Supervised control strategy in trajectory tracking for a wheeled mobile robot

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Abstract: In this study, a single input interval type-2 fuzzy logic (SI-IT2-FLC) supervised adaptive neural-fuzzy interface system (ANFIS) controller is proposed for the velocity tracking task of a two-wheeled mobile robot (WMR). The suggested technique can handle the inherent nonlinearities, uncertainties and external disturbances in the system model by a new supervised controller. The robot control design is accomplished by two separate phases including kinematic controller, which is characterized using the kinematic model of the robot, and dynamic controller, which is designed using the physical features of the robot dynamics. In particular, an SI-IT2-fuzzy PD (SI-IT2-FPD) controller is initially applied for the trajectory tracking problem in the two-WMR. In this way, the impact of the footprint of uncertainty (FOU) on control surface (CS) generation is studied, i.e. several CSs were generated by changing a single coefficient which shapes the FOU. Then, a new SI-IT2-FPD supervised ANFIS controller is developed for the concerned robot system. To enhance the efficiency of the suggested controller, the baseline PD gains of the SI-IT2-FPD are adjusted in a heuristic manner. Finally, a prototype of the concerned robot is implemented to investigate the feasibility and applicability of the proposed framework in a real-time platform.

1 Introduction

Recently, the problem of controlling wheeled mobile robots (WMRs) has been a hot topic, and many contemporary works were reported in [1–3] with promising results. Up to now, the most researchers concentrated on the theoretical aspects of the control motion issue of WMRs; however, they are usually unable to provide the satisfactory level of accuracy and reliability of conventional industrial robots. On the other hand, only a few works have been devoted to the real-time mobile robot platforms where the prototypes and manufacturing of WMRs were established and tested in some universities and educational institutions [4, 5].

In the context of WMR control, most control techniques developed so far are based only on robot vehicle kinematics [6, 7]. There are basically two main reasons for the popularity of these controllers; these are (a) since the dynamic controller depends on the inherent characteristics of the vehicle and its actuators (i.e. mass, electrical resistance etc.) its design is more complicated over the kinematic controller (b) mobile vehicles often have low-level of speed control loops, which it allows to receives a desired angular speed as input and maintain the motor angular speed at this value. On the other hand, the identification of robot vehicle dynamics, to design its dynamic controllers, is necessary for some applications of WMRs such as heavy load transportation and high-velocity motions. For example, an adaptive neural network (NN) was proposed in [8] for motion control of a robot vehicle considering the dynamic constraints and it was demonstrated the established technique offers dynamic balance and reference trajectory tracking. However, the sophisticated methodology employed in [8] was not investigated in an experimental platform. Based on the WMR dynamics, sliding mode control (SMC) is designed in [9, 10] for motion tracking and stabilising a real-time robot platform. Although the control techniques, which were implemented in [9, 10], demonstrated successful performance in the robot platform, the model-based schemes are not applicable in some practical applications due to their very rich mathematical design. To avoid the computational complexity, a model-free cascade control technique based on the interval type-2 fuzzy logic controller (IT2-FLC) has been developed in [11] and applied in the real world employing PIONEER 3-2 mobile robot platform. Since the control technique, in this paper, does not require the mathematical modelling of the robot vehicles it is straightforward to be practically applied. In addition, some trajectory control approaches that compensate for the robot dynamics were reported in the literature such as optimal control [12], robust adaptive control [13], model predictive control (MPC) [14, 15], fuzzy logic control (FLC) [16, 17] and cerebellar model articulation controller [18].

The literature reveals that most controllers for WMRs dynamic control are designed based on the measured torques or voltages signals [19, 20]. While in the commercial robots, the terms of the linear and angular velocities are used to generate the control actions of dynamic controllers. Following this idea, the authors of [21, 22] developed a velocity-based dynamic model to design their control algorithms. In [23], the parameter-updating laws of an adaptive controller were considered based on the linear and angular velocities to guide a unicycle-type mobile robot vehicle during path following. The authors claimed that the adaptive technique could be used for load transportation in the industrial WMRs due to the on-line parameter adaptation can keep small tracking error even when the vehicle load is varied greatly. Based on the linear parameterisation of a multi-robot model, the dynamic controller was designed in [24] by employing the linear and angular velocities as inputs. The main feature of the suggested controller is that its coefficients are directly associated with the robot coefficients. Therefore, the performance of the controller may deteriorate in the cases that the vehicle coefficients are not correctly identified or when they vary with time.

The concept of incorporating FLC into an NN has attracted greater attention in various fields of control engineering [25, 26]. The integrated adaptive neural-fuzzy interface system (ANFIS) combines the ability of fuzzy logic to handle the uncertainties and the ability of NNs to learn from plants/processes. In spite of the learning ability of the NN is an advantage from the viewpoint of the FLC, additional advantages can be achieved from an integrated system. The ANFIS methodologies have been successfully developed for the tracking control task in the context of robot vehicles [27]. Previous knowledge can be combined in the system since the FLS depends on linguistic rules, and this combination can remarkably decrease the learning process.
To acquire a more desirable performance than the existing control strategies (i.e. unsupervised controllers), a fuzzy supervised online ANFIS controller has been introduced recently [28, 29]. However, all the designed controllers in the research works focused on the Type-1 fuzzy logic controllers (T1-FLCs). The main drawback of the T1-FLCs is that their performance is significantly deteriorated in unstructured environments with uncertainties. Due to the limitation above of the T1-FLCs, the IT2-FLCs have been introduced due to the extra degree of freedom provided by the footprint of uncertainty (FOU) in their IT2 fuzzy sets. Motivated by Sarabakha et al. [30], a new SI-IT2-fuzzy PD (SI-IT2-FPD) supervised ANFIS controller is designed and applied to a real-time WMR platform in this work. This study presents the tracking problem of a non-holonomic robot vehicle while the kinematic and dynamic models of the robot are involved in the investigation. The main goal of this study is to consider the impact of the FOU on the control performance of the supervised technique. To ascertain the effectiveness of the supervised controller, the obtained real-time results are compared to the SI-IT2-FPD and PD controllers.

Overall, the contributions of this work are as follows:

i. A supervised model-free controller, as opposed to the model-based approaches (e.g. SMC [31–33], MPC [14, 34], adaptive backstepping controller [35, 36] etc.), is designed based on the linear and angular velocities for the control motion of a non-holonomic WMR.

ii. Since the overall performance of the supervised controller depends on the gains of the baseline PD controller, the PSO is employed for optimal settings of these parameters.

iii. One control coefficient is varied to investigate how different values of the FOU affect the performance of the controller.

iv. For experimental studies, a prototype of the concerned WMR is constructed and designed to validate the applicability of the suggested model-free supervised controller.

2 System model development

The dynamic model of the concerned WMR, which is sketched in Fig. 1a, is presented in this section. In Fig. 1a, the linear and angular velocities of the WMR's centre are represented by \( u \) and \( \omega \), respectively. \( G \) is the centre of mass of the vehicle, \( B \) is the wheel baseline centre, \( C \) is the position of the castor wheel, \( E \) is the location of a tool onboard the robot, \( h = [x, y]^T \) is the point of desired which path should be tracked, \( \psi \) is the orientation of the vehicle, \( a, b, c, d, e \) are the distances. The mathematical representation of the robot, without considering the disturbances and uncertainties, is expressed as [21]

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\psi} \\
\dot{u} \\
\dot{\omega}
\end{bmatrix} = \begin{bmatrix}
\cos \psi & -a \sin \psi \\
\sin \psi & a \cos \psi \\
0 & 1 \\
\end{bmatrix} \begin{bmatrix}
\dot{u} \\
\dot{\omega}
\end{bmatrix} + \begin{bmatrix}
0 & 0 \\
0 & 0 \\
1 & 0 \\
0 & 1
\end{bmatrix} \begin{bmatrix}
\eta_{ref} \\
\omega_{ref}
\end{bmatrix} \tag{1}
\]

where \( \eta_{ref} \) and \( \omega_{ref} \) denote the reference values of the linear and angular velocities, respectively. In (1), \( \theta = [\theta_1, \ldots, \theta_6]^T \) are the vehicle model parameters, which can be obtained by the equations describing the parameters as presented in [21].

The complete model of the WMR, which is represented in (1), can be divided into two separate parts:

**Kinematic model**

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\psi}
\end{bmatrix} = \begin{bmatrix}
\cos \psi & -\sin \psi & 0 \\
\sin \psi & \cos \psi & 0 \\
0 & 1 & 0
\end{bmatrix} \begin{bmatrix}
\dot{u} \\
\dot{\omega}
\end{bmatrix} \tag{2}
\]

**Dynamic model**
Fig. 1(b) shows the block diagram model for the trajectory tracking problem of the concerned system, which depicts kinematic and dynamic parts equipped with corresponding controllers. In Fig. 1(b), the external disturbances and measurement noises are also taken into accounts for a further challenging realisation, which adversely affects the path following the performance of the robot vehicle.

3 Control design of system under study

3.1 Kinematic controller

The kinematic controller receives the errors in the x and y coordinate's between the reference values and the actual values along with the orientation of the robot, as observed in Fig. 1(b). Then, the kinematic control actions are generated based on the received signals, where the references of linear and angular velocities are produced. In this work, the kinematic control law is considered as [21]

\[
\begin{bmatrix}
U \\
\omega
\end{bmatrix} = \left[ \frac{\partial_1 \alpha}{\partial_1} \begin{bmatrix} \frac{\partial_1 \alpha}{\partial_1} \\
-\frac{\partial_1 \alpha}{\partial_1 l} \end{bmatrix} \right] + \frac{1}{\partial_1} \begin{bmatrix} 0 \\
1
\end{bmatrix} \begin{bmatrix} u_{ref} \\
\omega_{ref}
\end{bmatrix}
\]  

(3)

where \( u_{ref} \) and \( \omega_{ref} \) are the references velocities given by the kinematic controller, \( \hat{x} = x_2 - x \), and \( \hat{y} = y_2 - y \) denote the current position errors of the x and y, respectively, \((x, y)\) and \((x_d, y_d)\) are the current and references points, respectively, \( k_1 > 0 \) and \( k_2 > 0 \) represent the controller gains, \( l_1, l_2 \in \mathbb{R} \) denote saturation constants. The relevant parameters for the kinematic controller of the concerned WMR are taken from [21].

3.2 Dynamic controller

The dynamic controller, established as a supervised controller, is designed based on the references of the linear and angular velocities which are produced by the kinematic control part, as illustrated in Fig. 1(b). Then, the dynamic control part generates its own linear and angular velocities actions which are sent to the robot vehicle actuators. The description and design of the suggested controller are presented in the following.

3.2.1 Suggested a supervised control strategy: Based on [29, 37], the supervised learning techniques are more efficient than unsupervised methodologies since the taking advantage of training data provides clear criteria for model optimisation. On the other hand, the SI-IT2-FLC considering the FOU coefficient has shown much robust performance than the conventional IT2-FLC [30, 38]. Motivated by the success of both methodologies, a new SI-IT2-FLC based on the ANFIS controller is suggested in this work. The structure of the supervised dynamic controller, which is used for the tracking problem of WMR, is depicted in Fig. 2a. According to Fig. 2a, the SI-IT2-FPD controller is implemented to provide supervised output for the ANFIS controller. The ANFIS controller receives the supervised error \((\varepsilon)\) by comparing the supervised output \((U_{IT2})\) and the output of the ANFIS \((U_{ANFIS})\). Generally, two types of learning approaches are used for the supervised learning of ANFIS including structure learning and parameter learning. In the structure learning, the rules of fuzzy logic are extracted from the input data through tuning of fuzzy partitions for the input and output spaces; while, the variables of each rule are adjusted by parameter learning. The two learning methods are simultaneously accomplished in the simulation, where scatter partitioning is used for the structure learning and the parameter learning is based on the SI-IT2-FLC control law.

3.2.2 Structure of the SI-IT2-FLC: The structure of the PD type SI-IT2-FLC and its design approach will be derived in this section [30]. In the established structure, a cascade combination of SI-IT2-FLC and baseline PD controller is employed. The input scaling factor (SF) of IT2-FPD \((k_d)\) is used for normalising the input to the universe of discourse. This SF is defined as \( k_d = 1/e_{max} \) where \( e_{max} \) is the value of the maximum error value. Thus, the error will be converted, after normalisation, into \( \sigma \) which is the input of the SI-IT2-FLC. Then, the output of the SI-IT2-FLC \((\varphi)\) is converted into a control signal as

\[
u_{pd} = k_0 \left( k_p \varphi_0 + k_d \frac{\varphi_0}{dt} \right)
\]  

(5)
where $k_b$ is the output SF and is determined as $k_a = k_b^{-1}$, $\{k_p, k_d\}$ are the baseline PD controller gains, respectively.

The generic rule structure of the SI-IT2-FLC is as

$$ R_i; If \; \sigma \; is \; A_{an} \; Then \; \varphi_o = B_{by} \quad (6) $$

where $B_{by}$ are the crisp consequents considered as $B_1 = 1$, $B_2 = 0$ and $B_3 = 1$. The triangular IT2 fuzzy sets (IT2-FSs) $A_{an}$ are chosen for the antecedent membership functions (MFs), as depicted in Fig. 2b. The IT2-FSs are defined in terms of lower MF ($\mu_{\bar{A}_{an}}$) and upper MF ($\mu_{\hat{A}_{an}}$). In Fig. 2b, $m/s$ represents the height of the lower MFs which generate different FOUs of the IT2-FSs (offer the extra design freedom). In this work, symmetrical MFs are considered, for simplicity, with the following definitions $m_1 = m_0 = 1 - \alpha$ and $m_2 = \alpha$. By applying the centre of sets type reduction scheme, the defuzzified crisp output of an SI-IT2-FLC is calculated as $\varphi_o = (\varphi_{o\downarrow} + \varphi_{o\uparrow})/2$. Where $\gamma$ and $\gamma_i$ are the end points of the type reduced set which are calculated as

$$ \varphi_{o\downarrow} = \frac{\sum_{k=1}^{n_\downarrow} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by} + \sum_{k=n_\downarrow+1}^{n_L} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by}}{\sum_{k=n_\downarrow+1}^{n_L} \mu_{\bar{A}_{an}}(\sigma)} + \frac{\sum_{k=n_{\downarrow+1}}^{n_U} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by} + \sum_{k=n_{\downarrow+1}}^{n_U} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by}}{\sum_{k=n_{\downarrow+1}}^{n_U} \mu_{\bar{A}_{an}}(\sigma)} \quad (7) $$

$$ \varphi_{o\uparrow} = \frac{\sum_{k=1}^{n_\uparrow} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by} + \sum_{k=n_\uparrow+1}^{n_R} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by}}{\sum_{k=n_\uparrow+1}^{n_R} \mu_{\bar{A}_{an}}(\sigma)} + \frac{\sum_{k=n_{\uparrow+1}}^{n_{\uparrow+1}} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by} + \sum_{k=n_{\uparrow+1}}^{n_{\uparrow+1}} \mu_{\bar{A}_{an}}(\sigma) \cdot B_{by}}{\sum_{k=n_{\uparrow+1}}^{n_{\uparrow+1}} \mu_{\bar{A}_{an}}(\sigma)} \quad (8) $$

Here, the $(L, R)$ is the switching points.

As proved in [39], the fuzzy mappings (FM) of the SI-IT2-FLC $\varphi_o(\sigma)$ are computed as

$$ \varphi_o(\sigma) = \sigma \cdot k(\sigma) \quad (9) $$

where $k(\sigma)$ is a non-linear gain which is defined as

$$ k(\sigma) = \frac{1}{2} \left( 1 - \frac{1}{\alpha + \sigma - \alpha \sigma} + \frac{\alpha - 1}{\alpha \sigma - 1} \right) \quad (10) $$

Let $\varphi_o(\sigma) = \varphi_o(\sigma) - \sigma$, then different control curves (CCs) can be obtained by

i. Aggressive CC (A-CC): when $0 < \alpha \leq \alpha_{c1}$, then $\sigma > 0$ for $\forall \sigma \in [0, 1)$ and $\alpha_1 = (3 - \sqrt{5})/2$.

ii. Smooth CC (S-CC): when $\alpha_{c1} < \alpha \leq 1$, then $\sigma < 0$ for $\forall \sigma \in [0, 1)$ and $\alpha_2 = (\sqrt{5} - 1)/2$.

iii. Moderate CC (M-CC): when $\alpha_{c2} < \alpha \leq \alpha_{c1}$, then $\sigma > 0$ for $\forall \sigma \in [0.5, 1]$.\n
Fig. 2c illustrates the profiles of the different CCs, i.e. A-CC, S-CC, and M-CC. For details of the CCs features of the SI-IT2-FLC, the readers are referred to [30].

Since the performance of the SI-IT2-FPD controller depends on the baseline PD controller gains, the optimal setting of these coefficients can play an important role in the quality of the dynamic control actions. Accordingly, the PSO algorithm is used for fine-tuning of the baseline PD gains, as shown in Fig. 2a. To fulfill the control objectives of the WMR by heuristic manner, an objective function needs to be defined so that the robot tracks the target with a small error and quick response. For this purpose, the objective function is given in (11) is used which includes the integrals of two weighted terms, i.e. the absolute error (IAE) and integral of squared error (ISE)

$$ F = w_1 f_1 + w_2 f_2 \quad (11) $$

$$ f_1 = IAE = \int_{0}^{t_{sim}} \left[ e_x(t) + e_y(t) \right] dt \quad (12) $$

$$ f_2 = ISE = \int_{0}^{t_{sim}} \left[ e_x(t)^2 + e_y(t)^2 \right] dt \quad (13) $$

where $e_x$ and $e_y$ are the changes in the $x$ and $y$, respectively, $t_{sim}$ is the final simulation time in s. In (11), $w_1$ and $w_2$ make each term competitive during the evolving process and $w_1 = w_2 = 0.5$ gives equal importance to both the objective functions (IAE and ISE).

The tracking problem can be formulated as a constrained optimisation problem by restricting the controller coefficients.

Minimise $F$ Subjected to:

$$ k_{p\downarrow} \leq k_p \leq k_{p\uparrow}, \quad k_{d\downarrow} \leq k_d \leq k_{d\uparrow} \quad (14) $$

where $k_{p\downarrow}$ and $k_{p\uparrow}$ are the minimum and maximum bounds of the baseline PD controller gains for both the paths $x$ and $y$, respectively.

3.2.3 ANFIS controller: ANFIS refers, in general, to an inference system which integrates the stringent of the fuzzy system and adaptability nature of artificial NN (ANN). This integration makes the controller adaptive and self-tuning. ANFIS predicts the relationship between the input and output according to the data set. The ANFIS architecture with a total of five layers is sketched in Fig. 2d [40]. The following assumptions are made here for the simplicity: (a) the model has two inputs error ($e$) and rate of change of error ($\Delta e$), one output $f$, (b) it has two rules ($R_1$ and $R_2$).

$$ R_1: If \; e \; is \; A_1 \; and \; \Delta e \; is \; B_1. \; Then \; f_1 = p_1 e + q_1 \Delta e + r_1 \quad (15) $$

$$ R_2: If \; e \; is \; A_2 \; and \; \Delta e \; is \; B_2. \; Then \; f_2 = p_2 e + q_2 \Delta e + r_2 \quad (16) $$

where $A_1$ and $B_1$ (for $i = 1, 2$) are the MFs for each input, while $p_i$, $q_i$, and $r_i$ are the output function parameters.

From the ANFIS architecture, which is dedicated in this work, the overall output is calculated by linear combinations of the consequent variables

$$ f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \hat{w}_1 f_1 + \hat{w}_2 f_2 \quad (17) $$

where $w_1$, $w_2$ are the firing strengths of each rule, $\hat{w}_1$, $\hat{w}_2$ denote the normalised firing strengths. For more details about the layers of the ANFIS, readers are referred to [40].

4 Results and discussion

To ascertain the performance of the proposed supervised based motion tracking control approach, the experimental analysis with a WMR platform is presented in this section. Fig. 3a shows a simplified type of WMR vehicle that allows investigating the complex mobile robotic problems, including modelling and control design. In the concerned WMR, the radius of the wheels is as 2.43 cm, which is assembled on the right and left sides equipped with 12 V DC motors as actuators for differential driving. Two encoders as well as a rate gyroscope with 1920 pulses/turn, assembled on the shaft of the motors, are established to estimate the coordinates. Moreover, a microcontroller embedded in the WMR generate the actual control signals by the pulse-width-modulation signals. To receive information from the controller, a wireless module is employed to transmit information to the PC. The deceive baseline PD controller gains are adjusted in a heuristic manner employing the PSO algorithm [41–46]. Initially, the effect of the FOU parameter $\alpha$ of the SI-IT2-FPD on the control surface, based on A-CC, M-CC and S-CC, is studied. Then, the proposed SI-IT2-FPD supervised ANFIS controller is applied to the concerned WMR and its efficiency is compared with the SI-IT2-FPD and conventional PD controllers. The lower and upper bounds for the optimal setting of the baseline PD controller gains are set as 0 and 40, respectively, and the simulation time of $t_{sim} = 60$ s is considered. In the concerned system, the uncertainty is added to the measurements of the WMR by a white noise as shown in Figs. 3b and c. Moreover,
the external disturbances are imposed to both $u_{ref}$ and $\omega_{ref}$ which are assumed as $0.3\sin (2.4t) + 0.25\cos (1.4t)$. The initial position of the vehicle is chosen as $x = 0.2 \text{ m}$ and $y = 0 \text{ m}$ with orientation $0^\circ$ in the experiment and it should track an eight-shape trajectory starting at $x = 0 \text{ m}$ and $y = 0 \text{ m}$. The optimal PD gains, by employing the PSO algorithm, are found as $k_{p1} = 39.37$, $k_{d1} = 33.529$ for the path $x$ and $k_{p2} = 40$, $k_{d2} = 24.34$ for the path $y$. To make a fair comparison, the optimal parameters are used for all of the controllers and also the input SF ($k_e$) and output SF ($k_u$) are set to 1.

The comparative target tracking of the SI-IT2-FPD controllers with different CCs (A-CC, M-CC, and S-CC), decomposed in the $X$ and $Y$ axes, is depicted in Figs. 4a and b. From the curves of Figs. 4a and b, it is evident the desired output of the controlled WMR can be tracked with high precision in spite of the presence of the disturbances above and noises. Moreover, the A-SI-IT2-FPD controller provides a superior tracking performance as compared to the path realised with the M-SI-IT2-FPD and S-SI-IT2-FPD controllers. Figs. 4c and d illustrate the tracking errors which are appeared during the trajectory tracking. As presented in Figs. 4c and d, after a relatively large overshoot, the tracking errors of $X$-axis are converted into a small region of zero in the range $[-0.0287 + 0.0209]$ (with A-SI-IT2-FPD), $[-0.0371 + 0.0323]$ (with M-SI-IT2-FPD controller) and $[-0.0558 + 0.0488]$ (with S-SI-IT2-FPD controller). The tracking errors of the $Y$-axis are fluctuated within the range $[-0.0205 + 0.0158]$ (with A-SI-IT2-FPD), $[-0.0244 + 0.0254]$ (with M-SI-IT2-FPD controller) and $[-0.0400 + 0.0441]$ (with S-SI-IT2-FPD controller) throughout the simulation time.

Fig. 5 depicts the performance of the robot with the considered SI-IT2-FPD controllers while following the eight-shape trajectory. From the response of Fig. 5, it is observed the WMR vehicle with the A-SI-IT2-FPD controller can track the desired trajectory more efficiently than two other SI-IT2-FPD controllers. The values of the considered objective function for all the SI-IT2-FPD controllers are listed in Table 1. It is clear from Table 1 that the lowest value of the objective function is obtained with the A-SI-IT2-FPD than the other SI-IT2-FPD controllers.

From the above discussions, the A-SI-IT2-FPD controller provides better robot trajectory tracking over the other CCs of SI-IT2-FPD controller (M-SI-IT2-FPD controller and S-SI-IT2-FPD controller). Now, the efficiency of the A-SI-IT2-FPD controller based on the ANFIS controller is compared to the A-SI-IT2-FPD controller and PD controller. The tracking responses of the
considered controllers are presented in Figs. 6 a and b. Figs. 6 a and b demonstrate that the trajectory tackled with a proposed supervised controller is more accurate than the A-SI-IT2-FPD controller and PD controller. The profiles of the tracking errors, calculated during the trajectory tracking, are depicted in Figs. 6 c and d. From the responses of Figs. 6 c and d, after a relatively large overshoot, the tracking errors of the X-axis are converged in the range $[-0.0270 +0.0198]$ (with A-SI-IT2-FPD supervised ANFIS controller), $[-0.0287 +0.0209]$ (with A-SI-IT2-FPD controller) and $[-0.1764 +0.0389]$ (with conventional PD controller). The tracking errors of the Y-axis are fluctuated within the range $[-0.0122 +0.0152]$ (with A-SI-IT2-FPD supervised ANFIS controller), $[-0.0137 +0.0158]$ (with A-SI-IT2-FPD controller) and $[-0.1420 +0.0331]$ (with conventional PD controller) throughout the simulation time. The comparative results of following the eight-shape path, obtained by the considered controllers, are presented in Fig. 7. It is perceived in Fig. 7 that the path tracked with the proposed controller is relatively more accurate than the A-SI-IT2-FPD controller and also is much more accurate than the PD controller. The values of the objective function for all the compared controllers are summarised in Table 2. It is noted from Table 2 that the lowest value of the objective function is obtained with the proposed controller. Therefore, it can be concluded from the discussion above that with tuning only a FOU coefficient in the SI-IT2-FPD controllers, better tracking responses will be obtained with the SI-IT2-FPD controllers compared to the conventional PD controller. Moreover, in spite of the A-SI-IT2-FPD controller provides a high precision of trajectory performance, the supervised control strategy can further improve the accuracy and speed in the WMR tracking responses.

5 Conclusion

In this paper, an attempt is conducted to design and implement a new supervised controller for the trajectory-tracking problem of a two-WMR. This robot vehicle is a typical example of non-holonomic systems and is subjected to external disturbances and measurement noises. The control mechanism of the robot vehicle is divided into two separate sections which rely on the kinematic and dynamic models of the WMR. In particular, the SI-IT2-FPD supervised controller is suggested and applied to solve the tracking problem of the concerned WMR system. To further improve the performance of the suggested control strategy, the baseline PD controller gains are optimally adjusted by the PSO algorithm. Then, a real-time WMR platform is established to investigate the efficiency and applicability of the suggested controller experimentally. Since the suggested control strategy does not require model identification, it can be applied to a reasonably wide class of mobile robots. This novel technique reaches successfully the WMR tracking targets with low computation burden and complexity. The experiments demonstrate that the supervised controller can control the WMR to follow the specific path with a slight deviation. These experiments also reveal the supremacy of the suggested controller for a complex robotic mission, disturbance rejection, and noise elimination over the SI-IT2-FPD controller with different CCs and PD controller. In the future, we may make efforts to establish the suggested supervised controller for the mobile robots to navigate efficiently unknown areas while cooperatively carrying an object.
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