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Adaptive and predictive non linear control for sliding vehicle guidance

Application to trajectory tracking of farm vehicles relying on a single RTK GPS

Roland Lenain◇, Benoit Thuilot⋆, Christophe Cariou◇, Philippe Martinet⋆

◇ Cemagref
BP50085 - 24, av. des Landais
63172 Aubière Cedex France
roland.lenain@cemagref.fr

⋆ LASMEA
24, av. des Landais
63177 Aubière Cedex France
benoit.thuilot@lasmea.univ-bpclermont.fr

Abstract— **When designing an accurate automated guidance vehicle system, a major problem is sliding and pseudo-sliding effects. It is especially the case in agricultural applications, where a five centimeters accuracy with respect to the desired trajectory is required, even if vehicles move on a slippery ground. Previous works have established that RTK GPS was a very suitable sensor to achieve automated guidance with such a high precision: several control laws have been designed for vehicles equipped with that sensor, and provide the expected guidance accuracy as long as vehicles do not slide. Further control developments have been previously proposed to take sliding into account: guidance accuracy in slippery environment has been shown to be preserved, except transiently at beginning/end of curves, ... In this paper, design of such a control law is first recalled and discussed. Model Predictive Control method is then applied in order to preserve guidance accuracy even during these transitions. Finally, the global control scheme is implemented, and improvements with respect to previous guidance laws are demonstrated through full scale experiments.**

I. Introduction

Environmental problems are taking more and more importance in politic stakes of industrialized countries, especially with respect to agricultural activities. Improvements in agronomic work can clearly be gained via developments of automatic devices and currently, manufacturers are indeed working on automatic vehicle guidance. Such systems allow to improve farmer's comfort, as well as precision and therefore quality of the work carried out all day long. In order to achieve guidance tasks, Global Navigation Satellite System (GNSS) appears to be a very suitable sensor: it can provide with high accuracy absolute position information (up to 2cm using Real Time Kinematic GPS technology). As our application domain concerns vehicles working on open fields (where there is no obstacle to satellite reception), such a sensor is well adapted to design automated guidance system.
Several research teams have been developing such systems with different performances and for dedicated applications. For the moment, only few devices are manufactured (by John Deere [10] or CLAAS [2] for example , ...). They are dedicated to perform specific tasks (straight line following for John Deere or harvesting for CLAAS) and can not be used for general path following. Moreover, most of them use several exteroceptive sensors (GPS and Laser in [2], RTK GPS and inertial sensor in [9], fusion between GPS and vision in [12] and [14]).
In previous work [15], it has been shown that a very satisfactory guidance accuracy (i.e 5 cm) can also be reached, relying on a unique RTK GPS unit. However, capabilities are strongly degraded when sliding appears (during curved path tracking or evolution on sloppy field). Since in agricultural application, vehicle velocity is expected to be tuned by farmer with respect to the work to be achieved, It is impossible to reduce sliding effect by decreasing speed of vehicle as it is done for example in [5]. A natural approach to deal with sliding effects could consist in investigating dynamical modeling and control of vehicle (as it is done in [4], for example). But this kind of approach needs to be fed by parameters, which are very hard to be estimated (such as tire adherence coefficient) especially in real time condition. This can not be done efficiently in our application, and control methods have to be based on a kinematic model.
In this paper, the following approach is developed: an extended kinematical model is defined to take into account for sliding effect. This allows to design a non linear control law with integration of estimated sliding. A Model Predictive Control method is then introduced to prevent guidance task from transient errors when sliding appears in a discontinuous way (e.g. transient errors occurring at beginning/end of curves, as pointed out in previous work [7]). Full scale experiments are discussed and demonstrate capability of such control schemes to follow with accuracy a reference path, whatever its shape is and whatever the ground on which vehicle moves.

II. Kinematic modeling

A. Notations and modeling in absence of sliding

As our objective consists in path following, parameters of model are tracking oriented. Position and orientation of vehicle are so described with respect to the path to be followed. Figure 1 shows this description. Vehicle is viewed as a bicycle (as in celebrated Ackermann model described for example in [16]). Parameters used to build model without sliding are hereafter listed:

- $\mathcal{C}$ is the path to be followed,
- O is the center of vehicle virtual rear wheel,
- M is the point on $\mathcal{C}$ which is the closest to O. M is assumed to be unique, which is realistic when the vehicle remains quite close from $\mathcal{C}$.
- s is the curvilinear coordinate of point M along $\mathcal{C}$, and $c(s)$ denotes the curvature of $\mathcal{C}$ at that point.

- y and $\tilde{\theta}$ are respectively lateral and angular deviation of the vehicle with respect to reference path $\mathcal{C}$.
- δ is the virtual front wheel steering angle.
- v is the vehicle linear velocity, considered here as a parameter, whose value may be time-varying during the vehicle evolution.
- L is the vehicle wheelbase.

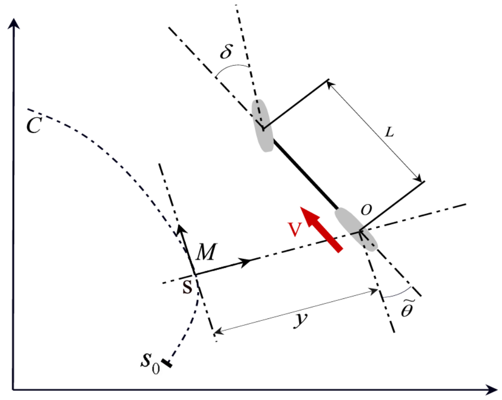


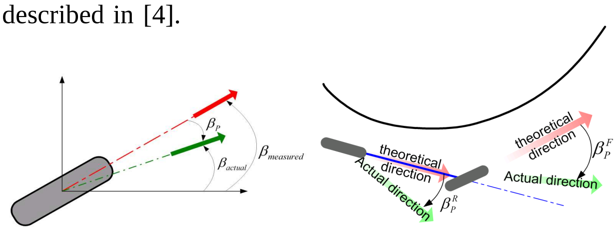
Fig. 1. Classical kinematic model parameters

Using these notations and under rolling without sliding contact conditions, vehicles evolution with respect to the path to be followed can be described by model (1) as established in [13].

$$\left\{\begin{array}{lcl} \dot{s} & = & \frac{V\cos(\tilde{\theta})}{1-c(s)y} \\ \dot{y} & = & V\sin(\tilde{\theta}) \\ \dot{\tilde{\theta}} & = & V\left[\frac{\tan(\delta)}{L} - \frac{c(s)\cos(\tilde{\theta})}{1-c(s)\,y}\right] \end{array}\right. \tag{1}$$

B. Sliding model: Tire Behavior Description (TBD)

Figure 2 shows a set of parameters which can be chosen to describe sliding influence into kinematic model. This sliding description meets theory of vehicle dynamics partially described in [1], [3], and behavior of a tire as described in [4].



(a) Tire behavior (b) Vehicle general behavior

Fig. 2. Sliding parameters to be used in TBD kinematic model

Figure 2(a) shows that the actual speed vector orientation at tire center for a given steering angle is different from direction given by this steering angle. Elasticity of tire material (pseudo-sliding) and non satisfaction of rolling without sliding condition (skidding) generate a cornering angle called here β_P (difference between expected tire speed vector direction and actual one). This tire behavior modifies general vehicle dynamics as described on figure 2(b), where each of the two tires has an actual speed vector direction different from theoretical one. Instead of being a standard car like vehicle model, this description becomes closer to a two steering axles mobile robot, where front steering angle consists in an actual angle and a cornering one $(\delta + \beta_P^F)$ and rear steering angle reveals rear cornering angle (β_P^R).

Relying on this remark, it can then be shown that vehicle dynamics can be described (see [8] for instance) by equations (2), which constitute vehicle model incorporating sliding effects based on tire behavior description (TBD). One can check than considering a null sliding $((\beta_P^F, \beta_P^R) = (0,0))$ model (2) becomes equal to classical model (1).

$$\left\{\begin{array}{lcl} \dot{s} & = & \frac{V\cos(\tilde{\theta}+\beta_P^R)}{1-c(s)y} \\ \dot{y} & = & V\sin(\tilde{\theta}+\beta_P^R) \\ \dot{\tilde{\theta}} & = & V\left[\cos\beta_P^R\frac{\tan(\delta+\beta_P^F)-\tan\beta_P^R}{L} - \frac{c(s)\cos(\tilde{\theta}+\beta_P^R)}{1-c(s)\,y}\right] \end{array}\right. \tag{2}$$

C. Sliding parameters estimation

One main problem in the approach chosen is estimation of sliding: the set of parameters here before introduced has to be estimated on line, as it is not constant, due to various and time varying parameters (steering angle, ground properties, slope, ...).

Since a unique exteroceptive sensor is used, we must assume that all vehicle dynamics is described using model (2). Several dynamic behaviors are so ignored (such as roll or pitch) but their effects on path tracking accuracy are considered negligible with respect to sliding and pseudo sliding. Using this assumption, sliding estimation is done by comparison between expected vehicle behavior using model without sliding accounted (i.e. model (1)) and actual vehicle dynamics, as described on scheme depicted on figure 3 (adaptive estimation using internal model).

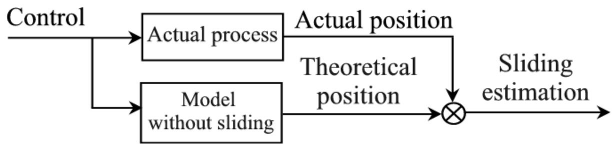


Fig. 3. Sliding detection

Since assumption of negligible pitch and roll effect on estimation is not always validated, misestimation on sliding parameters can be observed. However, as it has been established in [7], this estimation algorithm allows nevertheless an accurate description of vehicle behavior in presence of sliding.

III. Control Design

As it has been already pointed out, sliding model (i.e. model (2)) has a classical structure of car like mobile robot with two steering axles and can then easily be turned into a chain system to design a control law including sliding parameters. This control design is hereafter detailed.

1) Chained system conversion: As developed in [13], one way to build a nonlinear suitable control law for mobile robots is to turn their equations into a so called chained form. In dimension 3 (as expected in our application), chained form is given by:

$$\begin{cases} \dot{a}_1 &= m_1 \\ \dot{a}_2 &= a_3\, m_1 \\ \dot{a}_3 &= m_2 \end{cases} \qquad (3)$$

where $A = [a_1,\, a_2,\, a_3]^T$ and $M = [m_1,\, m_2]^T$ are resp. the state and control vectors. One can check that such a system is almost linear: replacing time derivation by a derivation with respect to a_1 leads to system (4) (with notation $a_i' = \frac{da_i}{da_1}$).

$$\begin{cases} a_1' &= 1 \\ a_2' &= a_3 \\ a_3' &= m_3 = \frac{m_2}{m_1} \end{cases} \qquad (4)$$

By analogy with chained transformations proposed for car like vehicle in the rolling without sliding case, the following state transformation $(s, y, \tilde{\theta}) \rightarrow (s, y, \tan\left(\tilde{\theta} + \beta_P^R\right)[1 - c(s)y])$ is here proposed in association with control transformation given by (5):

$$\begin{cases} m_1 &= \frac{V\cos\left(\tilde{\theta}+\beta_P^R\right)}{1-c(s)y} \\ m_2 &= \frac{d}{d\,s}\left(\tan\left(\tilde{\theta}+\beta_P^R\right)[1-c(s)y]\right) \end{cases} \qquad (5)$$

According to equation (5), calculation of control m_2 implies derivation of sliding parameter β_P^R provided by estimation algorithm (figure 3). For convenient reasons this time varying parameter will be treated as a constant. Such an approximation has appeared to be relevant during most experiments. Using this hypothesis, calculation of m_2 gives us, under existence conditions (satisfied in practical situations):

$$\begin{aligned} m_2 \;=\; & -c(s)V\sin\left(\tilde{\theta}+\beta_P^R\right)\tan\left(\tilde{\theta}+\beta_P^R\right) \\ & + \frac{1-c(s)y}{\cos^2\left(\tilde{\theta}+\beta_P^R\right)} V\left[\cos\beta_P^R\left(\frac{\tan(\delta+\beta_P^F)-\tan\beta_P^R}{L}\right)\right. \\ & \left. - \frac{c(s)\cos\left(\tilde{\theta}+\beta_P^R\right)}{1-c(s)y}\right] \end{aligned} \qquad (6)$$

2) Control law design: Since kinematical model (2) with sliding accounted is validated and can be turned into chained form (4), a natural expression for the virtual control law is:

$$m_3 \;=\; -K_d a_3 - K_p a_2 \quad (K_p, K_d) \in \Re^{+2} \qquad (7)$$

since it insures that a_2 obeys the following equation:

$$a_2'' + K_d a_2' + K_p a_2 = 0 \qquad (8)$$

Equation (8) establishes the following convergences :

- $\underline{a_2 \rightarrow 0}$: this is equivalent to $y \rightarrow 0$ (according to the state transformation) and ensures convergence of the vehicle to the path to be followed (null lateral deviation).
- $\underline{a_3 \rightarrow 0}$: this implies (according to the state transformation) that $\tilde{\theta} \rightarrow \beta_P^R$. This condition shows that, in presence of sliding, the vehicle heading will not be parallel to the reference path tangent, but will compensate effect of rear cornering angle to ensure the convergence of lateral deviation to zero. Vehicle then moves crabway.

The actual control variable is vehicle steering angle. It can be obtained by reporting (7) in (6), and inverting the resulting relation. We obtain:

$$\begin{aligned} \delta \;=\; & \arctan\left\{\frac{L}{\cos\beta_P^R}\left[c(s)\frac{\cos\tilde{\theta}_2}{\alpha} + A\frac{\cos^3\tilde{\theta}_2}{\alpha^2}\right]\right. \\ & \left. + \tan\beta_P^R\right\} - \beta_P^F \end{aligned} \qquad (9)$$

where: $$\begin{cases} \tilde{\theta}_2 &= \tilde{\theta} + \beta_P^R \\ \alpha &= 1 - c(s)y \\ A &= -K_d\alpha\tan\tilde{\theta}_2 - K_p y + c(s)\alpha\tan^2\tilde{\theta}_2 \end{cases}$$

Performances of such a control law can be adjusted by tuning gains K_p and K_d which can be viewed as proportional and derivative actions of a linear controller. In experimental results hereafter detailed, gains are set to values (10). They impose a convergence to the reference path within 15m, without overshoot.

$$\begin{cases} K_p &= 0.09 \\ K_d &= 0.6 \end{cases} \qquad (10)$$

IV. Experimental results

A. Experimental background

This paper deals with actual experiments carried out in partnership with manufacturer CLAAS. Figure 4 shows experimental vehicles (an Ares 640 tractor and a Dominator combine harvester manufactured by CLAAS) on which are tested control laws developed to perform automatic guidance applications.

Fig. 4. Vehicles used for actual experiments

The main sensor used to ensure control is a RTK GPS manufactured by Thales Navigation (Aquarius 5002 unit) which supplies a positioning signal, with a 2cm accuracy, at a 10Hz sampling frequency. Mobile antenna is placed on the top of the vehicle straight up the center of rear axle (since it is the vehicle control point as described on figure 1). In addition to absolute position informations, sensor system implemented on vehicle allows to access to several other data:

- Vehicle velocity: provided by GPS sensor.
- Vehicle heading: estimated via a Kalman filter.

Kalman filtering algorithm is achieved using vehicle kinematic model fed by steering angle and velocity measurements. Innovation part is constituted by model output and heading deduced from speed vectors supplied by GPS, Kalman gain is chosen as a constant and tuned to 0.1. This allows both to smooth and to improve accuracy of heading information.

B. Adaptive control law capabilities

Capabilities and drawbacks of control law (9) can be highlighted by the following experiment. It consists in curve following on an actual field at $6 km.H^{-1}$(figure 5). This path is representative of guidance conditions in which sliding appears and reduces trajectory tracking accuracy. Several other experimentations (especially on sloping fields) are detailed in [7] and confirm conclusions derived hereafter.

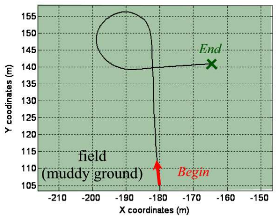


Fig. 5. Actual path to be followed

Figure 6 depicts lateral deviation of vehicle during curved path following relying on control law with sliding (9) (in red dotted line) and on control law without sliding accounted (in black solid line). It can be observed, that when curvature is constant (after 65m) new control law is able to ensure convergence of vehicle lateral deviation to zero.
However, at the beginning and at the end of the curve, curvature modifications introduce a step on sliding parameters β_P^F and β_P^R, and a non negligible lateral deviation is observed (at 40m and 80m). This effect is amplified as sliding is considered as constant or slow varying in control law design, see above.This is clearly not relevant at beginning/end of a curve. Sliding effects are then significantly compensated during the curve, but overshoots at transient phases have now to be addressed.

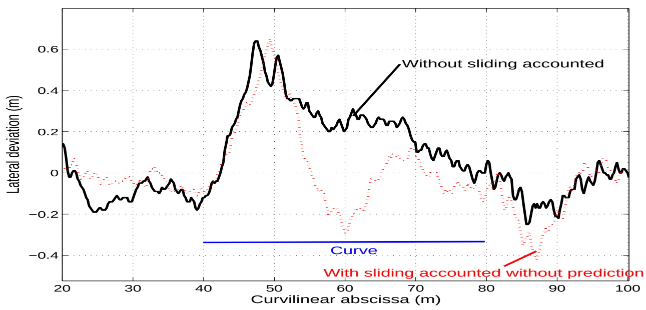


Fig. 6. Lateral deviation during curved path following

V. Predictive Control

Several phenomena explain the overshoots herebefore discussed: low level actuators delays, inertia of vehicle, delay for sliding estimation. However, reference path is totally known and low level properties can be identified. Consequently, it is possible to take into account for these data to anticipate control before variations of curvature. Even if other sources of overshoots (inertia, and sliding variation) are not yet embedded, prediction is expected to reduce significantly global overshoots. Application of Model Predictive Control principle to vehicle control in presence of sliding is hereafter detailed.

A. Separation of control with sliding accounted

Since correction of deviations $(y, \tilde{\theta})$ has not to be anticipated, and since sliding parameters cannot be predicted, prediction algorithm will only be applied on a subpart of control law defined by (9).

A key point in path tracking task is that under rolling without sliding conditions and without any path tracking deviation (when the vehicle is perfectly on the path to be followed), steering angle (which defines vehicle curvature radius) must obey to:

$$\frac{\tan\delta}{L} = c(s) \tag{11}$$

Naturally, geometrical condition (11) can also be obtained by applying null condition of sliding and deviation ($y = 0$,$\tilde{\theta} = 0$,$\beta_P^R = 0$,$\beta_P^F = 0$) to control law (9):

$$\delta_{(y=0,\tilde{\theta}=0,\beta_P^R=0,\beta_P^F=0)} = \arctan(Lc(s)) \tag{12}$$

Equation (12) invites to divide control law (9) into the two following additive terms:

$$\delta = \delta_{Traj} + \delta_{Deviation}$$
$$\left\{ \begin{array}{rcl} \delta_{Traj} &=& \arctan(u) \\ \delta_{Deviation} &=& \arctan(\frac{v}{1+uv+u^2}) - \beta_P^F \end{array} \right. \tag{13}$$

Equation (13) is built using the following definitions: u is the term which supplies equation (12) when sliding and deviation are null:

$$u = \frac{L}{\cos\beta_P^R} c(s) \frac{\cos\tilde{\theta}_2}{\alpha}$$

While v is defined using identification between equations (9) and (14):

$$\delta = \arctan(u + v) - \beta_P^F \tag{14}$$

Equation (13) is then obtained, using the trigonometrical relation: $\arctan(u + v) = \arctan(u) + \arctan(\frac{v}{1+u.v+u^2})$

Expression (13) of control law with sliding accounted is written as the addition of two terms:

- δ_{Traj}: Non null term when deviations and sliding are equal to zero. This term mainly depends on reference path properties. It will be used to design prediction algorithm.
- $\delta_{Deviation}$: Null term when deviations and sliding are equal to zero. This term mainly depends on deviations $(y, \tilde{\theta}_2)$ and ensures their convergence to 0. This term will stay unchanged by prediction algorithm.

B. Prediction technique applied on δ_{Traj}

Prediction algorithm developed in this paper is based on PFC (Predictive Function Control) detailed in [11] also called Model Predictive Control (MPC). Figure 7 presents notations used in PFC applied to our application and introduces the principle.

In the present case PFC will be applied only on δ_{Traj}. To feed PFC equation, it will be considered that only delay due to low level steering actuator (hereafter named process) is responsible for overshoots shown on figure 6. However, the predictive action thus introduced, thanks to a sufficiently long horizon of prediction, is expected to fight other kinds of delays (i.e: inertia of vehicle and estimation of sliding parameters). Then, let δ^C denote the desired steering angle, as computed from control law (9) (control law without prediction) and δ^R denote the actual steering angle (as measured by the steering sensor). These two quantities are related by the process model, assumed to be a linear second order one.

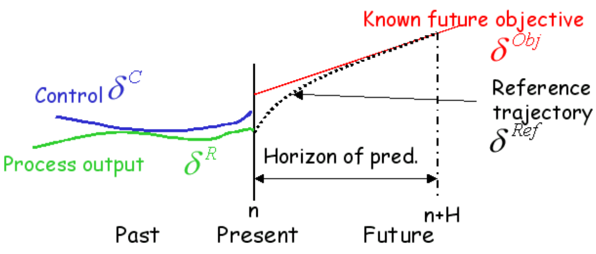


Fig. 7. Notations and general description of PFC

For implementation purposes, discrete control is hereafter used. At current iteration n PFC considers previous data (past), current data (present) and what will happen on a horizon of prediction called H (future). On this horizon H, PFC needs to access to the future objective for δ^R (called δ^{Obj}). When applying PFC to δ_{Traj}, this objective at iteration $[n+H]$ hereafter named $\delta^{Obj}_{[n+H]}$ is (considering we will have no deviation or sliding) $\delta^{Obj}_{[n+H]} = L.c(s+dH)$ (where dH is the distance associated to the horizon of prediction H computed from vehicle velocity). $\delta^{Obj}_{[n+i]}$ with i in $[0..H]$ can be computed in a similar way.

Then, a reference evolution for δ^R (called δ^{Ref}) is defined and shows the way chosen to make process output join $\delta^{Obj}_{[n+H]}$ (i.e. $\delta^{Ref}_{[n+H]} = \delta^{Obj}_{[n+H]}$). In our case, reference evolution is defined by equation:

$$\delta^{Ref}_{[n+i]} = \delta^{Obj}_{[n+i]} - \gamma^i.(\delta^{Obj}_{[n]} - \delta^R_{[n]})$$

where $i \in [0..H]$ and $\gamma \in [0;1]$ is a parameter which allows to tune response time to join final objective.

C. Prediction algorithm and control

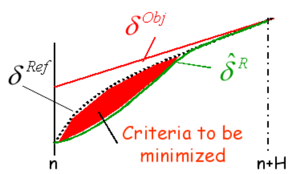


Fig. 8. Visualization of criteria to be minimized

For convenient reasons, details of predictive algorithm are not presented in this paper (see [11] for more development): only principle is here detailed. Using the different elements described herebefore and depicted on figure 7, the goal of the whole algorithm is to find the set of future control values $(\delta^C_{[n+1]} \dots \delta^C_{[n+H]})$ which minimizes difference between reference evolution δ^{Ref} and future process output δ^R. If $\hat{\delta}^R_{[n+j]}$ denotes output process computed from its second order model, then the criteria to be minimized is given by (15), and visually described on figure 8.

$$D(n) = \Sigma_{j=0}^{H} \left\{ \hat{\delta}^R_{n+j} - \delta^{Ref}_{n+j} \right\} \tag{15}$$

Final control law is the addition between $\delta_{Deviation}$, which stays unchanged, and δ^{Pred}_{Traj}, output of PFC algorithm applied on δ_{Traj}. Figure 9 depicts and synthesizes global scheme of Predictive Function Control applied on guidance task with sliding accounted.

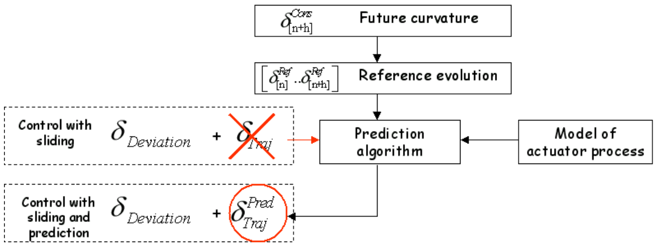


Fig. 9. Global scheme of predictive control used

As a theoretical check for this predictive algorithm applied to vehicle guidance, a simulation result with a curved path is presented on figure 10. Sliding and low level actuator properties are simulated, and the following plots are presented on figure 10:

- In black solid line: lateral deviation using control law without sliding accounted
- In red dotted line: lateral deviation using control law with sliding accounted (9) but without prediction
- In green dashed line: lateral deviation using control law with sliding accounted (9) and using prediction method depicted on figure 9. Horizon of prediction has been set to 0.8s (H =8 iterations) and $\gamma = 0.4$

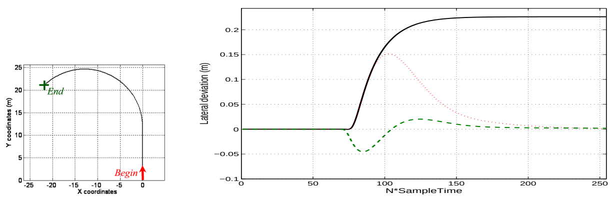


Fig. 10. Theoretical result of predictive control with sliding

As expected, control law using predictive method allows to reduce significantly overshoots at the beginning of the curve (iteration 75). Predictive control allows to anticipate the turning of the wheel before the beginning of the curve, so that actual steering angle is effective as soon as curve appears. On the contrary, without predictive control, wheels are steered as curve appears and delay on actuator process implies overshoots as curvature is modified.

D. Full scale experiments

In order to compare tracking accuracy with and without predictive part, automatic guidance along the same reference path than previously, shown on figure 5, has been achieved. Results are depicted on figure 11, with the same convention than on figure 10.

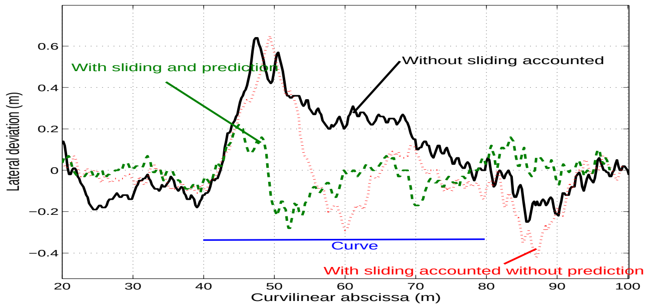


Fig. 11. Result of predictive control in full scale experiment

In this actual case, parameters for prediction are set to: $H = 1s$ (10 iterations) and $\gamma = 0.2$. We notice that during path following using prediction and sliding accounted, overshoots at the begin and at the end of the curve are considerably reduced (even null at the end of curve).
In predictive algorithm, only delay due to low level properties has been taken into account. Inertia of vehicle and delays due to sliding parameter estimation algorithm have been neglected. However, the length of the horizon of prediction allows to compensate for the delay due to these latter effects: tuning H and γ permits to optimize behavior of vehicle even if model of process takes only into account low level actuation. Currently, no optimization study about these parameters were carried out (horizon of prediction is constant whatever vehicle velocity is).
Another interesting property of predictive control in farm applications is that anticipation smoothes significantly control sent to actuator. This reduces large variations of sliding parameters and consequently delay on their estimation.
Several other tests have been achieved on various grounds (road, gravel), for different curvatures (S trajectory, sinusoidal path) at different speeds. They confirm results depicted on figure 11 and maximal lateral deviation observed is equal to 20cm.

VI. Conclusion and Future Works

This paper proposes two main developments with respect to automatic off-road vehicles guidance. First, adaptive control allows to make vehicle converge to a null deviation when sliding occurs in a slow varying way. Secondly, predictive principle applied to guidance task permits, on one hand, to reduce overshoots due to different delays applied on data used in control (due to hardware actuator, vehicle inertia, estimation, ...), and on the other hand to smooth control so that sliding evolution approaches slow-varying assumption.

According to first results here before presented and without optimization of prediction parameters, positive action of control method presented in the paper can clearly be seen. Indeed, maximal lateral deviation using this control remains inferior to 20cm, when a constant 50cm deviation was observed with control law which did not rely on predictive and sliding control. Moreover, during harsh guidance conditions, vehicle mainly stay around a null deviation.

To eliminate totally overshoots, especially at the beginning of a curve, optimization of prediction parameters must be studied. In particular, horizon of prediction must be related to vehicle velocity. Improvement in prediction can be investigated by integrating inertial parameters inside process model used in PFC (this is an important point, especially if tools are implemented on tractor). Finally, prediction principle has to be extended to guidance on sloping fields where sliding problems are very close to the curve case (especially in slope variation case).

Finally, a key point for automated farm vehicle guidance is estimation of data required for guidance task, which are strongly disturbed by parasitic movements such as cabin oscillation (as GPS antenna is situated on top of the cabin). Important works relying on observers, and making use of other sensors are currently investigated and aim at improving accuracy of measured signals.

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