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## Abstract

The weak spots have been examined, a solution has been suggested, the solution has been applied, and a comparison between the simulation and experimental test results has been given in this work. In order to do this, a nonlinear model predictive controller and a linear quadratic regulator controller have been utilized to control a four-wheel mobile robot during modeling and implementation. But the combination of these classic and modern controllers with machine learning can greatly help to make these controllers work more accurately; As a result, in order to increase the accuracy of the performance of these controllers, by training neural networks of multilayer perceptrons, the controllers have been made intelligent. Controllers with cost function have coefficients as weighting to the matrix of system state variables and control input, which are greatly affected by changing these two weighting matrices of problem solving and optimization. For this reason, it is necessary to extract these two matrices for each separate path in order to improve the performance of the controller by trial and error. But by applying the proposed network which is trained with a new algorithm, not only the performance accuracy has increased, but the network extracts these two matrices without the need to spend human energy. Additionally, by training additional neural networks to optimally extract the benefit of the forecast horizon, fewer calculations and faster solution times have been achieved, helping to reduce the current time delays, particularly in the implementation of the nonlinear controller on the robot in the experimental mode. In the hardware section, the solution time has been shortened by looking at and utilizing operators like the U2D2 interface and the pixy camera, which are quicker than the standard procedure. The information indicates that the proposed intelligence technology reacts 40%–50% quicker than the NMPC standard procedure. The suggested algorithm has also minimized the path tracking error since it extracts the optimal gain at each stage. Moreover, a hardware mode solving speed comparison betwee recommended and conventional methods is given. In this domain, a 33% increase in solving speed has been noted.



## Data availability statement

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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