

Intelligent Method of Adaptive Neuro-PWM Speed Control for a Mobile Robot in a Constrained Workspace

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Abstract: This paper proposes an intelligent method for adaptive Neuro-PWM speed control of a mobile robot in a constrained workspace, integrating a speed error model, an adaptive neural network controller, PWM signal generation, and a dynamic model of the DC drive. Numerical simulations performed under varying reference speeds, external loads, and obstacle distances confirmed the effectiveness of the proposed method, demonstrating adaptive PWM signal correction and stabilization of the neural network weights, thereby providing a basis for its practical implementation in mobile robot control systems.

Keywords: Industry 5.0, mobile robot, Adaptive Neuro-PWM, adaptive control, neural network, PWM control, DC drive, constrained workspace, intelligent control.

I. INTRODUCTION

The rapid development of autonomous mobile robots necessitates improved accuracy and adaptability in motion control, particularly in constrained workspaces, where variations in speed and delayed braking may lead to collisions with obstacles or deviations from the allowable trajectory. Conventional PWM-based control methods for DC motors do not always provide the required control performance under conditions of drive nonlinearity, varying loads, and dynamically changing environments, which motivates the application of intelligent adaptive approaches. The use of a neural network controller for adaptive PWM signal generation makes it possible to account for the current speed error, its rate of change, and the distance to obstacles or workspace boundaries, thereby enabling real-time adjustment of the mobile robot motion mode. Therefore, the development of an Intelligent Method of Adaptive Neuro-PWM Speed Control for a Mobile Robot in a Constrained Workspace is a relevant research task aimed at improving the accuracy, adaptability, and safety of mobile robotic platform control.

II. DEVELOPMENT OF AN INTELLIGENT METHOD FOR ADAPTIVE NEURO-PWM SPEED CONTROL OF A MOBILE ROBO

To ensure adaptive speed control of a mobile robot operating in a constrained workspace, an intelligent Neuro-PWM method is proposed, in which the control action is generated based on the current motion state and neural network-based correction of the drive PWM signal. Since the primary performance criterion of such control is the system's ability to maintain the reference speed under varying motion modes and load conditions, the initial stage of the proposed method involves determining the deviation of the actual speed from the reference value, which is described by the mobile robot speed error model.

$$e_v(t) = v_{ref}(t) - v(t) \quad (1)$$

To account for the dynamics of the error variation:

$$\dot{e}_v(t) = \frac{de_v(t)}{dt} \quad (2)$$

where:: $v_{ref}(t)$ - reference linear velocity of the robot, [m/s]; $v(t)$ - actual velocity, [m/s]; $e_v(t)$ - speed error, [m/s]; $\dot{e}_v(t)$ - rate of change of the speed error, [m/s²]; t - time, [s].

Model 2 makes it possible to determine the current deviation of the mobile robot's actual speed from the reference speed, while $e_v(t)$ and $\dot{e}_v(t)$ is used as the primary input to the adaptive neural network controller.

The adaptive Neuro-PWM controller model is expressed as follows, where the neural network output determines the required correction of the control signal:

$$u_{NN}(t) = f_{NN}(e_v(t), \dot{e}_v(t), d(t), \mathbf{W}(t)) \quad (3)$$

In a simplified form, for a single hidden layer:

$$u_{NN}(t) = \sum_{j=1}^N w_j^{(2)} \varphi \left(\sum_{i=1}^3 w_{ji}^{(1)} x_i(t) + b_j \right) \quad (4)$$

where:: $u_{NN}(t)$ - neural network controller output; $d(t)$ - distance to the obstacle or workspace boundary, [m]; $\mathbf{W}(t)$ - set of adaptive neural network weights; $w_{ji}^{(1)}$ - input-layer weights; $w_j^{(2)}$ - output-layer weights; b_j - neuron bias; $\varphi(\cdot)$ - activation function; N - number of neurons in the hidden layer;.

Models 3–4 determine the correction of the control action based on the speed error, its rate of change, and the distance to the workspace boundary/obstacle. They provide the “Neuro” component of the proposed Neuro-PWM method. The use of a neural compensator for unknown or nonlinear DC drive dynamics is a well-established approach in adaptive control.

The adaptive PWM signal generation model allows the neural network output to be converted into the PWM duty cycle:

$$D(t) = \text{sat}[D_0 + K_e e_v(t) + K_{\dot{e}} \dot{e}_v(t) + K_{NN} u_{NN}(t), D_{min}, D_{max}] \quad (5)$$

and the average voltage across the DC motor:

$$U_m(t) = D(t)U_s, 0 \leq D(t) \leq 1 \quad (6)$$

where: $D(t)$ - PWM duty cycle; D_0 - baseline PWM value; D_{min}, D_{max} - minimum and maximum allowable values; K_e - speed error gain; $K_{\dot{e}}$ - rate-of-change-of-error gain; K_{NN} - neural network correction scaling factor; U_s - supply voltage, [V]; $U_m(t)$ - equivalent average motor voltage, [V].

Neuro-PWM Models 5–6 convert the output of the neural network controller into the physical PWM signal applied to the motor driver and incorporate a saturation (sat) constraint, which prevents the generation of PWM values outside the allowable range.

The dynamic model of the mobile robot's DC drive describes the response of the mobile platform to changes in the PWM signal and enables the simulation of acceleration, braking, and the effects of external load.

$$\tau_v \frac{dv(t)}{dt} + v(t) = K_v U_m(t) - F_L(t) \quad (7)$$

Alternatively, after substituting Equation (6), the model can be expressed as follows:

$$\frac{dv(t)}{dt} = \frac{1}{\tau_v} [K_v U_s D(t) - v(t) - F_L(t)] \quad (8)$$

where: τ_v - drive time constant; [s]; K_v - voltage-to-speed gain; $F_L(t)$ - generalized effect of load and motion resistance; $v(t)$ - actual robot velocity; $U_m(t)$ - average motor control voltage.

III. NUMERICAL MODELING AND ANALYSIS OF THE OBTAINED RESULTS

The purpose of the numerical simulation is to verify the operability and adequacy of the developed intelligent method for adaptive Neuro-PWM speed control of a mobile robot under varying reference speed, external load, and approaching the boundaries of a constrained workspace. The expected simulation outcome is stable tracking of the reference speed, adaptive correction of the PWM signal, and reduction of the control error compared with a conventional PWM controller, evaluated using the RMSE, MAE, maximum absolute error, and IAE metrics. The simulation is performed over a period of 40s with an integration time step of 0.01s, a DC drive supply voltage of 12 V, a drive time constant of 0.65s, and a gain coefficient of $K_v = 0,085$, controller gains; $K_e = 0,75$, $K_{\dot{e}} = 0,06$ and the neural network correction gain; $K_{NN} = 0,18$. To investigate the adaptive properties of the proposed method, a neural network with a 3–6–1 architecture and a learning rate of is used. $\eta = 0,15$, while the reference speed, external load, and distance to the obstacle are varied throughout the experiment to reproduce different operating conditions of the mobile robot.

The simulation results are presented in Figures 1–6.

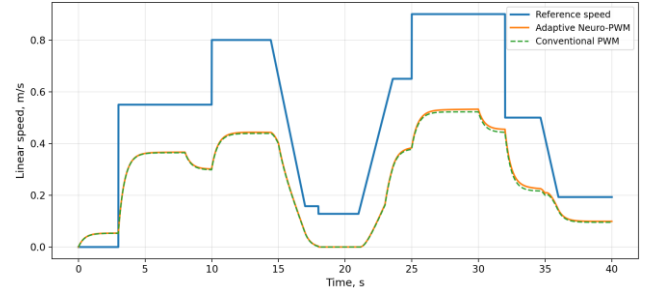


Figure 1. – Mobile Robot Speed Control

The results presented in Figure 1 demonstrate that Adaptive Neuro-PWM provides stable tracking of the varying reference speed within the approximate range of 0.13–0.90 m/s, with an automatic reduction in the actual speed as the robot approaches the workspace boundary. A comparison of the Adaptive Neuro-PWM and Conventional PWM curves shows similar dynamic behavior, while the neural network controller provides additional adaptive speed correction during transient operating conditions and load variations.

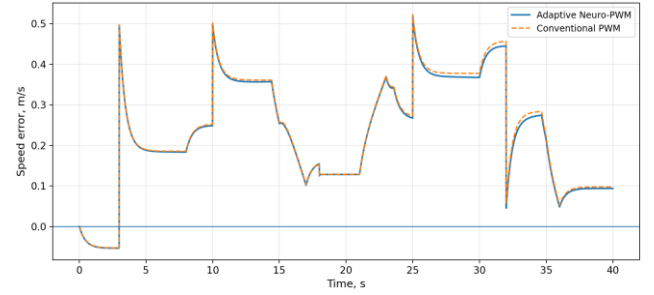


Figure 2. – Speed Control Error

The Speed Control Error graph presented in Figure 2 shows that the largest short-term speed errors occur during step changes in the reference speed, reaching approximately 0.50–0.52 m/s, after which the system transitions to a new steady-state operating mode. During the intervals between transient processes, the error stabilizes at approximately 0.08–0.37 m/s, depending on the reference speed, external load, and workspace constraints, while the curves of the two controllers remain close to each other.

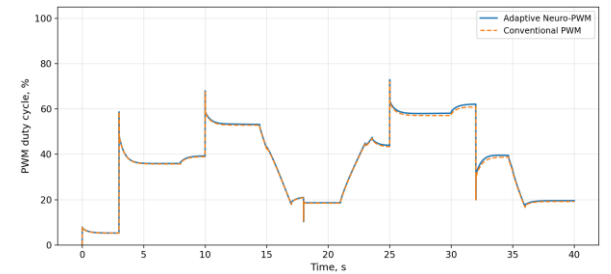


Figure 2. – PWM Control Signal

The results presented in Figure 3 demonstrate an adaptive variation of the PWM duty cycle from approximately 5% to 70%, with the highest values occurring during a sharp increase in the reference speed and changes in the load conditions. After the transient processes, the PWM duty cycle stabilizes within approximately 35–60%, while its

reduction to 10–20% under speed-limiting conditions confirms the response of the control system to changing motion conditions.

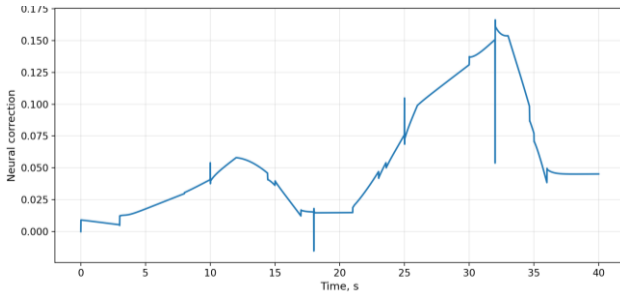


Figure 4. – Adaptive Neural Controller Output

Figure 4 shows that the output of the adaptive neural network controller u_{NN} varies from approximately 0 to 0.16, responding to changes in the speed error, its derivative, and the robot's motion conditions. The gradual increase in the neural correction to a maximum value of approximately 0.16 at 32s, followed by its stabilization at approximately 0.045, demonstrates the adaptation of the neural network component to varying operating conditions of the system..

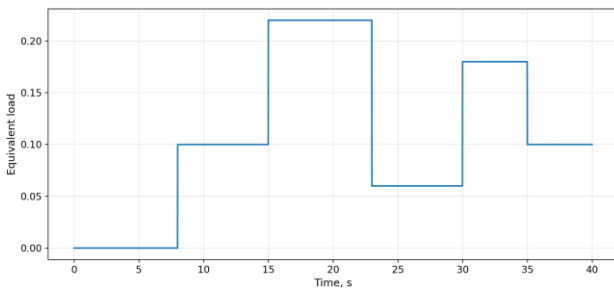


Figure 5. – External Drive Load Disturbance

The results presented in Figure 5 show a stepwise variation in the equivalent external load from 0 to 0.22, with the largest disturbance $F_L \approx 0,22$ occurs approximately within the interval of 15–23s, while the second significant disturbance $F_L \approx 0,18$ - occurs within the interval of 30–35s. Despite these load variations, the system continues to generate the control PWM signal and maintain stable speed dynamics, confirming the operability of the proposed method under external disturbances..

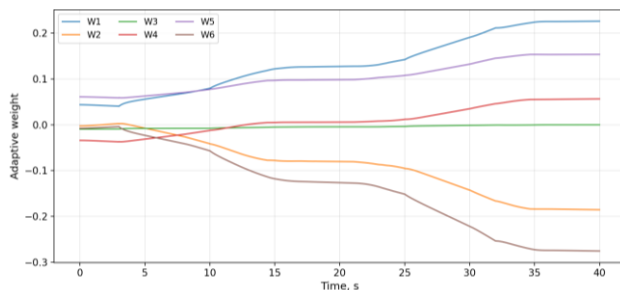


Figure 6. – Online Adaptation of Neural Network Weights

Figure 6 shows the online adaptation process of the six neural network weights $W_1 - W_6$: Over the 40s simulation period, some of the neural network weights increase to

approximately 0.22, 0.17, and 0.06, while others decrease to negative values of approximately -0.19 and -0.29 . The gradual variation of the weights without pronounced high-frequency oscillations and their convergence to nearly constant values by the end of the simulation indicate stabilization of the online adaptation process of the neural network controller.

IV. CONCLUSION

The study developed an intelligent method for adaptive Neuro-PWM speed control of a mobile robot in a constrained workspace, which takes into account the current speed error, its rate of change, and the distance to an obstacle to generate an adaptive correction of the DC drive PWM signal. The numerical simulation demonstrated the operability of the proposed method under varying reference speed and external load conditions: the PWM duty cycle adaptively varied from approximately 5% to 70%, while the neural network component provided correction of the control action according to the current motion mode of the robot. The simulation results also demonstrated the system's robustness to stepwise variations in the external load within the range of 0 to 0.22 and stabilization of the online adaptation process of the neural network weights without pronounced high-frequency oscillations, confirming the adaptive properties of the developed controller. The obtained results provide a basis for the further practical implementation of Adaptive Neuro-PWM on a mobile robotic platform and experimental validation of the proposed method in a real constrained workspace.

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