Automatic Steering Control for Agricultural Tractors in Vineyards

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Abstract— **Advanced Driver Assistance Systems (ADAS) and autonomous driving systems are relevant in the agricultural field, since they can ease personnel of demanding and repetitive tasks while increasing precision and productivity. This is particularly true in constrained environments represented by intensive and high value cultivations, like vineyards and orchards. Anyway, these contexts present numerous challenges: positioning accuracy in the range of centimeters is required in a environment with continuously-changing vegetation, reduced maneuvering space and unstable terrain.**

This paper presents an ADAS of level 3 for an agricultural tractor in a vineyard, focusing on its control system. The goal of the developed controller is to bring the vehicle at a desired distance from the crop rows and keep it aligned to them, so that the operator only has to set the tractor advancement speed and can focus on the ongoing agricultural procedures. This is achieved through a Linear Quadratic Integral (LQI) controller that relies on a control-oriented model of the system describing the dynamics of the vehicle position with respect to the vines. The system proves to be effective and easily tunable in order to obtain the desired behavior. An extensive experimental campaign validates the closed-loop system performance. In particular, the controller attains a steady state error of 5 cm, using a steering angle with Root Mean Square (RMS) of 1.05 deg.

I. Introduction

The agricultural field has always been one of the driving forces towards automation, seen as an opportunity to increase productivity while reducing costs, [1], [2]. Automatizing agricultural procedures means relieving personnel from the most burdensome and repetitive tasks, increasing the working hours, often limited due to adverse weather and lighting conditions, while simultaneously guaranteeing high precision and quality. Automation in agriculture ranges from tractors equipped with tools able to complete complex procedures unsupervised (like the one discussed in [3]), to cultivations monitoring, that consists in observing the plants state and needs, thus ensuring an efficient employment of resources and a reduction in the use of pesticides (examples of such applications can be found in [4] and [5]). A rising interest is directed to autonomous vehicles, tractors, and drones, whose diffusion and employment promises to be extensive over the next years, not only for their significant support to personnel, but also because regulations for off-highway vehicles are clearer and less strict than those for road vehicles.

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In this paper we present an Advanced Driver Assistance System of level 3 that we developed for an agricultural tractor, to be used in constrained environments like vineyards and orchards. ADAS for agricultural vehicles are relevant especially in contexts like the ones represented by intensive and high value cultivations. Here, tool-equipped small dimensions tractors are used to carry out complex procedures like pruning or harvesting. Hence, automatic positioning of the vehicle (e.g., by controlling its lateral dynamics) can ease the operator's driving task so that he/she can focus on the ongoing agricultural processes. High positioning accuracy is needed, given the complex and sensitive surroundings.

The ADAS we developed aims at controlling the steering of the tractor while it is between crop rows in order to bring the vehicle at a desired distance from the vines and keep it aligned to them. In this way, the driver only has to determine the advancement speed (which can be set on the vehicle cruise control) and can focus on the agricultural tasks. The system is designed to work with only the information coming from vehicle state sensors (i.e., speedometer and wheel encoder for the steering) and with the measures coming from a set of 12 ultrasonic sensors, that provide information about the vineyard position with respect to the tractor. The latter have been chosen because they are robust, cost-effective, and their data can be easily managed by standard CPUs. In this paper we will focus on the control system of the developed ADAS, and on specific control-related problems posed by the agriculutral context at hand. The description of the perception and localization system is out of the scope of this paper, but can be found in [6].

The trajectory the vehicle has to follow for the intent task is trivial, but the environment defined by vineyards and orchards presents several challenges. Firstly, vegetation is continuously changing, both due to seasonality and as a consequence of agricultural procedures. This results in the impossibility of using a priori known maps of the vineyard to plan the vehicle trajectory, as it is often done for tractors navigation in open field. For example, in [7] geographic information derived while seeding is recorded and used as a path to track for an autonomous hoeing system. An example of path tracking system for a combine harvester can be found in [8], while a trajectory control system and an automatic steering system for tractors are presented in [9] and [10]. All these works rely on vehicle localization based on Global Navigation Satellite Systems (GNSS): the objective is to follow a trajectory (that is either planned or pre-registered) and to control the absolute vehicle position.

In the case of vineyard navigation, the vehicle position must be always controlled with respect to the vines, rather than in a global reference frame. Given these systems main function (i.e., controlling the vehicle distance from the cultivations with an accuracy in the range of centimeters), the control system cannot neglect the continuously-changing vegetation and focus only on the vehicle dynamics. The desired vehicle position will vary according to the cultivations state: if the vegetation is scarce the vehicle needs to be kept closer to the the center line of the vine than in the case of flourishing vegetation. Lastly, reduced maneuvering space and unstable and uneven terrain pose further issues to the control task.

In order to tackle the above-mentioned issues, the problem can be divided into two sub-tasks:

- **localization** of the vehicle position, which can be in absolute coordinates (as done in the already cited [7]–[10]) or relative coordinates. While the first ones relies on Global Positioning System (GPS) technology, the second ones exploits proximity sensors, like cameras (as in [11], [12]), 3D LiDARs (as in [13], [14]), or acoustic sensors (like the system we propose in [6]). As previously outlined, localization in a global reference frame is a viable solution for open field navigation, but does not suit constrained environments like vineyards and orchards;
- **control**, which consists in computing a steering and velocity command. Based on the type of localization on which it relies, the control problem can be recast as a path tracking problem (in case of global coordinates localization) or as a reference tracking problem (for relative coordinates localization).

As far as the control is concerned, in both cases the objective is to minimize the distance from a reference. An expedient, especially adopted in the past, can be to use mechanical linkages that directly connect the vehicle and the path to be followed, like the ones in [15] and [16]. Anyway, these solutions lack practicality and robustness. Interesting approaches can be found in [8], [9], which propose a fuzzy control method for the path tracking problem, and a proportional-derivative controller working in parallel with a fuzzy neural network for trajectory control, respectively. Despite being a promising control technique, fuzzy control does not have optimality guarantees. In [17], [18] more classic Proportional Integral Derivative (PID) controllers are designed for tractors path following. However, PID tuning for shaping the desired controller behavior can be demanding, since these regulators only act on the tracking error.

The ADAS we developed achieves a relative localization of the vehicle with respect to the vines, that relies on simple and cost-effective sensors. This is obtained by a control-oriented modeling of the vehicle, which has the objective to describe the dynamics of the vehicle position with respect to the crop rows. In our solution, the controlled variable is the distance of the vehicle from the vines, rather than its absolute position. In this way, it is possible to always keep the vehicle at a desired distance from the external layer of the vine thus ensuring that the mounted tools are at the correct distance from the plants. The proposed regulator is a Linear Quadratic Integral controller, a model-based type of control with optimality properties. LQI technique facilitates the refinement of the controller behavior by acting not only the reference tracking error, but also on the control action, that can be weighted and, thus, moderated.

The rest of the paper is structured as follows: Section II discusses the control objectives and the system modeling; Section III describes the structure of the developed control algorithm; Section IV illustrates the experimental setup used for data acquisition and algorithm validation, and shows the experimental results, including the on-field tuning of the controller and its validation and performance assessment. Finally, Section V draws some conclusions.

II. Problem Set-up and Modeling

This section states the control problem with its objectives and illustrates the overall closed-loop architecture of the developed system. The control-oriented model of the system is derived.

A. Problem Formulation and Modeling

As mentioned in Section I, the controller objective is to bring the vehicle at a desired distance from the crop rows and keep it aligned to them, while the vehicle procedes at constant speed. The overall closed-loop system architecture is shown in Figure 1. The controller receives as input the vehicle state information (i.e., the longitudinal speed and the current curvature), the estimates of the tractor position with respect to the crop rows (i.e., the distance from the left row and the incident angle), and, based on the reference distance, computes a suitable control action. The error the controller aims at bringing to zero is the lateral distance error between the desired distance from the left row and the actual one. The control action, $u_{c,req}$, is sent to the actuator, which activates an hydraulic circuit thus modifying the front wheels steering angle. As required from the steering actuator, the control action is expressed as a curvature command, defined as the inverse of the curvature radius, R, and measured in [1/km].

The steering actuator response has been judged fast enough to permit to neglect the actuator dynamics in the controller design.

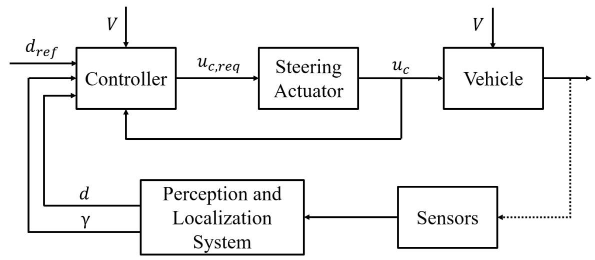


Fig. 1: Block scheme of the closed-loop system.

The controller, thus, needs to know the values of the distance of the vehicle from the left row and of the incidence angle of the tractor with respect to the crop rows. These can be measured or estimated. In our implementation they are estimated by a perception and localization system based on an Extended Kalman Filter and on measures coming from ultrasonic sensors (details can be found in [6]). Anyway, the control algorithm does not depend on the filter or measurement system that produces the required quantities. Matter-of-factly, the controller design and the model used in the controller do not take into account the observer dynamics.

The tractor position is controlled with respect to the left row, conventionally, the one on which the farmers operate. Figure 2 depicts the main variables of interest. With d, we indicate the controlled varibale, the distance from the left row; γ is the incidence angle with respect to the crop rows (supposed to be the same for the left and right side under the hypothesis of linear and parallel crop rows); V is the longitudinal speed and δ the steering angle of the vehicle; L is the tractor wheelbase length and l_c is the distance from the rear axle to an arbitrary point on the vehicle, chosen as reference point of which we want to control the distance from the vine.

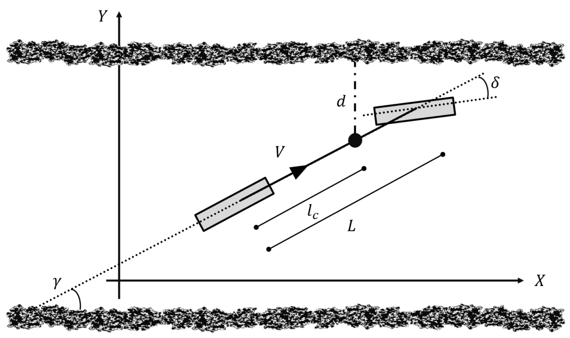


Fig. 2: Single track model and main variables.

To model the dynamics of the relative position of the vehicle with respect to the vines, we started from the standard kinematic bicycle model. The choice of using a kinematic model is justified given the low speed considered for the agricultural procedures. The vehicle position and orientation in the global reference frame are the starting point to derive the required distance and incidence angle of the tractor with respect to the row, and can be expressed as follows:

$$\begin{cases} \dot{X} = V\cos(\gamma) - l_c r \sin(\gamma) \\ \dot{Y} = V\sin(\gamma) + l_c r\cos(\gamma) \\ \dot{\gamma} = r \end{cases} \tag{1}$$

where r is the vehicle yaw rate and it is related to the current curvature and speed by the following:

$$r = -\frac{V}{L}\delta.$$

From model (1), it is possible to derive an equation describing the distance of the vehicle from the left row, d, by defining it as $Y_{row} - Y$, where Y_{row} is the y-coordinate of the left vine row, if one considers the global reference frame oriented as in Figure 2 (i.e., with the x axis parallel to the crop rows). Since Y_{row} can be considered constant, the model describing the relative position and orientation of the vehicle with respect to the crop rows becomes:

$$\begin{cases} \dot{d} = -V(\gamma - l_c u_c) \\ \dot{\gamma} = -V u_c \end{cases} \tag{2}$$

where we made the assumption of small incidence angle, which leads to the simplification: $\sin(\gamma) \simeq \gamma,\ \cos(\gamma) \simeq 1$. The relation between the steering angle δ and the vehicle curvature is:

$$u_c \simeq \frac{\delta}{L}.$$

III. Control Algorithm

This section describes the developed control algorithm. The controller receives as input the longitudinal vehicle velocity, the current curvature of the vehicle, and the estimates of the vehicle distance from the left row and incidence angle with respect to the rows. Based on the current state of the tractor and on the desired distance from the left row, the regulator computes a suitable control action, which is a reference curvature, as required from the steering actuator. As mentioned in Section II, the control algorithm is agnostic to the way the estimates of the relative position of the tractor with respect to the vines are produced: the distance and incidence angle received as input are assumed to be the real ones.

A. *LQI Controller*

The core of the control algorithm is represented by a Linear Quadratic Integral controller, a kind of optimal control according to which the control action is a state-feedback control law in the form:

$$u_{c,req}(k) = -K\hat{x}(k)$$

where $\hat{x}$ is the state estimate, and the gain matrix K is computed minimizing the following cost function:

$$J = \lim_{k\to\infty} \frac{1}{k} \sum_{k=0}^{k-1} \left[x^T(k)Qx(k) + u^T(k)Ru(k) \right] \tag{3}$$

with x and u states and inputs vector. Matrices Q and R, which weight the system states and inputs respectively, can be considered the tuning parameters of the controller.

The regulator works with an extended version of the model (2) presented in Section II. Together with the distance from the left row and the incidence angle of the vehicle with respect to the crop rows, two additional state variables are modeled:

- the **requested curvature**, u_c, considered as a fictitious state variable. In this way, the system input becomes the variation of the curvature command between two consecutive time instants and it is possible to moderate the maneuvers aggressiveness;
- the **integral of the distance error**, i, introduced in order to bring the steady-state error to zero.

The resulting discrete-time model is the following:

$$\begin{cases} d(k+1) = d(k) - TsV(k)(\gamma(k) - l_c u_c(k)) \\ \gamma(k+1) = \gamma(k) - T_s V(k) u_c(k) \\ u_c(k+1) = u_c(k) + \Delta u_c(k+1) \\ i(k+1) = i(k) + T_s(d_{ref}(k) - d(k)) \end{cases} \tag{4}$$

where T_s is the controller sampling time and d_{ref} is the reference distance that must be tracked by the controller. $\Delta u_c(k)$, which becomes the system input, is defined as $u_c(k) - u_c(k-1)$.

The model extension enables to weight in the cost function (3) not only the maximum value of the required steering action, but also the variation of said action in time, thus limiting the control aggressiveness. Matrices Q and R have been therefore defined as follows:

$$Q = \begin{bmatrix} q_1 & 0 & 0 & 0 \\ 0 & q_2 & 0 & 0 \\ 0 & 0 & q_3 & 0 \\ 0 & 0 & 0 & q_4 \end{bmatrix}, \qquad R = [r]$$

with their elements weighting the four states and the new system input. Parameter q_1 does not weight simply d, but the difference between d_{ref} and d.

Elements of matrices Q and R are tuned in order to obtain the desired controller behavior. The tuning has been performed firstly in simulation: a simulator including the controller and the system model has been used to refine the controller design and to identify the starting values for the cost function weights. The fine-tuning of the controller has been carried out on-field, as it will be shown in Section IV.

The model (4) exhibits a dependency on the vehicle longitudinal speed. Therefore, the gains computed from the minimization of the cost function (3) will vary for different velocities. This arises questions about wether the controller needs a gain-scheduling in order to guarantee satisfactory performance. Anyway, as it will be presented in Section IV, the experimental analysis proves that the controller using gains computed for a constant reference speed of 1 m/s is robust to different vehicle speed (in a range that is consistent with the selected use case), and that a gain-scheduling is not necessary.

IV. Experimental Analysis and Validation

This section illustrates the experimental setup with which the outlined algorithm has been designed and validated. Additionally, it discusses, with the help of data collected from the instrumented vehicle, the experimental analysis carried out firstly, to validate the model used in the controller, secondly, to evaluate the control system performance. The analysis includes the on-field fine-tuning of the controller and the validation of the implemented control algorithm. The experimental campaign has been conducted in a vineyard in different seasons (hence, different vegetation conditions).

A. Experimental Set-up

The vehicle for which the algorithm has been developed and that has been used for the experimental campaign is a SAME Frutteto, a small agricultural tractor with high maneuverability, generally used to carry out procedures and treatments in vineyards and orchards. The tractor is equipped with the following sensors:

- a wheel velocity sensor: mounted on one of the rear wheels, it is part of the standard production tractor equipment and provides the longitudinal velocity of the vehicle at the rear axle;
- a wheel steering sensor: mounted on one of the front wheels, it is part of the standard production tractor equipment and provides the steering angle at the wheel;
- a set of 12 ultrasonic sensors: mounted on the hood of the vehicle, these are standard automotive acoustic sensors and are used to derive an estimate of the vehicle state with respect to the vines.

The vehicle is endowed with an hydraulic steering actuator that controls the steering angle of the front wheels, and that is used by the control system. The tractor is also provided with a cruise control system, with which it is possible to set a desired longitudinal speed.

B. Model Validation

Figure 3 plots the comparison between distance and incidence angle simulated using the model (2) and the real ones, for a test in which the tractor performs a maneuver to approach the left row at constant speed of 2 m/s. The perception and localization system mentioned in Section II reconstructs the real quantities. As it is clear from the figure, the model correctly captures the dynamics of interest.

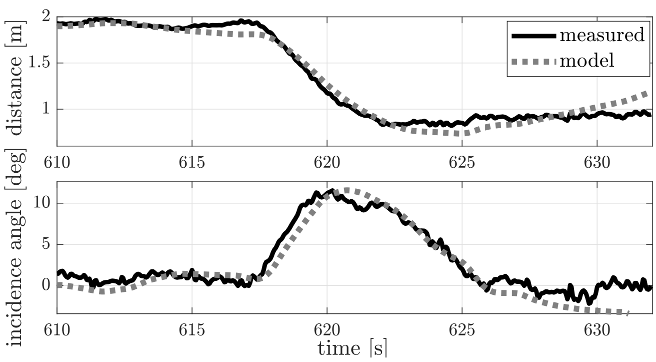


Fig. 3: Simulated distance and incidence angle of the vehicle with respect to the vines compared to measured ones.

C. Controller On-field Tuning

Elements of matrices Q and R are the weights of the tracking error on the distance from the left row, of the incidence angle with respect to the crop rows, of the control action, of the integral of the distance error, and of the variation of the control action in time. They represent the tuning knobs that can be used to obtain the desired controller behavior. As mentioned in Section III, the starting values for these weights have been identified in simulation, while their fine-tuning has beeen managed directly on-field. Once reasonable closed-loop performance were obtained, for the on-field fine-tuning, three main objectives have been considered: limit maneuvers agrressiveness, bring asymptotic error to zero, avoid steady-state oscillations.

Two parameters are mainly responsible for the desired behaviors: q_3 and q_4, weighting the control action and the integral distance error, respectively. In particular, we expect that for high values of parameter q_3 the required control action will be small, thus ensuring smooth maneuvers and modest or no oscillations at steady-state. High values of q_4 supposedly reduce the asymptotic error. The tests consisted in taking the vehicle at a desired distance from the left row and then providing a step in the reference distance, and they were conducted at costant speed of 1 m/s. In order to assess the closed-loop system performance for different values of the tuning parameters, we define three performance indexes:

- **tracking error**, computed as root mean squared distance error. The latter, is defined as the difference between the reference distance and the one received as input by the controller (i.e., the estimated one);
- **RMS of the steering angle** used when the vehicle has reached the desired distance (this index quantifies the steady-state oscillations);
- **settling time index**, computed on a filtered version of the step response of the system, being the original one very noisy. Therefore, the index represents an indication of the response time of the system rather than the actual settling time.

Figure 4 shows the sensitivity to parameter q_3: as expected, for increasing q_3 the steering angle is reduced, both during the maneuver and in the straight part of the test, but the system is slower. Same conclusions can be drawn looking at the performance indexes, shown in Figure 5 for multiple tests.

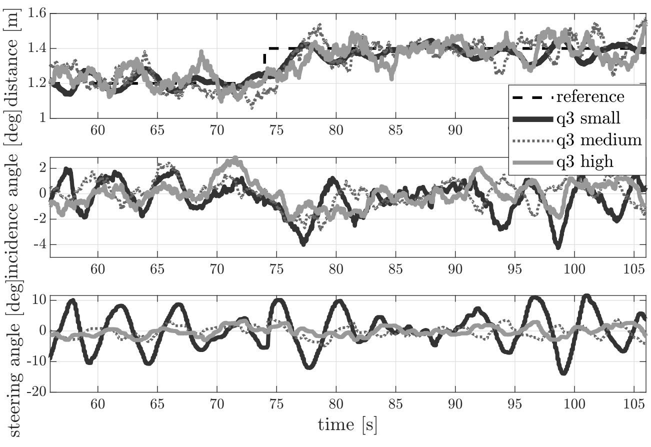
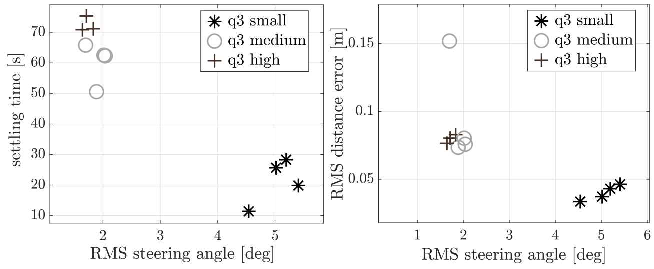


Fig. 4: Sensitivity to q_3 parameter.

Figure 6 shows instead the results of tests conducted for varying q_4. In this case, anyway, increasing the parameter at hand does not reduce significantly the asymptotic error, but



(a) (b)

Fig. 5: Performance indexes for varying q_3.

triggers undesirable oscillations. This results in an increase of the RMS distance error, as shown in Figure 7.

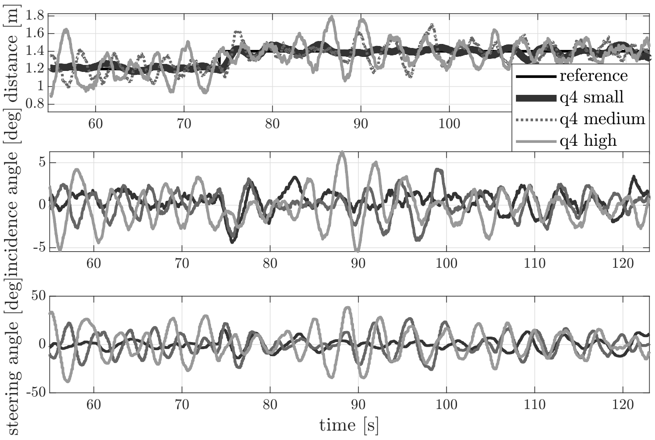
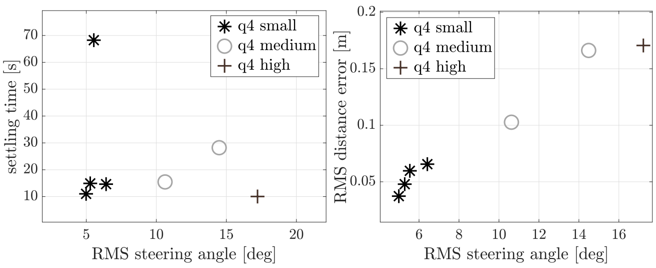


Fig. 6: Sensitivity to q_4 parameter.



(a) (b)

Fig. 7: Performance indexes for varying q_4.

D. Controller Performance

After selecting values for the tuning parameters that guarantee a satisfactory behavior, the control system performance has been assessed and validated at different vehicle velocities. We considered speeds of up to 2 m/s, which are consistent with the selected use case. In fact, agricultural treatments and procedures are generally carried out at low speed.

Figure 8 shows the closed-loop performance for tests in which the tractor proceeds straight at constant speed of 1 m/s and 2 m/s, at a desired distance from the left crop row. A step in the reference distance forces the system to bring the vehicle farther from the left row. From the figure, it is clear that the system performances for the two different velocities are comparable and both satisfactory. These conclusions are confirmed by the performance indexes shown in Figure 9.

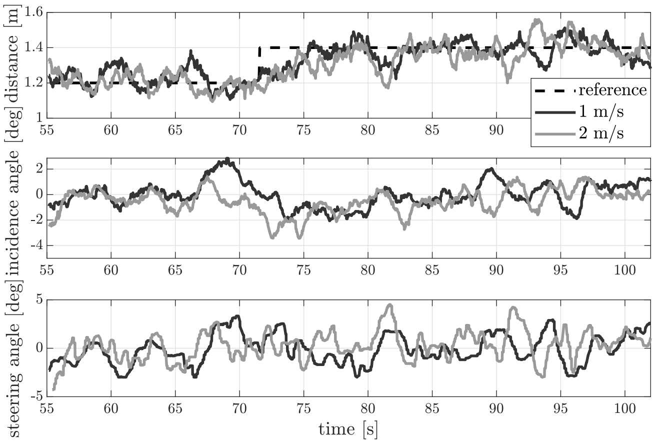


Fig. 8: Controller performance for different vehicle velocities.

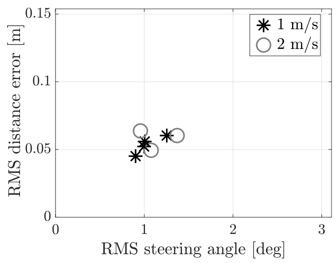


Fig. 9: Performance indexes for different vehicle velocities.

The system is therefore robust to vehicle velocity variation and does not need a gain scheduling, despite the dependency on speed shown in the model (4).

In conclusion, the developed control algorithm presents satisfarctory performance, even for increasing speed. The overall performance indexes have the following mean values, computed over all the available tests and at different speed: the steady-state error is of 5 cm, and the controller uses a steering angle with RMS of 1.05 deg.

V. Conclusions

The paper discusses the control system of an ADAS of level 3 for agricultural tractors in vineyards. The controller brings the vehicle at a desired distance from the left row and keep it aligned to it. For its functioning it needs the vehicle state information (i.e., longitudinal speed and current curvature) and the estimates of the relative position and orientation of the tractor with respect to the rows. The control system is based on a LQI controller, that has optimality properties and helps designing the desired controller behavior by weighting not only the tracking error but also the control action (that can be thus moderated). The regulator relies on a model which describes the relative position of the vehicle with respect to the vines, rather the absolute one. The proposed solution proves to be effective, even for increasing speed. An extensive experimental campaign validates the developed system. In particular, we can guarantee a steady-state error of 5 cm, while the controller uses a steering angle with RMS of 1.05 deg.

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