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Model Predictive Control for Vehicle Guidance in Presence of Sliding: Application to Farm Vehicles Path Tracking

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Abstract— **One of the major current developments in agricultural machinery aims at providing farm vehicles with automatic guidance capabilities. With respect to standard mobile robots applications, two additional difficulties have to be addressed: firstly, since farm vehicles operate on fields, sliding phenomena inevitably occurs. Secondly, due to large inertia of these vehicles, small delays introduced by low-level actuators may have noticeable effects. These two phenomena may lower considerably the accuracy of path following control laws.**

In this paper, a vehicle extended kinematic model is first built in order to account for sliding phenomena. These latter effects are then taken into account within guidance laws, relying upon nonlinear control techniques. Finally, a Model Predictive Control strategy is developed to reduce the effects induced by actuation delays and vehicle large inertia. Capabilities of this control scheme is demonstrated via full scale experiments carried out with a farm tractor, whose realtime localization is achieved relying uniquely upon a RTK GPS sensor.

I. Introduction

Pollution concern is taking a growing place in all activities. This is especially true in agriculture, since several tasks (e.g. fertilizer spraying) may be environmental-unfriendly (e.g. imperfect farm tractor trajectories lead to overlapping spraying areas within the field, where fertilizer concentration will be abnormally high). One possibility to deal with such problems is to provide farm vehicles with automatic guidance capabilities. Such devices could clearly increase guidance accuracy and moreover guarantee it during the all day long, leading to improvements on both the quality of the agronomic tasks carried out and on productivity. Furthermore, farmers would appreciate to be delivered from the arduous driving task.

Several guidance devices have already been marketed (e.g. CLAAS [1], John Deere [7], see also [10]). However, these systems have been designed to perform specific tasks (harvesting [1], achieving perfectly straight runs [7],and so on). Moreover, they do not take into account for sliding phenomena, despite these effects inevitably occur during agricultural tasks, and considerably lower guidance accuracy (as pointed out in [12]). Most of these devices rely on GPS sensor, since it can provide a centimeter accuracy in its Real Time Kinematic version (RTK-GPS). Additional exteroceptive sensors are generally used jointly with RTK GPS, such as INS, laser, cameras, and so on.

In previous works, automatic guidance of farm vehicles along arbitrary curved paths, relying uniquely upon a RTK-GPS sensor, has been addressed ([13]). Nonlinear control techniques are shown to provide with very satisfactory guidance accuracy (about 10 cm), excepted when vehicles undergo sliding (when entering into sharp curves or when moving along sloping fields). The most natural way to design guidance laws accounting for sliding phenomena should be to rely upon a vehicle dynamical model. However, this implies on-line estimation of numerous parameters (such as adherence conditions, see [2]...), very hard to be measured or induced, especially in real-time conditions. Therefore, nonlinear control law accounting for sliding effects is designed in [3] relying upon an extended kinematic model. Guidance accuracy in presence of sliding is shown to be improved. However transient overshoots due to actuation delays and vehicle large inertia are still observed at beginning/end of curves, since sliding effects appear/disappear in a discontinuous way. The opportunity for using Model Predictive Control strategy to address this difficulty has been discussed in [4], and preliminary results have been displayed. In this paper, Model Predictive Control law is designed, and its efficiency is investigated via full-scale experiments.

This paper is organized as follows: vehicle modelling in presence of sliding is first recalled. Estimation of variables required to feed it is described as well as experimental material (vehicle and sensor on boarded). Derivation of a nonlinear control law accounting for sliding effects is then presented, and its capabilities are discussed. Next Model Predictive Control techniques are applied in order to guarantee satisfactory guidance accuracy, even when sliding effects undergo discontinuities. Finally, full scale experiments in actual agricultural conditions (wet fields) and with respect to reference paths enclosing high curvature parts, are reported. Guidance accuracy is shown to stay within the satisfactory range $\pm 15cm$.

II. Extended Kinematic model

A. Notations

Vehicle modelling proposed in this paper takes into account for sliding phenomena by extending standard kinematic model built under the assumption of pure rolling without sliding (named bicycle or Ackermann model, e.g. [14] or [13]). Notations are hereafter described and depicted on figure 1:

- $\mathcal{C}$ 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 vehicle lateral and angular deviation 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 vehicle evolution.
- L is the vehicle wheelbase.

Two sliding parameters, similar to side slip angles in vehicle dynamical models (see [2] e.g.) are introduced to account for sliding effects (details about these parameters are available in [3]).

- β_P^R is rear side slip angle defined by the difference between actual speed vector direction at rear axle center O (described by the rear arrow v on figure 1) and theoretical one under rolling without sliding assumption (this direction is superposed with vehicle centerline).
- β_P^F is the front side slip angle. It is the difference between actual speed vector direction depicted by the red arrow on figure 1 and theoretical one without sliding accounted (defined by actual steering angle δ).

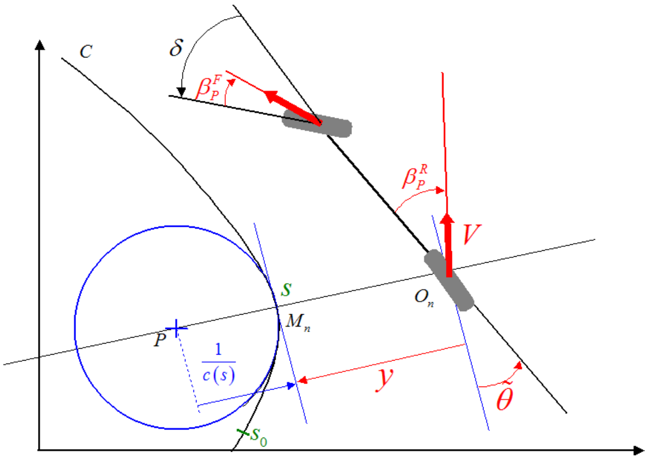

Fig. 1. Classical kinematic model parameters

B. Modelling and equations

Vehicle description shown on figure 1 accounting for the actual speed vectors directions (and therefore accounting for sliding effects) is equivalent to a vehicle with two steering angles moving under rolling without sliding conditions. More precisely, considering an equivalent front steering angle δ^F as the sum of the actual steering angle and front side slip angle ($\delta^F = \delta + \beta_P^F$) and an equivalent rear steering angle δ^R equal to rear side slip angle ($\delta^R = \beta_P^R$), our model is consistent with classical descriptions of two steering wheeled mobile robots. Then, as it has been established for example in [5], vehicle evolution with respect to the path to be followed can be described by model (1).

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

With respect to model (1), the objective of path tracking control laws is to ensure the convergence of lateral deviation (denoted y) to 0. In agricultural applications, vehicle velocity v is assumed to be controlled by the driver (v is generally constant during work period). As a consequence, steering angle δ is the only control variable available to achieve guidance task.

Classical model (e.g. without sliding accounted) used in mobile robots literature can be recovered from model (1) by applying null sliding parameters: $(\beta_P^R, \beta_P^F) = (0, 0)$.

C. Model feeding: measurements and estimations

1) Direct measurement data: The main sensor used to achieve path tracking is a RTK GPS manufactured by Thales Navigation (Aquarius 5002 unit). It supplies an absolute position with a 2cm accuracy at a 10Hz rate. Furthermore, velocity vectors are also available. As it can be viewed on figure 2, GPS antenna is located on the top of the vehicle (a CLAAS Ares 640 tractor), straight up control point O (see also figure 1). In addition an angular sensor, mounted on front wheel, provides the actual steering angle.

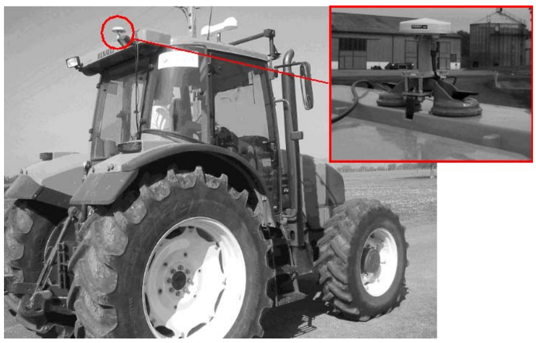

Fig. 2. GPS antenna location on vehicle

With such an equipment, s and y can be directly measured. A Kalman filter (using speed vector measurement and vehicle modelling) is used to provide $\tilde{\theta}$. Therefore, all state variables of classical kinematic model (i.e. s, y, $\tilde{\theta}$) are available. On the contrary, the sliding parameters β_P^F and β_P^R cannot be measured directly without additional sensor. On line estimation of these parameters is important, since they are not constant and depend on tire/ground contact properties.

2) Sliding parameters estimation: To complete the knowledge of the extended model variables, sliding parameters are estimated using an adaptive internal model scheme, such as depicted on figure 3. This estimation algorithm relies upon the following assumption: difference between actual position measured by RTK-GPS sensor and foreseen position computed from classical kinematic model (without sliding) is only due to sliding effects. Therefore, model without sliding accounted is simulated in parallel to the actual process and outputs are compared to calculate the two sliding parameters. As it has been shown in [3], simulations using model (1) fed by sliding parameters computed according to this adaptive algorithm supplies results very close to actual behavior recorded.

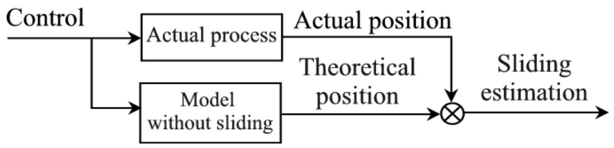

Fig. 3. Sliding detection

III. Control design

As it has already been pointed out, model accounting for sliding (i.e. model (1)) is consistent with standard models of car like mobile robots with two steering axles. Therefore, it can easily be turned into a chain system in order to design control laws. This control design is hereafter detailed.

A. Chained system conversion

It is established in [11] that mobile robots kinematic models can be converted, in an exact way, into a so called chained form. In the case of Model (1), state and control transformations achieving this conversion can be built from those proposed in [11]. They can be shown to be:

state transformations

$$(a_1, a_2, a_3) = \left(s, y, \tan\left(\tilde{\theta} + \beta_P^R\right)[1 - c(s)y]\right)$$

control transformations

$$\left\{\begin{array}{lcl} m_1 & = & \frac{V\cos\left(\tilde{\theta}+\beta_P^R\right)}{1-c(s)y} \\ m_2 & = & \frac{d}{ds}\left(\tan\left(\tilde{\theta}+\beta_P^R\right)[1-c(s)y]\right) \end{array}\right. \quad (2)$$

Reporting (2) in model (1) leads to the expected chained form, where only the two last equations (a_2', a_3') are required for process description:

$$\left\{\begin{array}{lcl} a_2' & = & a_3 \\ a_3' & = & m_3 = \frac{m_2}{m_1} \end{array}\right. \quad (3)$$

Derivation with respect to curvilinear abscissa (with notation $a_i' = \frac{d\,a_i}{d\,a_1} = \frac{d\,a_i}{d\,s}$) has been substituted to time derivation in order to reveal linear structure of chained form equations.

According to equation (2), calculation of new control m_2 requires derivation of sliding parameter β_P^R. As no evolution model is available for β_P^R (since it is provided by estimation algorithm, see figure 3), this time varying parameter will be treated as a constant. Such an approximation has appeared to be relevant during most experiments.

B. Preliminary control design

Since vehicle extended kinematic model (1) can be turned into chained form (3), a natural expression for the virtual control law is:

$$m_3 \;=\; -K_d a_3 - K_p a_2 \quad (K_p, K_d) \in \Re^{+2} \quad (4)$$

since it insures that a_2 obeys the following equation:

$$a_2'' + K_d a_2' + K_p a_2 = 0 \quad (5)$$

Equation (5) establishes the following convergences :

- $\underline{a_2 \to 0}$: in view of state transformation (2), this is equivalent to $y \to 0$ Therefore, vehicle convergence to the path to be followed is ensured (null lateral deviation).
- $\underline{a_3 \to 0}$: in view of state transformation (2), this implies that $\tilde{\theta} \to \beta_P^R$. 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 (4) into (2), and inverting the resulting relation. We obtain:

$$\begin{array}{lcl} \delta & = & \arctan\left\{\frac{L}{\cos\beta_P^R}\left[c(s)\frac{\cos\tilde{\theta}_2}{\alpha} + A\frac{\cos^3\tilde{\theta}_2}{\alpha^2}\right]\right. \\ & & \left. + \tan\beta_P^R\right\} - \beta_P^F \end{array} \quad (6)$$

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

Control law (6) has been designed from an exact linearization approach. Therefore, it is more robust than any control laws relying on tangent linearization techniques. Moreover, its performances can easily be adjusted by tuning gains K_p and K_d, which can be viewed as proportional and derivative actions of a linear controller. Since error equation (5) is driven by $a_1 = s$ (instead of time), gain tuning allows to impose a settling distance (instead of a settling time), so that control performances are clearly independent from vehicle velocity. In experimental results hereafter detailed, gains are set to $(K_p, K_d) = (0.09, 0.6)$. They impose a convergence to the reference path within 15m, without overshoot.

C. Capabilities of nonlinear control law (6)

Full scale experiments reported in [3] establish that control law (6) provides with accurate guidance capabilities ($\approx$ 10cm) when sliding conditions are almost constant (i.e. when the vehicle follows paths with a constant curvature, or when it describes a straight line on a field with a constant slope). However, when sliding is varying (i.e. when the vehicle is entering into a curve), transient overshoots in lateral deviation can be observed (some experimental results obtained with control law (6) are reported in forthcoming section V). These overshoots originate from delays induced by low-level actuators and to vehicle large inertia that has not been taken into account in control law (6), since Model (1) does not describe vehicle dynamical features. These difficulties are addressed in the next section, relying on Model Predictive Control techniques.

IV. Predictive Control

One way to reject delays phenomenon and overshoots then generated is to design a predictive algorithm. For instance, in order to reduce overshoots at beginning of curve, control law values delivered to the actuator should be anticipated, in such a way that, when the vehicle actually enters into the curve, actual steering angle is consistent with curvature of reference path, despite actuator delay. To achieve this objective, Model Predictive Control (MPC) algorithm (such as developed in [8] and in [9]) is used.

A. Control law reformulation

The only reliable data on which anticipation can be achieved is reference path curvature. Therefore, control law (6) has to be split into two terms: the first one consisting in the contribution of reference path curvature to the value of δ, and the second one gathering the contributions of deviations y and $\tilde{\theta}$ and of sliding parameters β_P^F and β_P^R. Anticipation could be achieved on the first term, but of course not on the second one.

To achieve such a separation, just consider the case where the vehicle is perfectly on the path to be followed. Steering angle δ must then be equal to:

$$\frac{\tan\delta}{L} = c(s) \tag{7}$$

This geometrical condition can be graphically verified on figure 1 and can be deduced from control law (6), by setting deviations and sliding parameters to zero: $(y, \tilde{\theta}, \beta_P^R, \beta_P^F) = (0, 0, 0, 0)$. The term which is non null in that situation can be isolated by rewriting control law (6) as:

$$\delta = \delta_{Traj} + \delta_{Deviation}$$
$$\begin{cases} \delta_{Traj} &= \arctan(u) \\ \delta_{Deviation} &= \arctan(\frac{v}{1+uv+u^2}) - \beta_P^F \end{cases} \tag{8}$$
$$\text{where:} \quad u = \frac{L}{\cos\beta_P^R} c(s) \frac{\cos\tilde{\theta}_2}{\alpha}$$
$$v = \frac{L}{\cos\beta_P^R} A \frac{\cos^3\tilde{\theta}_2}{\alpha^2} + \tan\beta_P^R$$

Relation $arctan(u+v) = arctan(u) + arctan\left(\frac{v}{1+u\,v+u^2}\right)$ has been used to derive expression (8) from control law (6). The two terms in (8) exhibit the following expected features:

- 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.

B. Predictive control design

Since the shape of the reference path is totally known, the desired value for δ_{Traj}, (called hereafter δ^{Obj}) after a defined time (called horizon of prediction H) can be inferred straightforwardly from s and V (*resp.* vehicle curvilinear abscissa and velocity). Moreover, via some experiments, actuator behavior can be identified. Therefore, future actual steering angle (called $\hat{\delta}^{actual}$) to a set of control δ_{Traj} can be predicted. In our case, actuator behavior has been identified as a second order. These notations are depicted on figure 4. This figure shows also δ^{Ref}, which defines the desired convergence shape for $\hat{\delta}^{actual}$ to reach δ^{Obj} at the horizon H. In our case, this reference trajectory has been chosen as a discrete first order:

$$\delta^{Ref}_{[n+i]} = \delta^{Obj} - \gamma^i.(\delta^{Obj}_{[n]} - \hat{\delta}^{actual}_{[n]}) \tag{9}$$

Parameter γ allows to tune the settling time to the future objective and can be set with respect to the application.

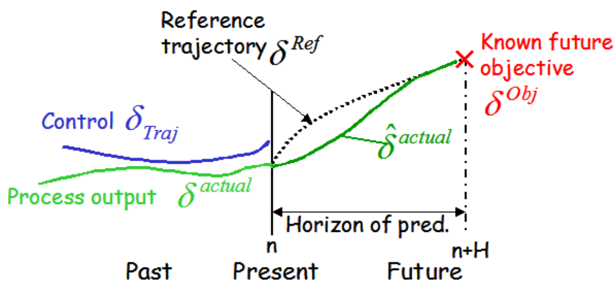

Fig. 4. Notations and general description of MPC

MPC algorithm dedicated to this application is detailed in [4]. It consists in finding the future set of control δ^{Pred}_{Traj}, which minimizes difference between $\hat{\delta}^{actual}$ and δ^{Ref} during prediction horizon H. The first value of set δ^{Pred}_{Traj} is then substituted to δ_{Traj} inside control law (8), so that final control law is given by:

$$\delta = \delta^{Pred}_{Traj} + \delta_{Deviation} \tag{10}$$

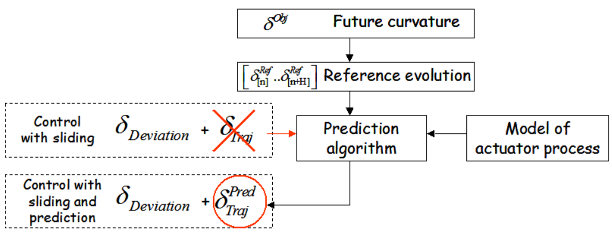

Fig. 5. Application of prediction on control expression

The overall control scheme is depicted on Figure 5. Two parameters can be tuned inside the predictive part of the control algorithm: prediction horizon H and gain γ which determines the shape of reference trajectory δ^{Ref}. Since steering actuator has been identified to be a second order process, it could be natural to set prediction horizon H equal to actuator settling time (about 0.5s) and γ close to zero.

However, as delay introduced by the actuator is not the lonely phenomenon which generates overshoots during transient phases, H and γ must be chosen bigger. This allows to reduce reactivity of δ^{Pred}_{Traj} and therefore offers a good robustness with respect to vehicle behaviors following from its large inertia. In experiments, prediction horizon H is set to 1s and γ has been experimentally chosen to 0.2. Finally, the introduction of a predictive term smoothes considerably nonlinear control law (6). As a result, sliding parameters variations are slower, so that the assumption of slow varying sliding (in control transformation (2)) is much more valid.

V. Experimental validation

A. Description of reference paths

Both of the reference path detailed hereafter have been obtained by a previous manual run. Successive positions are recorded by GPS, while tractor is driven by human.

Curved path on an even field:

This path has been drawn on a wet even field. Sliding phenomena appear during curve, since inertial forces and tires deformation generate side slip angles and then sliding effects. The long curve (three quarters of a circle) allows observing how steering laws react with respect to sliding effects when sliding conditions are almost constant. Path following has been achieved at a $8km.H^{-1}$ constant speed.

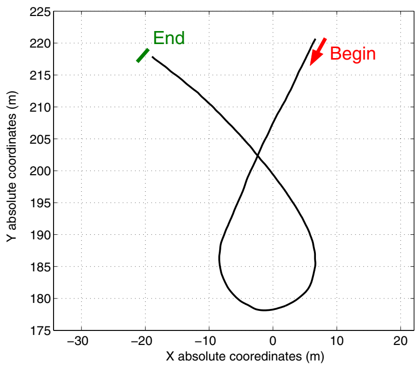

Fig. 6. path #1: long constant curve on field

Half turns path on an even field:

Half turn is often used during agricultural tasks (when farmer is coming to the end of field). However, they are more spaced than on the reference path depicted on figure 7. This fast succession of half turns is a very unfavorable case, since vehicle has not enough time to converge to the reference path on each straight lines part linking half turns. The ground on which this path is recorded is the same than for path #2, i.e. it presents the same bad adherence properties. Path following executed on this path has been carried out at a $8.5km.H^{-1}$ constant speed.

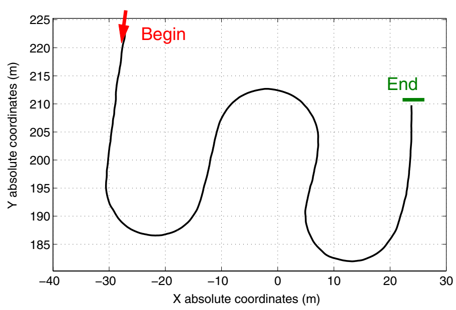

Fig. 7. path #2: several half turn on field

B. Effects of prediction on steering angle

As a preliminary result, let us consider the benefits of predictive control on steering angle evolution. On figure 8, comparison of recorded steering angle with and without prediction are compared during path #1 following. Steering angle recorded using control law without prediction (6) is depicted in red dashed line, while steering angle recorded using control law with prediction (10) is shown in green dotted line.

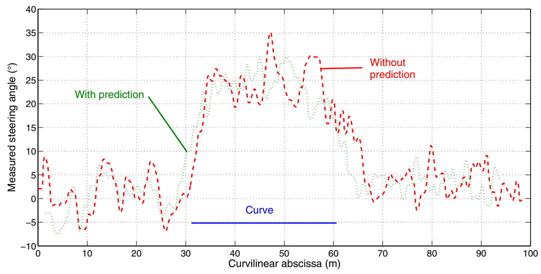

Fig. 8. Steering angle (path #1 following) with and without prediction

First, we can notice that, as expected, steering angle computed from predictive control law begins to react prior to the modification of reference path curvature (at 30m and 65m). This is of course not the case when prediction is not used. Secondly, since δ_{Traj}^{Pred} is computed from (9) which acts somehow as a filter, steering angle evolution with predictive control law is smoothed, as it can be seen on figure 8. As a consequence, assumption of slow varying sliding parameters is much more valid. Passengers comfort is also improved. Guidance accuracy resulting from these two control laws can be studied on the forthcoming figure 9

C. Guidance accuracy

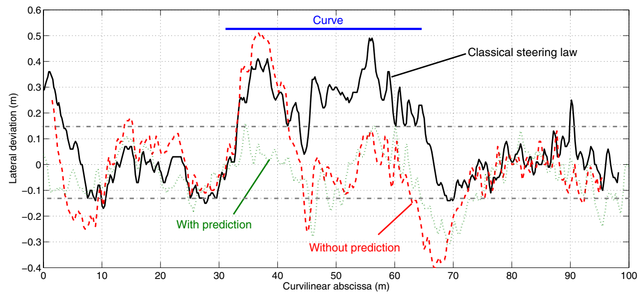

Fig. 9. Lateral deviation during path #1 following

On the following figures (figures 9 and 10), vehicle lateral deviation with respect to the reference path is depicted for several control laws:

- In black solid line: lateral deviation when classical control law (i.e. without sliding accounted and without prediction, as in [13]) is used.
- In red dashed line: lateral deviation when control law (6) with sliding accounted and without prediction is used.
- In green dotted line: lateral deviation when control law (10) with sliding accounted and with prediction is used.

Reference path #1 following allows studying the capabilities of control laws with respect to almost constant sliding conditions (during a long and constant curve). Indeed, figure 9 shows that a classical control law (control law (6) with sliding parameters set to zero), such as developed in [11] or in [13], does not allow preserving a null lateral deviation once sliding effects are present (lateral deviation during curve grows up to 40cm). Control law (6), which takes into account for sliding but does not use any prediction, is able to steer vehicle on the path to be followed (the lateral deviation mean value is about 0) when sliding conditions are constant (i.e. when the vehicle describes the curve with a constant curvature). However, during the transient periods (beginning of the curve at 35m, and end of the curve at 65m) overshoots are present with an important value. The use of predictive algorithm in addition to sliding accounted allows reducing considerably these overshoots. Vehicle stays in an acceptable range of deviation (about $\pm$15cm). The punctual peek in lateral deviation at 45m is due to a hole crossing the reference path and its effect can be observed on the three lateral deviation evolutions. However, this peek is not representative of a loss of accuracy, but an external disturbance recorded by GPS.

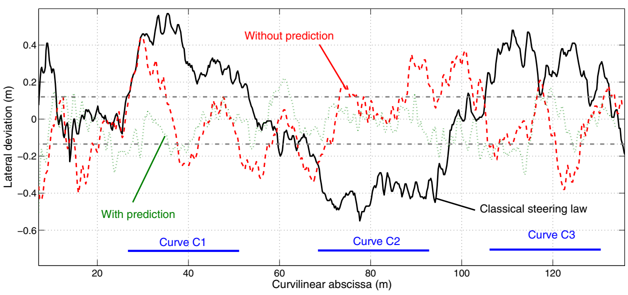

Fig. 10. Lateral deviation during path #2 following

Reference path #2 following shown on figure 10 confirms these remarks. As it has been said here before, this path is a very unfavorable one, especially for control law (6) (without prediction), since the consecutive transient periods generate consecutive overshoots. Guidance accuracy is still better than those obtained with a classical law, but benefits of accounting for sliding are not so obvious. On the contrary, predictive control with sliding accounted allows steering the vehicle very close to its reference path, despite these successive half turns.

VI. Conclusion and Future Works

This paper has proposed a Model Predictive Control to achieve path following when vehicles or car like mobile robots undergo important sliding effects, such as the ones that can be encountered in agricultural applications. An adaptive nonlinear control law accounting for sliding effects has first been designed. Then a predictive algorithm has been added, in order to reduce transient overshoots due to actuation delays and vehicle large inertia. Moreover, prediction algorithm smooths control variable, so that assumption of slow varying sliding parameters (used to build adaptive nonlinear control law) is quite valid during experiments.

Capabilities of the proposed control scheme have been studied via full scale experiments, demonstrating important improvements. Guidance accuracy is preserved, not only when sliding conditions are constant (when the vehicle describes a curve), but also transiently when the vehicle enters/exits into/from a curve, which is the most unfavorable situations since sliding parameters undergo discontinuities. Overshoots phenomena is so significantly reduced. For instance, when achieving path following with successive half turns (the most unfavorable case for mobile robot control), maximal lateral deviation is about 20cm, when it was superior to 40cm when predictive term was not used. Moreover, such deviations are recorded punctually: guidance accuracy stays in the acceptable range of $\pm$15cm during almost all automated steering.

Improvements in predictive algorithm can be achieved by integrating some dynamical effects inside the model used for prediction (currently, only actuator properties are taken into account). We are currently working on the design of a suitable dynamical model, bringing relevant information without leading to untractable computations. Another benefit can be gained by improving sliding estimation algorithm. Currently, a direct calculation using difference between actual process and a simulated one where sliding is not accounted allows to extract sliding parameters. More elaborate observers are been investigated to improve estimation of these two sliding parameters.

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