \dot{0} \end{array} \right] \]  

(3)

was used to confirm that the system is stable, controllable and observable.

4. PID controller design
The general transfer function for a PID controller in Laplace domain can be written as follows

\[ PID(s) = K_p + \frac{K_i}{s} + K_d s = \frac{K_d s^2 + K_p s + K_i}{s} \]  

(4)
where $K_p$ is the proportional gain, $K_d$ is the derivative gain and $K_i$ is the integrator gain. The PID gains were choose by hand and were then tuned by simulation with following values: $K_p=0.68$, $K_i=0.6$, $K_d=0.01$.
The open loop and closed loop transfer function of the system with PID controller is given by (5) and (6) respectively:

$$G_{open\_loop\_PID}(s) = \frac{24.15 s^2 +1389 s+1213}{s^3+28.58 s^2 +60.34 s} \quad (5)$$

$$G_{closed\_loop\_PID}(s) = \frac{24.15 s^2 +1389 s+1213}{s^3+52.74 s^2 +1450s+1213} \quad (6)$$

This PID controller was designed by hand. Therefore, automatic design methods utilizing intelligent techniques such as neural network and fuzzy logic are a promising alternative.

5. Intelligent control

An intelligent approach is proposed to address the weaknesses of the PID approach. The adaptive neuro-controller is carefully designed to correctly tackle the control of non-linear dynamical system task under uncertainty of the environment.

5.1. Fuzzy logic controller design.

A typical structure of a fuzzy logic controller is shown in Fig. 2.

![Figure 2. Fuzzy logic controller.](image)

In our work, knowledge was borrowed from proportional integral control error and change of error to define fuzzy membership functions. The inputs that were in the form of crisp values generated from feedback error ($e$) and change of error ($de$) were conditioned in terms of multiplying by constant gains before entering into the main control block. The fuzzification block converts input signals into appropriate way to membership functions, invokes appropriate rules, generates a result for each rule, and combines the results of those rules. The Mamdani-type inference engine combined the output state and assigned a membership value at the truth level of the premise. The truth values are then defuzzified using a discrete centroid computation. The post processing block then transforms these crisp values into control signals. The fuzzy logic controller’s rules had triangular membership function and were implemented in the simulation. These rules provide control signals based on several if-then statements about ($e$) and ($de$), i.e., if the error is equal Negative Big (NB) and change of error is equal to negative medium (NM), then the change in control ($c$) is positive big (PB). The numbers of fuzzy logic controller’s rules were determined based on experiment and tuning of the system.
5.2. The adaptive neuro-controller design
With onboard resources often limited, this paper considers the development of an effective control method that remains easy to implement. The formed as the fuzzy selective neural net the adaptive neuro-controller on the base of system’s state, creates the effective control signal under random perturbations (Fig. 1). First, in order to obtain the dynamics of the system, the fuzzy sets $A_j$ with membership function $\mu_j(X)$ formed base on GNG’s clustering of the data (1), $j \in \{1, 2, 3\}$. Second, for each $j$ an identifier is constructed by a two-layer feed forward neural network. Third, an adaptive neuro-controller is carefully designed to correctly tackle the control task under uncertainty of the robot and of the environment. To make the neural network become adaptive, it needs to have some idea on how the actual robot’s behavior is differing from its expected behavior, so that the controller can recalibrate its behavior intelligently during run time, and try to eliminate the constant tracking error. Hence the input signal of the neuro-controller will be non-zero, and it will give useful feedback for telling the controller how to adapt to the dynamically changing robot’s conditions. This control approach does provide a more intelligent method of implementing the control signal.

6. Simulation and results
All the simulations for this study are implemented in MATLAB, Simulink. The Simulink block diagram for the implementation is shown in Figure 4.

![Figure 4. Simulation diagram of controllers for DC motor speed.](image)

To illustrate the benefits of the newly proposed intelligent control, the numerical examples from the previous section 4 is revisited. The true benefits of the proposed controller are best demonstrated through a simulation study.

In this comparison study, the performance of the adaptive neuro-controller is compared against fuzzy logic and standard PID controllers, under the same conditions. Fig. 5 to 11 shows the simulation’s results.
It can be seen that the PID controller takes a huge numerical value of control signal in the step changes (Fig. 6), while the other two controllers remain in the range of reasonable values of [-2, 2] (Fig. 5). One of the result curves (Fig. 5) is for adaptive neuro-controller, another is fuzzy logic controller.
**Figure 8.** Plot of errors to the controllers responses.

**Figure 9.** Plot of sinusoidal response and performance comparison for the designed controllers.

**Figure 10.** Plot of errors to the controllers responses for sinusoidal input.
The control signal of the adaptive neuro-controller is more robust and less intensive in compare with the fuzzy logic controller (Fig. 5, 11). The tolerance of an adaptive neuro-controller to noise explained by two factors: the ability of the model to have similar responses for patterns contaminated with different intensities of noise and the resilience to noise of the low similarity of the responses for patterns of different system’s state.

Use of the adaptive neuro-controller provides a more suitable approach to the control problem, with the pointing accuracy. Extensive simulation studies on Simulink model have been carried out on different initial conditions, different disturbance profiles and variation in robot parameters. It shows consistent performance has been achieved for the proposed adaptive neuro-controller with good stability and robustness.

7. Conclusions

It is shown that the adaptive neuro-controller is robust to system uncertainties. Unlike popular approaches to nonlinear control, an adaptive neuro-controller is used to approximate the control law, and not the system nonlinearities, which makes it suitable to handle a wide range of nonlinearities. Simulations on the intelligent control system for wheel speed and steering of mobile robot demonstrate the effectiveness of the adaptive neuro-controller.

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