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INTELLIGENT CONTROLLERS FOR VELOCITY TRACKING OF TWO WHEELED INVERTED PENDULUM MOBILE ROBOT

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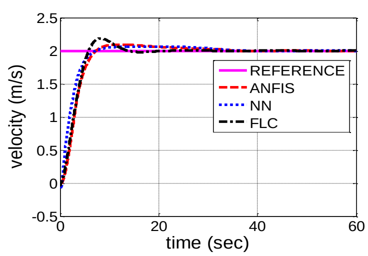
Graphical abstract



Abstract

Velocity tracking is one of the important objectives of vehicle, machines and mobile robots. A two wheeled inverted pendulum (TWIP) is a class of mobile robot that is open loop unstable with high nonlinearities which makes it difficult to control its velocity because of its nature of pitch falling if left unattended. In this work, three soft computing techniques were proposed to track a desired velocity of the TWIP. Fuzzy Logic Control (FLC), Neural Network Inverse Model control (NN) and an Adaptive Neuro-Fuzzy Inference System (ANFIS) were designed and simulated on the TWIP model. All the three controllers have shown practically good performance in tracking the desired speed and keeping the robot in upright position and ANFIS has shown slightly better performance than FLC, while NN consumes more energy.

Keywords: Two wheeled inverted pendulum (TWIP), Fuzzy Logic Control (FLC), Neural Network Inverse Model control, Adaptive Neuro-Fuzzy Inference System (ANFIS)

1.0 INTRODUCTION

Problems like pollution, congestion, parking availability, which are caused by conventional vehicles, have made life difficult these days. To overcome the situation, Two Wheeled Inverted Pendulum (TWIP) mobile robots (Figure 1) have been introduced [1-7] to overcome these problems. Due to its much smaller in size compared with conventional four wheeled vehicles, TWIPs can occupy less parking space than other vehicles, hence reducing congestion and solving availability of parking space issue. Also TWIP uses DC motors for operation hence eliminating carbon pollution, hence safer environment. However, they are categorized as under actuated mobile robots which makes it difficult to control. Many researchers in the past two decades have been working in developing the controllers for balancing the robot and also for tracking the desired position and velocity [2, 4, 6, 8-30]. Among the recent works, linear controllers were implemented in [2, 8, 11, 16, 27, 31]. In [2] pole placement controller was applied at different linearized points and was used to balance and track a desired velocity for the robot. In [8], system decoupling control techniques with pole placement was used to control the velocity and yaw angle movement. A Linear Quadratic Regulator (LQR) was compared with partial feedback linearization for speed control in [11], while Proportional-Derivative (PD) control was used in [16] for position tracking and tilt balancing. Another LQR technique was investigated in [32] for velocity and position tracking.

Nonlinear controllers were also investigated and studied by researchers [11, 12, 22, 33]. Partial feedback linearization was demonstrated in [11, 33] for velocity tracking while Sliding Mode Control (SMC) method using LQR technique was used to control the robot behavior while driving on uniform slopes [12]. The SMC technique was also used and implemented in [22] for velocity tracking. To show the robustness of the controller, adaptive controllers were implemented not only for position and velocity tracking but also for tilt balancing [10, 18, 26].

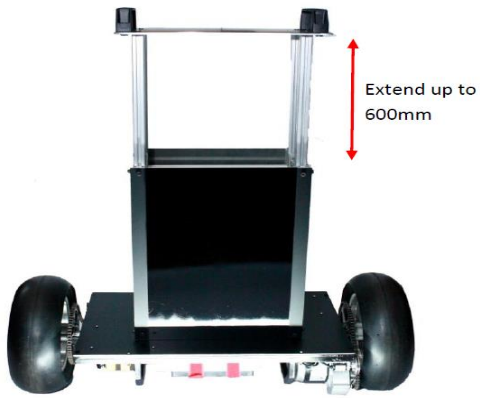


Figure 1 TWIP Mobile Robot

Metaheuristic controllers, also known as intelligent controllers, have been used in controlling velocity of TWIP. Some works on Fuzzy Logic Control (FLC) were implemented in [15, 17, 20]. In [15, 20] FLC was used to balance the tilt position of the TWIP only, but in [17], the tilt angle, position control and orientation angle of the robot were all controlled using FLC. Adaptive intelligent controller like Adaptive Neuro-Fuzzy and Adaptive Neural Network, were shown in [14, 24, 28]. In [14], a T-S Adaptive Neural Network Fuzzy controller was used in balancing the robot and controlling the position movement, while Adaptive Neural Network for balancing and yaw angle motion control was investigated in [24]. The position tracking and tilt angle balancing using PID and Neural Network controller was shown in [28].

Based on the review stated above, velocity tracking has been one of the major objectives of controlling the TWIP. Many works in the past years have been published in the area. Model based controllers like LQR [32, 34], and Pole placement controller [27], which are designed based on the linearized model of the robot making the model uncertainties to affect the controllers gain. Nonlinear controllers like partial feedback linearization [11, 19, 33] and SMC [1, 12, 22] performs well in rejecting modelling inaccuracies, parameter variations and disturbances, but SMC has the problem of chattering. Intelligent controllers were used by researchers to track a desired speed of the TWIP, in [6] a direct adaptive model reference control scheme was used, fuzzy logic which is a non-model based controller, was used in [15, 20]. Adaptive neural SMC method for trajectory tracking was shown in [35]. In this paper, three intelligent metaheuristic control techniques will be investigated. Neural Network inverse model control strategy, Adaptive Neuro Fuzzy Inference System (ANFIS) used in mimicking another controller, and PD-Fuzzy logic will be used and analyzed to track a desired velocity of the robot. The three schemes have the advantages of being none model dependent, hence there is no problem of model uncertainties [36]. The main contribution of this paper is developing intelligent controller, ANFIS controller, mimicking another intelligent controller, FLC, instead of mimicking any conventional controller for velocity tracking of the under actuated mobile robot. The performance will be compared with the original FLC and another intelligent controller NN in inverse model form.

The rest of the paper is organized as follows; section II discuss the overview of the control strategies, section III presents the model description, section IV gives the details of the controllers design, and section V is where the results are discussed and analyzed, and finally section VI concludes the findings of the work.

2.0 INTELLIGENT CONTROL STRATEGIES

This section describes the concept of FLC, Neural Network Inverse Model Control as well as ANFIS controller.

2.1 Fuzzy Logic Control

It has been almost 50 years when the first paper on fuzzy sets was published by Zadeh [37]. Fuzzy sets differ from traditional classical set by omitting crisp boundaries that are essential with classic sets. It is this idea that evolved too many disciplines and has various applications [38]. Control using fuzzy logic is an algorithm based on a linguistic control strategy, which is achieved from expert knowledge and does not need any mathematical model [39]. Fuzzy logic used as a controller is of two forms; a PD type direct control strategy. The control strategy uses linguistic IF THEN rules that is originated from human knowledge and experience. The input to the FLC is usually two inputs. First is the error signal, that is the difference between the reference and the output signal, and the second is the derivative of the error. The inputs are also called antecedent, and the decision is made based on the human knowledge known as fuzzy rules, to evaluate the control output known as consequence. The combination of the antecedent, consequents, fuzzy rules and fuzzy reasoning, gives what is called a fuzzy inference system (FIS) [38]. The block diagram for FLC in a direct form is shown in Figure 2. The second form of controller for FLC is internal model control structure as shown in Figure 3 [39]. The inverse model of the plant and the internal model are developed by using fuzzy logic (concept of internal model control is explained in the next section).

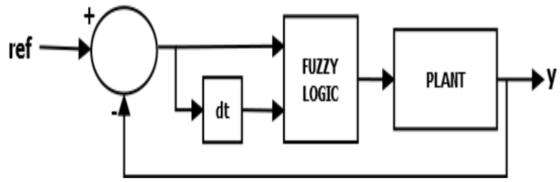


Figure 2 Direct FLC Block Diagram

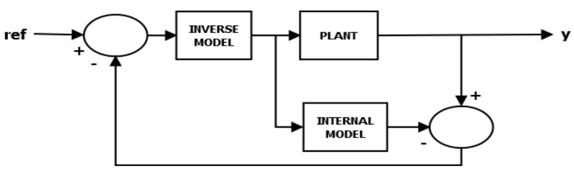


Figure 3 Internal Model Controller Block Diagram

2.2 Neural Network Inverse Model

The same structure used in fuzzy logic internal model control is applied in neural network inverse model control as shown in Figure 2. The difference is the inverse model is formulated using neural network rather than fuzzy logic. The concept behind inverse control is to place the inverse of the plant in series with the plant so the control action becomes feed forward. The aim is to make the plant nonlinearities handled efficiently by the use of the plant inverse model as controller [36]. Consider a nonlinear plant:

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx \end{aligned} \tag{1}$$

The closed loop response is required to follow a certain input reference r, so the controller has to generate the control signal $u(t)$ such that $y = r$. The output explicitly does not involve the input $u(k)$, therefore making the inverse very difficult to obtain [39]. To overcome this problem the control law is carried out using inputs and outputs measurements to get the inverse model. Problem arises when the model is invertible, many literature proposes several algorithms to find the inverse of plant models [39]. To find the inverse of a model, the input to the model is taken as the output and the output of the model as the input to the neural network learning process. The scheme is illustrated in Figure 4. Neural network inverse model control has been practiced by researchers [40-44].

2.3 ANFIS Controller

The combination of fuzzy logic and neural network in applications give rise to neuro fuzzy systems [36, 38]. Among the most common neuro fuzzy is the adaptive neuro-fuzzy inference system (ANFIS). ANFIS is a fuzzy logic system where the rules, membership function ranges are computed automatically using neural network, in fuzzy logic all the tunings are done manually. Full concept and the principles of ANFIS can be found in [38]. ANFIS can be used as a controller in two forms, either as inverse controller just like the neural network previously discuss as shown in Figure 4, or mimicking another working controller. Using the input/output data, ANFIS can refine the working rule of the controller and provide better performance, this mode are shown in [45-49].

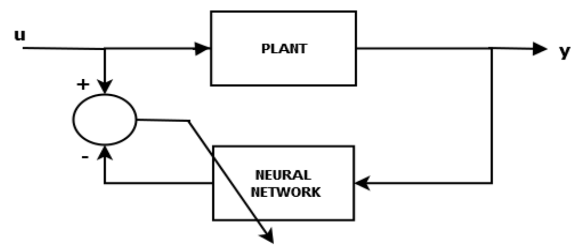


Figure 4 Neural network Learning

3.0 MODEL DESCRIPTION OF THE TWIP

The dynamics equation used to develop the robot is derived using Kane's method of modelling in [3]. The free body diagram is shown in Figure 5. The three direction of movement of the robot are x transitional motion, φ tilt angle, and ψ yaw angle, the dashed line on the free body diagram present the robot straight position when tilt angle = 0. The dynamics equations of the TWIP are given in equation (2-4), where the parameters used are listed in Table 1. The TWIP is based on the assumption that the wheels of the robot always stay in contact with the ground and the wheels do not slip.

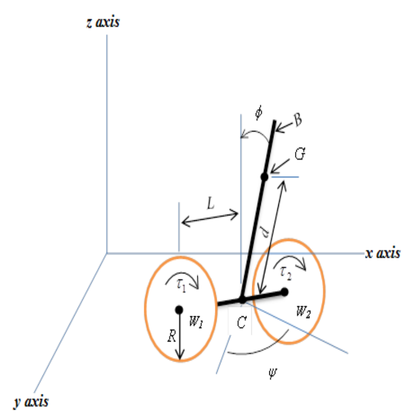


Figure 5 Schematic diagram of TWIP

$$\begin{aligned} \ddot{x} = {} & \frac{M_b d \sin\phi \left(M_b d^2 \cos^2\phi - (M_b d^2 + I_z)\right)}{M_b d^2 \cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)} \dot{\psi}^2 \\ & + \frac{M_b^2 d^2 g \sin\phi \cos\phi}{M_b d^2 \cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)} \\ & - \frac{(M_b d^2 + I_z) M_b d \sin\phi}{M_b d^2 \cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)} \dot{\phi}^2 \end{aligned} \tag{2}$$

$$+\frac{(M_b d^2 + I_x) + M_b dR\cos\phi}{M_b d^2\cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)}(\tau_1 + \tau_2)$$

$$\ddot{\psi} = \frac{L}{R\left[M_w\left(3L^2 + \frac{1}{2}R^2\right) + M_b d^2 \sin^2\phi + I_y\right]}(\tau_1 - \tau_2) - \frac{M_b d^2 \sin\phi\cos\phi}{\left[M_w\left(3L^2 + \frac{1}{2}R^2\right) + M_b d^2 \sin^2\phi + I_y\right]}\dot{\psi}\,\dot{\phi} \qquad (3)$$

$$\ddot{\phi} = \frac{3M_w M_b d^2 \sin\phi\cos\phi}{M_b d^2\cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)}\dot{\psi}^2 - \frac{M_b^2 d^2 \sin\phi\cos\phi}{M_b d^2\cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)}\dot{\phi}^2 + \frac{(M_b + 3M_w)M_b g d\sin\phi}{M_b d^2\cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)} - \frac{R(M_b + 3M_w) + M_b d\cos\phi}{M_b d^2\cos^2\phi - (M_b + 3M_w)(M_b d^2 + I_z)}(\tau_1 + \tau_2) \qquad (4)$$

Table 1 TWIP parameters and variables

Parameter	Symbol	Value
Mass of Main Body	M_b	13. 3 kg
Mass of Each Wheel	M_w	1.89 kg
Center of Mass (gravity) of the whole body from Base	d	0.13 m
Diameter of Wheel	R	0.130 m
Distance between the Wheels	L	0.325 m
Mass moments of Inertia of Body WRT x-axis	I_x	0.1935 kgm^2
Mass moments of Inertia of Body WRT z-axis	I_z	0.3379 kgm^2
Mass moments of Inertia of Wheel about the center	Ia	0.1229 kgm2
Acceleration due to gravity	g	9.81 ms-2

4.0 CONTROLLERS DESIGN

This section describes the design of fuzzy logic controller, the neural network inverse model controller and ANFIS controller for the velocity tracking of the TWIP robot. A simple PID controller was used for the tilt balancing of the robot, while the proposed controller were used for the velocity tracking. The PID gains for the tilt balancing are k_p = 10, k_i = 5, k_d = 1. The overall control scheme is shown in Figure 6.

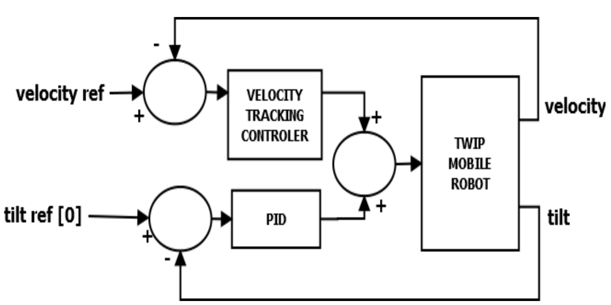


Figure 6 TWIP control scheme

4.1 Fuzzy Logic Controller

The steps of fuzzy logic controller design include selection of type and number of membership function, selection of rule base, inference mechanism and defuzzification process. For tracking velocity of the TWIP, triangular membership function is used. The rules are developed using fuzzy AND rules only with velocity error and error rate as the input. The rules for DC motor position control where used initially and further adjusted by trial and error to suit the given task. Combinations of these rules are used to generate 49 fuzzy rules. Table 2 shows the fuzzy rules.

Table 2 TWIP parameters and variables

$\dot{e}/e$	NB	NM	NS	ZE	PS	PM	PB
NB	PB	PB	PB	PB	PM	PS	ZE
NM	PM	PM	PM	PM	PS	ZE	NS
NS	NB	NB	NM	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PM	PB	PB
PM	NS	ZE	PS	PM	PB	PB	PB
PB	ZE	PS	PM	PB	PB	PB	PB

The membership functions of the error, error rate and output are implemented with seven membership function [NB, NM, NS, ZE, PS, PM, PB] and after tuning, the range of [-20 20] was used for the error, [-100 100] for the error rate, and [-200 200] for the output. A triangular membership function is used due to the nature of the robot [17].

4.2 Neural Network Inverse Model Controller

The TWIP mobile robot has many outputs, tilt angle, tilt rate, position and velocity. Yaw angle and the yaw rate are also considered depending on the application. The horizontal velocity of the robot is taken as the output of the robot since it is the desired manipulated variable. The data was taken when in closed loop form since the robot is open loop unstable. Simple PID controller was used for balancing and the model was simulated in MATLAB Simulink environment and the data for the neural network training was acquired and use for training the inverse model as shown in Figure 4. A two layered feedforward back propagation network with 10 weights was used. A sigmoid transfer function in the first layer and purelin transfer function in the last layer were chosen. Levenberg-Marquardt back propagation algorithm was used in the training of the network. An MSE of 0.16779 was achieved after 252 iterations.

4.3 ANFIS Controller

The fuzzy logic controller designed in the previous section was obtained via lengthy and time consuming trial and error process, therefore to enhance the performance, numerical information was taken from the fuzzy controller and used to train and refine the membership functions in systematic way using ANFIS. Just like the neural network controller, the input to the FLC and the output was acquired and then used to train the ANFIS controller. Two membership function and a Sugeno type output were used. After training, the ANFIS controller generated has two rules, two triangular membership function in the input and two linear membership function in the output.

5.0 RESULTS AND DISCUSSION

The results and analysis of the proposed controllers are examined in this section. MATLAB and Simulink were used to simulate and test the controllers. A speed of 2m/s, which is considered as averagely fast, was used for the tracking purpose. Figures 7-9 shows the velocity response, tilt angle position and the control signal respectively. The control signal is shown for 1 second to see the initial response clearly.

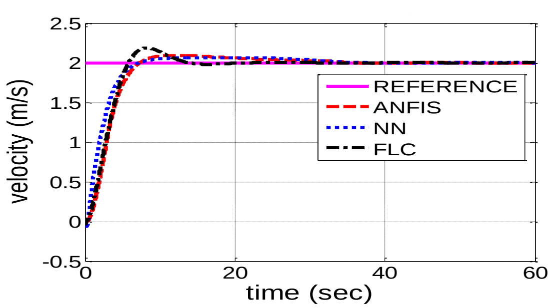


Figure 7 Velocity Response for step input

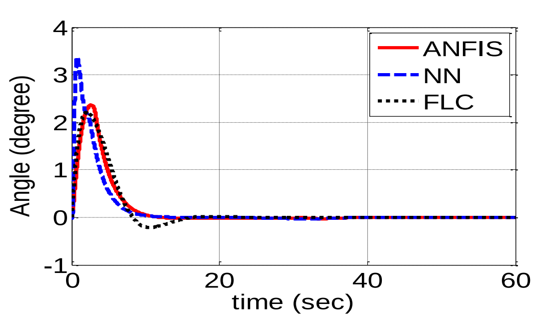


Figure 8 Tilt angle for step input

A slightly better performance is observed by the ANFIS controller as compared to FLC, it has less overshoot than the FLC, with the neural network having the less overshoot but in the expense of higher tilt angle initial swing compared to the other two. The

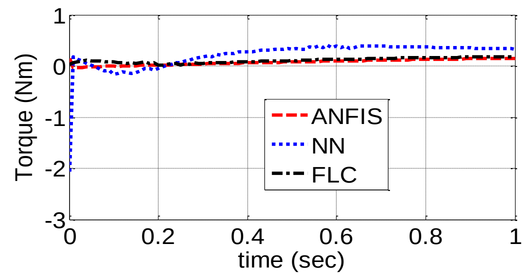


Figure 9 Control signal for step input

NN has higher energy consumption. The summary of the step tracking performance is shown in Table 3.

Table 3 Comparative assessment of controllers to step input

Controller	Rise time (s)	Settling time (s)	% OS	Torque (NM) [Max]	Tilt angle (deg) [Max]
ANFIS	11	30	12	0.4	2.4
NN	11	32	11	2.1	2.4
FLC	10	17.5	20	0.4	3.4

To test the robustness of the controllers, a sinusoidal input signal of frequency 0.2 rad/sec and amplitude of 1 is used. Figures 10-12 shows the results.

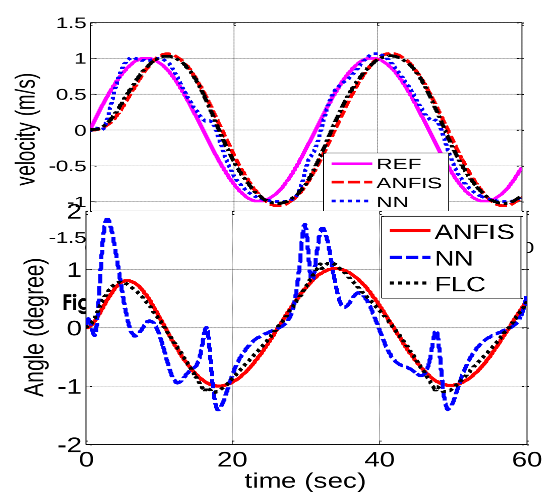


Figure 11 Tilt angle for sine input

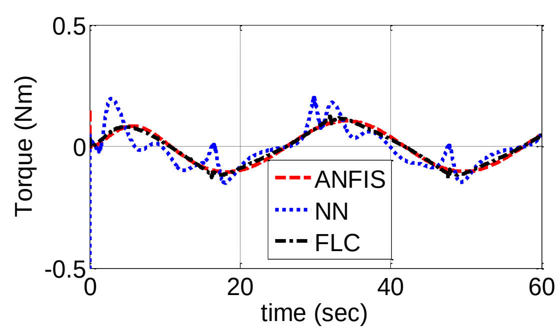


Figure 12 Control signal for sine input

The ANFIS controller and FLC almost have similar responses, the neural network have faster tracking response as compared to the other two and less overshoot but less tracking smoothness. The NN seems to have higher energy consumption. This is because, the inverse model obtain by the NN is not exactly 100% the inverse of the robot model, this discrepancy brought the need of high input energy to achieve desired results. The summary of the sine input tracking performance is shown in Table 4

Table 4 Comparative assessment of controllers to sine input

Controller	% OS	Torque (NM) [Max]	Tilt angle (deg) [Max]
ANFIS	5	0.2	0.8
NN	0	2.1	1.8
FLC	5	0.2	0.8

Further testing reveals that the three controllers have a bandwidth of 0.6 rad/sec, meaning the controllers can perform up to expectation when the input is sine wave signal with input frequency less than or equal to 0.6 rad/sec. Above that, the output of the robot will be less than 70% of the desired input.

6.0 CONCLUSION

Three soft computing techniques were proposed to track a desired velocity of a two wheeled inverted pendulum mobile robot. Fuzzy logic controller, NN and ANFIS were investigated in this work and have shown great performance in velocity tracking and maintaining the balance of the robot in simulations. A slight improvement was shown by ANFIS when compared to FLC, this is because the ANFIS controller was trained from the FLC to enhance the trial and error work of the FLC controller. Neural network controller has high energy consumption due to discrepancy in obtaining the exact inverse model of the nonlinear plant. All controllers are acceptable and the real time implementation of the controllers on real robot can be considered for future work.

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