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Data Driven Control and slip estimation for Agricultural Tracked Vehicles

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ABSTRACT

This paper focusses on the path following problem for autonomous Unmanned Ground Vehicles developed for precision agriculture. Such vehicles typically face rough terrain and narrow navigating spaces, so reliability of odometry is largely reduced. In this context, slip estimation/accommodation becomes crucial for localization and navigation of vehicles. In this work, a control architecture is presented coupling MIMO Data-Driven Control and Sliding Mode Control, with the inclusion of a fault estimation mechanism aimed at mitigating the actuators' loss of effectiveness associated to slipping. The supporting theoretical development makes use of previous results available in the Model Free Adaptive Control framework, which have been extended in order to deal with the path following problem for the vehicle. On the basis of extensive simulations, the proposed control policy is shown able to strengthen the recovery capability and robustness inherently owned by the original adaptive mechanism and control laws.

1. Introduction

Application of Mobile Robotics to outdoor scenarios, and in particular to Precision Agriculture (PA), is currently facing an increasing interest as a powerful tool for the optimization of farming processes [1, 2]. Nonetheless, in the particular case of Orchard PA (OPA) the design of effective autonomous platforms is still an open issue, due to the absence of reliable GPS data in contrast to open-field farming. Unmanned Ground Vehicles (UGVs) designed for rough terrains need a wide contact surface with the ground but, because of different velocities driving the two tracks, the robot is led to skid over the ground and the reliability of odometry is largely reduced [3]. As a consequence, slip estimation is crucial for localization and navigation of such Skid-Steering Vehicles (SSVs) and, in turn, for the execution of relevant OPA tasks. In other words, the presence of slip causes an SSV to behave differently from a Differential Wheeled Robot (DWR), and makes the problem of path following more complex. It is worth noticing that, from a kinematic standpoint, the pure rolling and non-slipping constraint, holding ideally for a DWR, is violated of an unknown amount. Several papers are available in the literature aiming at the estimation or compensation of the described slipping effect. In a number of applications, an efficiency reduction model is adopted by the introduction of efficiency coefficients [4], associated to control inputs, to represent slip [3] and, in this view, the addressed problem becomes the effective tackling of actuators' Loss Of Effectiveness (LOE). As a consequence, it is likely that slipping of UGVs could be managed making resort to available methods for actuators' fault accommodation.

As well know, the research on fault detection, estimation, accommodation has been intensively conducted in recent decades (see [5,6] and the references therein), largely with reference to model-based methods. In recent years, exploiting the availability of measured process data nowadays easily collected in real time, Data-Driven Control (DDC) methodologies have come into play, and Data Driven (DD) fault tolerant design methods have been proposed as well, starting from more than a decade ago [1]. An integrated DD approach to fault-tolerant control has been proposed exploiting the Youla parameterization for MIMO linear systems in [2], while a new DD feedback controller architecture was developed, in the traditional feedback framework, to couple robustness and performance [7]. A DD method using data for the design of the Linear Quadratic Regulator problem has been proposed very recently [8], and a DD fault-tolerant control approach for discrete-time linear systems with actuator failure has been addressed in [9], where stability conditions are derived solving data-based LMIs. The class of addressed processes, limited in the cited papers to linear plants hence excluding UGVs, has been widened in [10] by the adoption of a SISO Model Free Adaptive Control (MFAC) framework [11], based on an equivalent representation of the original unknown system obtained by Pseudo Partial Derivatives (PPD), which would need anyway to be extended to MIMO non-square plants to possibly be applied to UGVs . Sensor faults have been there considered, and a neural network has been adopted to approximate the fault dynamics and redesign the controller. With reference to actuator faults of control systems, which are recognized as source of instability and performance degradation, few results are available in the DDC literature in addition to [9], at least at the author's knowledge. The present paper aims at filling this

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gap, with reference to a specific Multi-Input Multi-Output (MIMO) non-square plant, the UGV.

In the specific case considered here, in consideration of the time-varying nature of slipping, adaptive approaches have been used in the past. The paper [12] adopted a random walk representation to models the slip, then using a recursive least squares approach for its estimation and the successive modulation of the control action using a direct model reference adaptive control technique. Conversely, an adaptive feedback linearization control method has been pursued in [13], while [3] proposed an adaptive observer for the robust estimation of slip coefficients, featuring exponential convergence rate under the (restrictive) assumption of the vehicle moving at constant velocities. The cited references share the need of the Persistency of Excitation (PE) assumption. Finally, representing the kinematic slip as a constant plus an additive zero-mean stochastic process, its estimation has been carried out using Kalman filters in [14–17] .

In this paper, a control architecture coupling MIMO DD control and Sliding Mode (SM) control is presented, with the inclusion of a fault estimation mechanism aimed at mitigating the actuators' LOE associated to slipping. In particular:

- Taking advantage of the MIMO MFAC framework, with reference to the (x, y) vehicle subsystem, it is here explored the tracking controller originally proposed in [11] for square systems in the presence of possible LOE affecting the plant actuators;
- a robust SM controller, able to manage the LOE of the θ subsystem (the heading angle), is presented, which inherently guarantees the fulfillment of the nonholonomic constraint and the vanishing of the angular tracking error;
- an identification algorithm is presented for the estimation of the LOE, along with a proof proving the boundedness of the estimation error;
- a tracking controller accommodating actuators' LOE for the UGV is finally proposed, achieved by a control redesign of the original controller, able to strengthen the recovery capability inherently owned by the MFAC adaptive mechanism.

The paper organization is the following. Preliminary issues about the considered system and the control problem are presented in Section 2. The main technical results are reported in Sections 5 and 6, where a fault identification algorithm is given and the SM controller is proposed, accommodating the LOE and guaranteeing bounded tracking errors. A simulation study supporting the presented development is then reported in Section 7, and the obtained accommodation performances are discussed in terms of tracking accuracy. Final remarks are finally given in Section 8. The following symbols and notation will be used in the paper, and are here listed for convenience. $\mathbb{R}$ denotes as usual real numbers, $\mathbb{R}^n$ is the n-dimensional space, $\|\cdot\|$ the Euclidean norm.

2. Preliminaries

As previously discussed, since an SSV should ideally behave as DWR, the standard unicycle kinematic model can be adopted:

$$\dot{x}(t) = v(t)\cos(\theta(t))$$
$$\dot{y}(t) = v(t)\sin(\theta(t))$$
$$\dot{\theta}(t) = \omega(t) \tag{1}$$

where the variables (x, y) denote the vehicle position in inertial coordinates while v is its linear velocity in body coordinates. Moreover, the heading angle is denoted by θ while ω is the angular velocity around the body axis z. In the ideal hypothesis of pure rolling and nonslipping condition, the vehicle is subject to the well known constraint

$$\dot{x}(t)\sin(\theta(t)) - \dot{y}(t)\cos(\theta(t)) = 0 \tag{2}$$

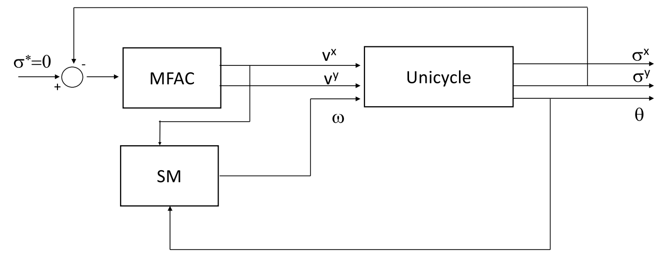

Fig. 1. Control scheme.

If slipping is not negligible, a widely used model for describing kinematic slip is the so called efficiency reduction model [4], holding for DWR:

$$v(t) = \frac{1}{2}(v_R(t)\rho_R(t) + v_L(t)\rho_L(t))$$
$$\omega(t) = \frac{1}{2d}(v_R(t)\rho_R(t) - v_L(t)\rho_L(t)) \tag{3}$$

where $\rho_{R/L}(t)$ are time-varying slip coefficients, $v_{R/L}(t)$ are the wheels linear velocities and d is half the distance between wheels. In this context, $\rho_{R/L}(t)$ can be interpreted as efficiency coefficients associated to control inputs, and the nominal model (1) can be rewritten as:

$$\dot{x}(t) = \delta_v(t)v(t)\cos(\theta(t))$$
$$\dot{y}(t) = \delta_v(t)v(t)\sin(\theta(t))$$
$$\dot{\theta}(t) = \delta_\omega(t)\omega(t) \tag{4}$$

with $\delta_{v/\omega}(t)$ being bounded time-varying coefficients describing the LOE of the actuators due to slipping [4]. In order to let the vehicle track a desired trajectory $(x_d(t), y_d(t), \theta_d(t))$ fulfilling the constraint (2), in the presence of slipping, the approach pursued in this paper is to couple a SM controller with an adaptive DDC law, along with an on-line estimator of the LOE coefficient in order to mitigate its effects.

In order to obtain a discrete-time formulation of the considered problem, a sampling time T_c has been chosen, small enough such that negligible variations of $\sin(\theta(t))$, $\cos(\theta(t))$ occur within a sampling period. Considering a zero-th order hold for the control inputs and integrating along a sampling interval, the following discrete-time model of the vehicle is obtained:

$$x(k+1) = x(k) + T_c\delta_v(k)v(k)\cos(\theta(k))$$
$$y(k+1) = y(k) + T_c\delta_v(k)v(k)\sin(\theta(k))$$
$$\theta(k+1) = \theta(k) + T_c\delta_\omega(k)\omega(k) \tag{5}$$

and, defining the incremental quantity $\Delta z(k+1) \triangleq z(k+1) - z(k)$ for any discrete-time variable $z(k)$, $k \in \mathbb{Z}_+$, the following error system is immediately derived:

$$e_x(k+1) = e_x(k) - \Delta x_d(k+1) + T_c\delta_v(k)v_x(k)$$
$$e_y(k+1) = e_y(k) - \Delta y_d(k+1) + T_c\delta_v(k)v_y(k)$$
$$e_\theta(k+1) = \theta(k) - \Delta\theta_d(k+1) + T_c\delta_\omega(k)\omega(k) \tag{6}$$

where $v_x(k) \triangleq v(k)\cos(\theta(k))$, $v_y(k) \triangleq v(k)\sin(\theta(k))$.

3. The control scheme

The control scheme proposed in this paper is summarized in Fig. 1 and will be described in the following. Define the following variables, with $\gamma_x, \gamma_y \in (-1, 1)$:

$$\sigma_x(k+1) \triangleq e_x(k+1) + \gamma_x e_x(k)$$
$$\sigma_y(k+1) \triangleq e_y(k+1) + \gamma_y e_y(k) \tag{7}$$

The vector $\sigma(k) = [\sigma_x(k), \sigma_y(k)]^T$ is considered as the output of the vehicle (x, y) subsystem, driven by the input vector $u(k) = [u_1(k), u_2(k)]^T =$

$[v_x(k), v_y(k)]^T$. With this choice, the associated control problem for this subsystem becomes a regulation problem.

Adopting the Partial Form Dynamic Linearization (PFDL) technique [18], an equivalent I/O data-based model can be obtained for this square, nonlinear, unknown MIMO subsystem [19], represented as:

$$\sigma(k+1) = \bar{f}(\sigma(k), \dots, \sigma(k-n_\sigma), u(k), \dots, u(k-n_u)), \tag{8}$$

where $\sigma, u \in \mathbb{R}^2$, $n_u, n_y \in \mathbb{Z}_+$, and $\bar{f} : \mathbb{R}^{2\cdot(n_u+1)+2(n_y+1)} \to \mathbb{R}^2$. Define the following vector $\in \mathbb{R}^{2L}$:

$$\bar{U}(k) \triangleq [u_1(k), u_2(k), u_1(k-1), u_2(k-1), \cdots, u_1(k-L+1), u_2(k-L+1)]^T \tag{9}$$

where $u_i(k) = 0\ \forall k \leq 0$ for $i = 1, 2$, with a fixed $L \in \mathbb{Z}_+$.

Remark 3.1 (*19*). Each component $\bar{f}_i$ of $\bar{f}(\cdot)$, $i = 1, 2$, has continuous partial derivatives with respect to each argument.

Remark 3.2 (*19*). The system (8) is generalized Lipschitz, i.e $\|\sigma(k_1+1) - \sigma(k_2+1)\| \leq b\|\bar{U}(k_1) - \bar{U}(k_2)\|, \forall k_1, k_2 \in \mathbb{Z}^+$, $k_1 \neq k_2$, $\bar{U}(k_1) \neq \bar{U}(k_2)$ and $b > 0$.

In view of Remarks 3.1, 3.2, the following Theorem holds.

Theorem 3.1 (*19*). *Consider the system (8). If $\|\Delta\bar{U}(k)\| \neq 0\ \forall k$, then it can be equivalently represented by the following equivalent PFDL form, i.e. there exists the so-called PPD parameter matrix $\bar{\phi}(k)$ such that*

$$\Delta\sigma(k+1) = \bar{\phi}(k)\Delta\bar{U}(k), \tag{10}$$

with $\bar{\phi}(k) \triangleq [\bar{\phi}_1(k), \bar{\phi}_2(k), \dots, \bar{\phi}_L(k)]$, $\bar{\phi}(k) \in \mathbb{R}^{2\times 2L}$ and $\bar{\phi}_i(k) = \{\phi_{lmi}(k)\}_{\substack{l=1,2\\ m=1,2}}$ for $i = 1, \dots, L$ and $\|\bar{\phi}(k)\| \leq b$.

In the present set-up, the actuator is considered subject to possible LOE. To this respect, the following assumption is introduced.

Assumption 3.1. The LOE coefficient $\delta_v(k) \in \mathbb{R}$ affecting the actuator $v(k)$, inherently bounded, is slowly varying in a time span of L samples, i.e. it holds:

$$\delta_v(k) \simeq \delta_v(k-1) \simeq \cdots \simeq \delta_v(k-L+1)$$
$$0 < m_v \leq |\delta_v(k)| \leq 1 \quad \forall k \in \mathbb{Z}_+$$

Remark 3.3. The previous assumption is not particularly restrictive, considering that the simulations reported here have been obtained with $L = 3$ and sampling period $T_c = 0.02$ s. It is worth mentioning that previous estimation/observation approaches required other assumptions, difficult to check in practice, such the persistency of excitation [3].

With the previous assumption, the PFDL representation (10) becomes:

$$\Delta\sigma(k+1) = \delta_v(k)\bar{\phi}(k)\Delta\bar{U}(k), \tag{11}$$

In the (x, y) subsystem considered so far, the control inputs $v_x(k), v_y(k)$ are not independent, since the control variable $v(k)$ satisfies $v(k) = \sqrt{v_x(k)^2 + v_y(k)^2}$ and the following condition has to be imposed:

$$\theta(k) = \arctan\left(\frac{v_y(k)}{v_x(k)}\right). \tag{12}$$

It should be also recalled that the reference trajectory (x_d, y_d, θ_d) fulfills the constraint (2) which, if T_c is small enough such that the incremental ratio approximates the time derivative, is equivalently written as

$$\theta_d(k) \simeq \arctan\left(\frac{\Delta y_d(k)}{\Delta x_d(k)}\right). \tag{13}$$

As a consequence, defining the following sliding variable

$$s(k+1) \triangleq \arctan\left(\frac{v_y(k)}{v_x(k)}\right) - \theta(k+1) \tag{14}$$

it follows that the imposition of the condition $s(k+1) = 0$ implies that asymptotically it holds $T_c v_x(k) \to \Delta x_d(k)$, $T_c v_y(k) \to \Delta y_d(k)$, hence ultimately $\theta(k) \to \theta_d(k)$.

In conclusion, the following Proposition summarizes the control scheme:

Proposition 3.1. *Consider the plant (5) subject to possible actuators' LOE. The imposition of the following simultaneous conditions, robustly with respect to actuators' LOE:*

$$\sigma_x(k+1) = 0; \quad \sigma_y(k+1) = 0; \quad s(k+1) = 0 \tag{15}$$

imply that asymptotically it holds: $\theta(k) \to \theta_d(k)$ for $k \to \infty$, inherently fulfilling the constraint (2), and $e_x(k), e_y(k) \to 0$ for $k \to \infty$.

This result immediately follows from the preceding discussion. It is worth recalling here that the dynamic PFDL model (10) is completely equivalent to the original plant in I/O terms, as proved in [19].

4. DDC of the (x, y) subsystem

Following the standard procedure [19] to estimate $\bar{\phi}(k)$ one gets

$$\hat{\bar{\phi}}(k) = \hat{\bar{\phi}}(k-1) + \frac{\eta(\Delta\sigma(k) - \hat{\bar{\phi}}(k-1)\Delta\bar{U}(k-1))\Delta\bar{U}^T(k-1)}{\mu + \|\Delta\bar{U}(k-1)\|^2}, \tag{16}$$

$\mu > 0$, $\eta \in (0, 2)$, coupled with the following reset mechanism $\hat{\bar{\phi}}_{ii1}(k) = \hat{\bar{\phi}}_{ii1}(1) \wedge \hat{\bar{\phi}}_{ij1}(k) = \hat{\bar{\phi}}_{ij1}(1)$, if $det(\hat{\bar{\phi}}_1(k)) \neq 0$ or $\|\hat{\bar{\phi}}_1(k)\| > M$ or $sign(\hat{\bar{\phi}}_{ii1}(k)) \neq sign(\hat{\bar{\phi}}_{ii1}(1)) \wedge sign(\hat{\bar{\phi}}_{ij1}(k)) \neq sign(\hat{\bar{\phi}}_{ij1}(1))$, for a predefined $M > 0$.

Consequently, the standard control law in the unperturbed case reads

$$u(k) = u(k-1) - \frac{1}{\lambda + \|\hat{\bar{\phi}}_1(k)\|^2}\left\{\rho_1\hat{\bar{\phi}}_1(k)^T\sigma(k) - \hat{\bar{\phi}}_1(k)^T\sum_{i=2}^{L}\rho_i\hat{\bar{\phi}}_i(k)\Delta u(k-i+1)\right\} \tag{17}$$

with $\lambda > 0$ being a design parameter, $\rho_i \in (0, 1)$, $i = 1, \dots, L$.

Corollary 4.1. *Consider the plant (11) and its estimated parameters given by (16). Even in the case of LOE, the estimated parameters are norm bounded.*

Proof. The statement derives immediately from the proof of Th.2 in [11] considering the estimation error $\tilde{\bar{\phi}}(k) \triangleq \hat{\bar{\phi}}(k) - \delta(k)\bar{\phi}(k)$ where $\|\delta_v(k)\| \leq 1$. In case of LOE the plant reads $\Delta\sigma(k+1) = \bar{\phi}(k)\Delta(k)\Delta\bar{U}(k)$, with $\Delta(k) \triangleq diag(\delta_v(k), \delta_v(k-1), \dots)$ and then (11) in view of Assumption 3.1. △

With reference to the boundedness of the tracking error when the plant is fed by the standard control input (17) proposed in [11], it is apparent that a different choice of the parameter $\lambda > 0$ is needed in view of the proof of Th.2 in [11], since some steps need to be modified to account for the possible LOE of the actuator, as specified in the following Corollary.

Corollary 4.2. *Consider the plant (11) fed by (17). In the case of possible LOE, there exists $\lambda_{min} > 0$ such that for $\lambda > \lambda_{min}$ the tracking error vanishes asymptotically.*

Proof. According to the proof of Th.2 in [11], considering that $\|\Delta(k)\| \leq \sqrt{L}$, λ_{min} can be easily redefined, and the original development still works even in the case of LOE of the actuator. △

5. LOE estimation

In order to mitigate the effects of a possible LOE affecting actuators, it would be useful to find an estimated value $\hat{\delta}_v(k)$ of the coefficient $\delta_v(k)$ possibly attenuating the control input $v(k)$.

Remark 5.1. The same LOE coefficient $\delta_v(k)$ affects the first and second components of (5). As a consequence, its estimation can be performed using one of them, say the ℓ-th component, ℓ either 1 or 2.

Define:

$$\hat{\bar{\phi}}_\ell(k) \triangleq \left\{\hat{\bar{\phi}}_{Iji}(k), i=1,\dots,L;\ j=1,2\right\}$$
$$\Delta\sigma_\ell(k) \triangleq \left\{\Delta\sigma_x(k)\ if\ \ell=1;\ \Delta\sigma_y(k)\ if\ \ell=2\right\} \tag{18}$$

and consider the following algorithm:

$$\hat{\delta}_v(k) = \hat{\delta}_v(k-1) + \eta_\delta \frac{(\Delta\sigma_\ell(k) - \hat{\delta}_v(k-1)\varphi(k-1))}{\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2} \quad if\ \ |\Delta u_\ell(k)| \geq \epsilon \tag{19}$$
$$\hat{\delta}_v(k) = \hat{\delta}_v(k-1) \qquad if\ \ |\Delta u_\ell(k)| < \epsilon$$

with $\varphi(k-1) \triangleq \hat{\bar{\phi}}_\ell(k-1)\Delta\bar{U}_\ell(k-1)$, $\Delta\bar{U}_\ell(k-1)$ being the ℓ-th component of the vector $\Delta\bar{U}(k-1)$, and where $\epsilon, \mu_\delta, \eta_\delta \in \mathbb{R}^+$ are positive design parameter. Under the following assumption, which can be easily fulfilled by a suitable choice of the sampling time:

Assumption 5.1. The plant PPD representation (11) is such that the PPD parameters are slowly varying, i.e. $\hat{\bar{\phi}}_\ell(k) \simeq \hat{\bar{\phi}}_\ell(k-1)$.

the estimation error $\tilde{\delta}_v(k) = \hat{\delta}_v(k) - \delta_v(k)$ reads:

$$\tilde{\delta}_v(k) = \tilde{\delta}_v(k-1) + \eta_\delta \frac{(\delta_v(k-1)\bar{\phi}_\ell(k-1)^T - \hat{\delta}_v(k-1)\hat{\bar{\phi}}_\ell(k-1))\Delta\bar{U}_\ell(k-1)}{\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2}$$

i.e.

$$\tilde{\delta}_v(k) = \left[1 - \eta_\delta \frac{\varphi(k-1)}{\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2}\right]\tilde{\delta}_v(k-1) + - \eta_\delta \frac{(\delta_v(k-1)\tilde{\phi}_\ell(k-1)\Delta\bar{U}_\ell(k-1))}{\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2} \tag{20}$$

Theorem 5.1. *For the plant (11) under Assumptions 3.1 and 5.1, subject to possible actuator's LOE, the algorithm (19) guarantees bounded estimation errors (hence boundedness of $|\hat{\delta}_v(k)|\ \forall k$) setting*

$$\eta_\delta = \eta_\delta(k) = \bar{\eta}\frac{1}{|\varphi(k-1)|} sign\left(\varphi(k-1)\right), \tag{21}$$

for a suitable choice of $\bar{\eta}, \mu_\delta > 0$.

Proof. With the setting reported in the statement, the expression (20) provides:

$$|\tilde{\delta}_v(k)| \leq |\zeta(k-1)||\tilde{\delta}_v(k-1)| + \xi(k-1) \tag{22}$$

with

$$\zeta(k-1) \triangleq \left[1 - \frac{\bar{\eta}}{\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2}\right] \tag{23}$$
$$\xi(k-1) \triangleq \bar{\eta}\frac{|\tilde{\phi}_\ell(k-1)\Delta\bar{U}_\ell(k-1)|}{\left(\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2\right)|\varphi(k-1)|}$$

It can be easily verified that $\bar{\eta}$ and μ_δ can be chosen in order to ensure that $|\zeta(k-1)| < \frac{1}{2}$ holds $\forall k$, in fact it is enough to select the parameters as to satisfy

$$\frac{1}{2}(\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2) < \bar{\eta} < \mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2 \tag{24}$$

Setting $\bar{\eta} = \kappa(\mu_\delta + \|\Delta\bar{U}_\ell(k-1)\|^2)$, with $\kappa \in (\frac{1}{2}, 1)$, the previous inequality is fulfilled $\forall\mu_\delta$. The selection of $\bar{\eta}$ is always possible since $\|\Delta\bar{U}_\ell(k-1)\|$ has been proved to be bounded. With reference to the second term of (22), the parameter μ_δ can be always selected large enough such that it holds $0 < |\xi(k-1)| < \gamma$ for a real positive γ, in fact it holds:

$$|\xi(k-1)| \leq \kappa\left\|1 - \frac{\phi_\ell(k-1)\Delta\bar{U}_\ell(k-1)}{\hat{\phi}_\ell(k-1)\Delta\bar{U}_\ell(k-1)}\right\| \tag{25}$$

where $|\hat{\phi}_\ell(k-1)\Delta\bar{U}_\ell(k-1)|$ is bounded from below according to (16) and the reset mechanism contained therein, and $|\tilde{\phi}_\ell(k-1)\Delta\bar{U}_\ell(k-1)|$ is upper bounded in view of Theorem 3.1.

With the previous choices (22) provides:

$$|\tilde{\delta}_v(k)| \leq 0.5|\tilde{\delta}_v(k-1)| + \gamma \tag{26}$$

and, proceeding as in [11] by iterations one gets:

$$|\tilde{\delta}_v(k)| \leq (0.5)^k\,|\tilde{\delta}(0)| + 2\gamma(1 - \left(\frac{1}{2}\right)^k) \leq 1 + 2\gamma \tag{27}$$

where the last inequality has been derived in the worst case since $|\tilde{\delta}(0)| \leq 2$. Interestingly, when $\hat{\phi}_\ell(k)$ approaches $\phi_\ell(k)$, then $\gamma \to 0$ in (25) and in this case the estimation error vanishes asymptotically according to (26). △

In order to exploit the estimated LOE, the following result holds.

Theorem 5.2. *Consider the plant (11) under Assumption 5.1, subject to possible actuator LOE fulfilling Assumption 3.1. The system is assumed fed by*

$$\Delta u(k) = -\frac{1}{\lambda + \|\hat{\bar{\phi}}_1(k)\|^2}\left\{\frac{\rho_1\hat{\bar{\phi}}_1(k)^T\sigma(k)}{\lambda + \|\hat{\bar{\phi}}_1(k)\|^2} + \hat{\bar{\phi}}_1(k)^T\sum_{i=2}^{L}\rho_i\hat{\bar{\phi}}_i(k)\Delta u(k-i+1)\right\}\frac{1}{\bar{\theta} + |\hat{\delta}_v(k)|} \tag{28}$$

with $\bar{\theta} > 0$ being a design parameter and $\hat{\delta}_v(k)$ defined in Theorem 5.1. The parameter λ can be selected such that the asymptotic vanishing of the tracking error is guaranteed: $\lim_{k\to\infty}\|\sigma(k)\| = 0$.

Proof. According to the proof in [19], considering that $|\hat{\delta}_v(k)| \leq 1$, the original development still holds, and the vanishing of the tracking error (here $\sigma(k)$) follows accordingly. △

6. Robust control of the heading angle

According to the control scheme discussed in Section 3, the final step consists in the fulfillment of the condition $s(k+1) = 0$, robustly with respect to the LOE affecting the last equation of (5). To this aim, the following theorem holds.

Theorem 6.1. *Consider the plant (5) under Assumptions 3.1 and 5.1, subject to possible actuator LOE. if the sampling time is chosen small enough such that*

$$\arctan\left(v_y(k)\ v_x(k)\right) \simeq \arctan\left(v_y(k-1)\ v_x(k-1)\right) \tag{29}$$

the sliding variable $s(k)$ vanishes asymptotically and it holds $\theta(k) \to \theta_d(k)$ for $k \to \infty$, inherently fulfilling the constraint (2), if $\omega(k)$ is designed as:

$$T_c\omega(k) = 2\tau s(k); \quad \tau \in (0,1) \tag{30}$$

Proof. The following inequality, equivalent to the standard vanishing condition $|s(k+1)| < |s(k)|$, is here considered: $s(k)\Delta s(k+1) < -\frac{1}{2}\Delta s(k+1)^2$, yielding

$$T_c^2\delta_\omega(k)^2\omega(k)^2 - 2f(k)T_c\delta_\omega(k)\omega(k) + f(k)^2 - s(k)^2 < 0 \tag{31}$$

with $f(k) \triangleq \arctan\left(\frac{v_y(k)}{v_x(k)}\right) - \theta(k)$. In the worst case, the solution interval is

$$\frac{f(k) - |s(k)|}{m_\omega} < T_c\omega(k) < f(k) + |s(k)| \tag{32}$$

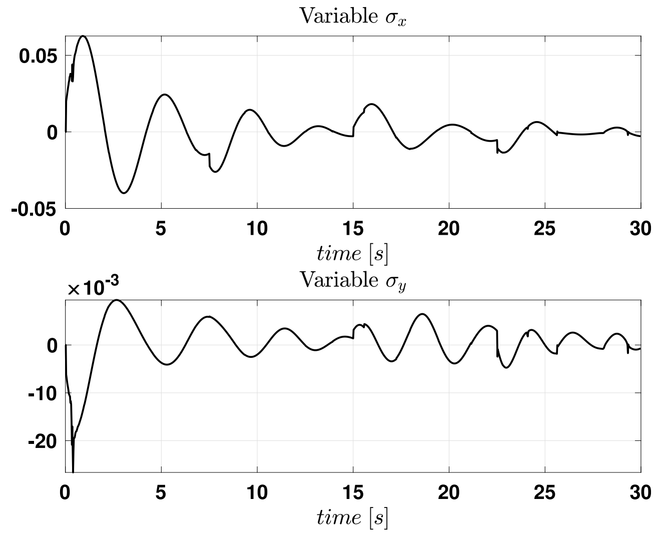

Fig. 2. Output variables $\sigma_x(k), \sigma_y(k)$.

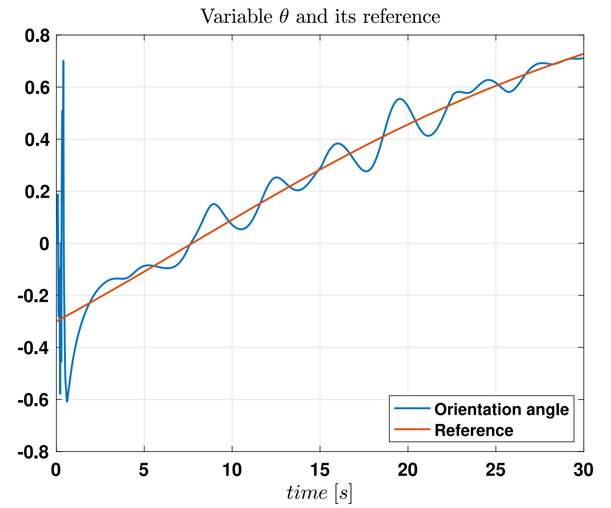

Fig. 3. Heading angle $\theta(t)$ along with its reference variable.

Since (29) holds, $f(k) \simeq s(k)$ and (32) provides:

$$\begin{aligned} &if\ s(k) > 0 \quad 0 < T_c\omega(k) < 2s(k) \\ &if\ s(k) < 0 \quad \frac{2}{m_\omega}s(k) < T_c\omega(k) < 0 \end{aligned} \tag{33}$$

Collecting the previous inequalities, (30) immediately follows. △

7. Simulation studies

Tests have been performed in simulation using the unicycle vehicle model available in the Matlab Robotics System Toolbox, with a sampling time $T_c = 0.02$ s, affected by time-varying LOE coefficients of square-wave form, with levels switching from 1 to $\bar{\delta}_v = 0.7$, $\bar{\delta}_\omega = 0.6$ after 7.5 s. The PFDL model of the (x, y) subsystem has been derived using the following parameters: $\gamma_x = \gamma_y = 0.9$, $L = 3$, $\mu = 0.1$, $\eta = 2$, $\lambda = 3$, $\bar{\phi}_1(0) = \begin{bmatrix} 1 & 0.1 \\ 1 & 2 \end{bmatrix}$, $\bar{\phi}_2(0) = \begin{bmatrix} 1 & 1 \\ 1 & 0.1 \end{bmatrix}$, $\bar{\phi}_3(0) = \begin{bmatrix} 1 & 0.1 \\ 0.1 & 1 \end{bmatrix}$ with I_2 being the 2×2 identity matrix. The identification/accommodation algorithm (19), (28) has been designed with $\mu_\delta = 1$, $\bar{\eta} = \frac{\mu_\delta}{2000}$, $\bar{\theta} = 0.00001$.

The proposed control algorithm does apparently need the setting of a number of design parameters. According to the reported theoretical development, the most critical parameter affecting stability is λ [11], and should be carefully set at first. In addition, selection of the initial condition $\hat{\bar{\phi}}_1(0)$ has been found in previous literature to possibly affect performances, particularly tracking accuracy. The remaining parameters μ, $\gamma_{x/y}$, μ_δ on the contrary, affect shape and promptness of the response (or of the LOE estimation), while the tuning of L has a limited impact but should be kept low to cope with Assumption 3.1.

Some simulation results have been reported in Figs. 2, 3, 4 showing the tracking accuracy, and in Fig. 5, which displays the estimated LOE $\delta_v(k)$. The actual and reference trajectory is shown in Fig. 6.

Remark 7.1. A meaningful comparative analysis with different techniques showing enough consistency with the proposed scheme is indeed difficult, either because of the linearity assumption of the plant (not needed here) or because the non-square MIMO structure of the vehicle, or because the taken approach is not fully replicable by simulation.

Calculation of the IAE criterion gave the scores reported in Table 1, suggesting that the tracking accuracy improvement provided by LOE accommodation is approximately in the range 10%–15%, for the reported setting of the algorithms (an initial transient of 20 samples has been removed to exclude the warming up of the algorithm).

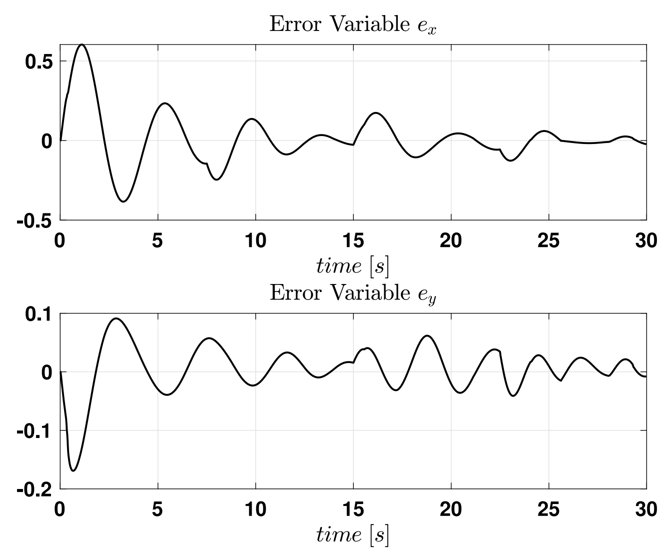

Fig. 4. Tracking errors $e_x(k), e_y(k)$.

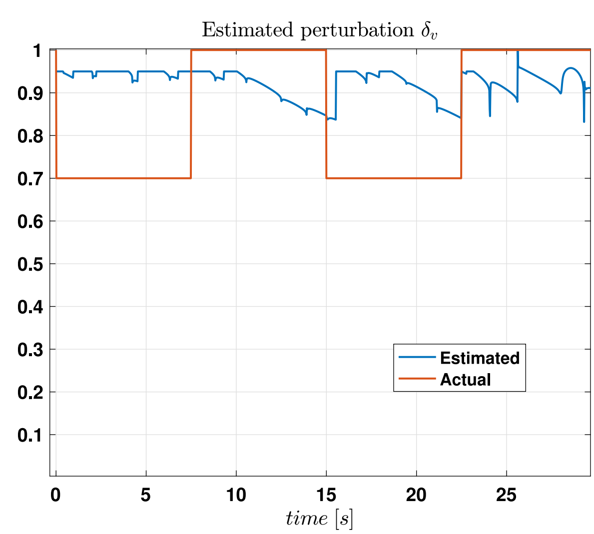

Fig. 5. Estimated loss of effectiveness $\delta_v(k)$.

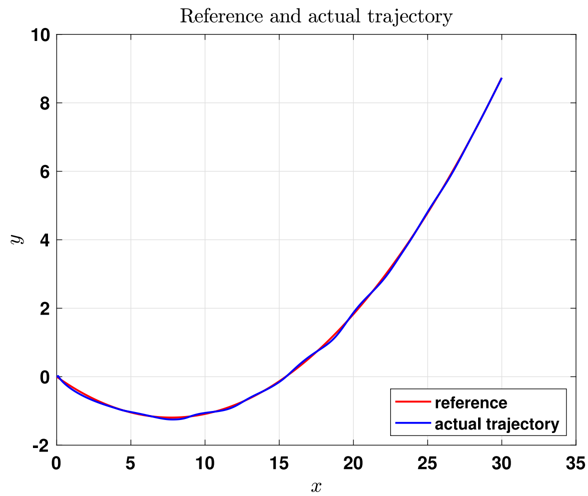

Fig. 6. Actual and reference trajectory of the unicycle.

Table 1
IAE of the tracking error.

	No accommodation	With accommodation
e_x	167.56	150.17
e_y	50.92	43.22

8. Conclusions

In this study, the path following problem of skid-steering vehicles used for precision agriculture contexts has been considered. A robust control architecture including a slip estimation mechanism has been within the DDC framework, in order to accommodate the actuator loss of effectiveness associated to slipping. A redesign of a tracking control algorithm proposed in the literature has been presented, able to ensure fault accommodation with asymptotically vanishing tracking error and coupled with the identification algorithm with proved bounded estimation error. The paper is accompanied by a simulation study supporting the technical development. Results have been shown to provide a noticeable performance improvement in terms of tracking accuracy and control authority, enforcing the adaptation features inherently owned by controllers belonging to the MFAC class. This work is to be considered as a preliminary study, showing indeed promising results. The proposed control scheme is currently undergoing experimental validation, and methodological investigation is being directed towards weakening the assumption of slowly-varying LOE coefficient.

CRediT authorship contribution statement

Maria Letizia Corradini: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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