# CP-DGPS based combine harvester control without orientation sensor

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## BIOGRAPHY

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## ABSTRACT

Mobile robot control is a classic problem in the robotic community. It is particularly true in the agricultural field where repetitive tasks can be handled using AGV.

In this paper, we address the problem of combine harvester control using a single CP-DGPS receiver, without any attitude measurement unit. A non linear, velocity independent control law has been designed. It relies upon the kinematic model of the combine harvester.
Two approaches aimed at estimating the heading of the farm vehicle have been investigated. One uses GPS velocity measurements: the kinematic model of the harvester imposes that its linear velocity is directed along the vehicle axle. So the heading of the vehicle can be roughly estimated from raw velocity measurements. The other relies upon a Kalman state reconstructor and produces an indirect measurement of the heading. The reconstructor has been designed thanks to the kinematic model of the harvester, and taking into account for the sensor noise.

The control law has been implemented on a combine harvester. Experiments have been carried out using both kinds of heading estimations on an almost flat ground. The standard deviation from the mean of the lateral position is about three centimeters, and the bias smaller than five centimeters. Both methods are compared an some conclusions are drawn.

## INTRODUCTION

One can describe precision agriculture quoting "to perform the right task at the place at the right time".

Precision farming can be described as a three steps process. Land surveying is the first one, while agricultural maps recording is the second one. The last one could be variable rate seeding, fertilizing, according to the previous steps. We will focus on the third step, as most agricultural tasks rely on accurate vehicle guidance. Lets illustrate this concept in the particular case of a combine harvester. The need for automatic vehicle guidance systems seems obvious on this machine: the driver would only have to finely tune different functions of this machine and perform a half-turn. Meanwhile, the guidance system would achieve a very accurate positioning, thus insuring neither overlapping nor missing areas.

Many situations could be reported. Most of them could be classified as two categories. The first one is a "previously-recorded" path-following task: the machine must follow a previously recorded trajectory. This trajectory could have been stored during the seeding for instance. In the second one, the machine must follow a new curve. This new reference is computed from the last passage plus an offset (the tool length for instance). We could also mention new possibilities, such as optimal attack point search, or automatic half-turn for driver assistance.

Many experiments have been conducted and reported in the literature. Most approaches can be classified into two categories, as they rely upon two kinds of sensors and information.

The first one uses relative information. Researchers focused for instance on the video camera sensor. Mounted at the end of the implement or at another appropriate location, it provides the operator with a set of " eyes " near the demarcation line. This contact-free sensing system presents the same offset information as earlier furrow following or edge-detecting sensors. But it has the nice feature of providing anticipation to the control system, which is interesting from a control point of vue. Various approaches have been tested. Some rely on 2D information extracted from the image plane [2], [5] and [9]. Other are based on 3D sensors, for instance made of a laser scanning and a video camera. Two kinds of difficulties arise: the first one is the reference detection. The whole guidance system relies upon the quality and robustness of the detection algorithms. Extreme conditions of dust, for example, reveal the weakness of the detection side. The other problem is that the new reference is computed from structured environment in an iterative process. It can oscillate too. If the edge of the work area tends to oscillate in successive passes, human operators frequently and periodically sacrifice for efficiency in one pass to " straighten out " the edge of the worked area.

The second one uses absolute information. A recent technological development allows accurate three dimensional (3D) positioning of the vehicle in a field without the need for buried cables, field-installed beacons or video sensors: the Global Positioning Systems (GPS). Today, flow control devices are coupled to a GPS to produce a yield map. It allows farmers to adjust seed, pesticide, and fertilizer to each field location. This sensor also allows the design and implementation of an absolute vehicle guidance system with the availability of a very accurate positioning system. This technology can be used in special operations, in which the vision system is unable to proceed, for instance, in a spraying or fertilizing operation with no visible markers such as boom wheel tracks or foam marks. Researches have been carried out in this area, using fiber optic gyroscopes (FOG) and GPS [6]. The influence of navigation sensors in GPS based land navigation has also been studied in [1]. Promising results have been reported where an " all-GPS " solution has been preferred [8].

In this paper, we will first describe the information required to achieve line following control of a farm vehicle. We will propose a non linear and velocity independent control law based upon the non linear kinematic model of the harvester. Moreover, two heading estimation methods will be investigated. And last, we will compare experimental results and draw some conclusions.

## VELOCITY INDEPENDENT CONTROL LAW

Most agricultural tasks are performed at constant velocity. This is particularly true on a combine harvester. Unfortunately, this velocity relies upon various factors, such as crop density, variety, and is tuned by the driver. This is the reason why we decided to design a velocity independent control law, as in [3]. After a brief presentation of the non linear kinematic model of the harvester, we will derive a bounded, velocity independent control law.

### KINEMATIC MODEL OF THE HARVESTER.

We used the kinematic model of the harvester. From a practical point of view, the harvester can be considered as a rear wheel bicycle model of length $l$. The theoretical description can be found in [4]. The configuration of the harvester can be described without ambiguity by the state vector $\underline{X} = (z, x, \phi)^T$, with:

- $(z, x)$: coordinates of the vehicle front axle center (denoted as $O$ on Figure 1) in the reference frame $[W, Z_w, X_w]$,

- $\phi$: vehicle heading. More precisely, $\phi$ is defined as the orientation of the vehicle axle with respect to $[W, Z_w]$, see also Figure 1.

Two control variables are available, namely $\underline{U} = (v, \delta)^T$

- $v$: linear velocity at point $O$ (the control variable is actually the rotation velocity of the front wheels, from which the value of $v$ can be inferred).

- $\delta$: orientation of the rear wheels (assumed to be superposed, see Figure 1).

The vehicle kinematic equations are derived according to pure rolling and non-slipping assumptions, and rigid body assumptions. The former imposes that the linear velocity vector at point O is directed along the vehicle axle. The latter implies that an instantaneous rotation center exists (IRC). Combining these two results, we infer that it is located on the wheels axle. When the vehicle movement is a translation, this IRC moves towards infinity.
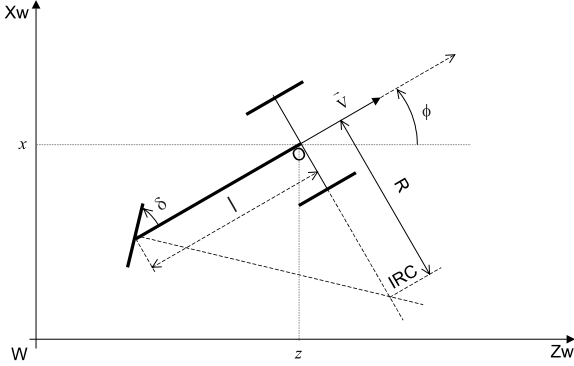


Figure 1: Kinematic model of the harverster

One can now derive the kinematic equations of the harvester. They are clearly non linear:

$$\begin{cases} \dot{z} & = & v \cos \phi \\ \dot{x} & = & v \sin \phi \\ \dot{\phi} & = & -\frac{v \tan \delta}{l} \end{cases} \tag{1}$$

## NON LINEAR CONTROL LAW.

The objective of the control law is to achieve path following under the simplifying assumptions: the harvester linear velocity $v$ is assumed to be constant, and the reference path is a straight line.

These assumptions are those of our very first experiments, as reported in the next section. Nevertheless, the design of the control law is based upon general results in Automatics, namely chained systems theory, see for instance [10]. So, one can extend the control law presented in this paper to more general path following problem.

Control laws can be derived from first order development of the kinematic model equations. The non linear model is then approximated by a linear one, and the linear systems theory can be used to design the control law. This is the tangent linearization approach. Nevertheless, since this control law is derived from an approximation of the system equations, it is therefore valid only locally around the configuration chosen to perform linearization. As, in our case, the initial conditions may be far away from the reference path, tangent linearization cannot be used.

Recent researches deal with obtaining -if possible- state and control variables changes which convert without any approximation non linear systems into linear ones (exact linearization approach). Unfortunately, mobile robots cannot be exactly linearized [12]. However, it has been proved that one can convert these non linear systems in almost linear systems, termed as chained form. We have used this chained form as it allows us to design the control law using, for a large part, linear systems theory.

The harvester model (1) can be converted into chained form. We first choose a new state vector: $\underline{Y} = (y_1, y_2, y_3)^T$ defined by the diffeomorphism:

$$\underline{Y} = \Theta(\underline{X}) \quad \text{with} \quad \Theta(\underline{X}) = (z, x, \tan \phi)^T$$

Moreover, a new control vector $\underline{M} = (m_1, m_2)^T$ is defined thanks to:

$$\underline{M} = \Upsilon(\underline{U}, \underline{X}) \quad \text{with} \quad \Upsilon(\underline{U}, \underline{X}) = \left( v \cos \phi, -\frac{v \tan \delta}{l \cos^2 \phi} \right)^T \tag{2}$$

These transformations are invertible as long as $v \neq 0$. The harvester chained model writes then as:

$$\begin{cases} \dot{y}_1 & = & m_1 \\ \dot{y}_2 & = & y_3 \, m_1 \\ \dot{y}_3 & = & m_2 \end{cases} \tag{3}$$

In order to get a velocity independent control law, one can replace the time derivative in (3) by a derivation with respect to the curvilinear abscissa $z$. The normalized model becomes:

$$\begin{cases} y_1' & = & 1 \\ y_2' & = & y_3 \\ y_3' & = & m_3 \end{cases} \quad \text{with} \quad m_3 = \frac{m_2}{m_1} \tag{4}$$

The lower part of model (4) is completely linear, so it can be brought to zero using the following control law:

$$m_3 = -K_d y_3 - K_p y_2 \qquad (K_p, K_d) \in \mathcal{R}^{+2} \tag{5}$$

One can check, reporting (5) in (4), that one has:

$$y_2'' + K_d y_2' + K_p y_2 = 0 \tag{6}$$

which implies that both $x$ and $\phi$ converge to zero. As the above error dynamics is expressed with respect to $z$, the resulting trajectories are velocity independent. Reporting (5) in (2), the real control is:

$$\delta = \arctan((K_d tan\phi + K_p x) l \cos^3 \phi) \tag{7}$$

Unfortunately, this control law did not prevent from actuator saturation. We have therefore saturated $m_3$ (and thus $\delta$) using a sigmoid. The stability is then preserved [11]. The new expression of the control law becomes:

$$\delta(x, \phi) = \arctan \left( K \, l \, \cos^3 \phi \frac{1 - e^{-\tau(K_d \tan \phi + K_p x)}}{1 + e^{-\tau(K_d \tan \phi + K_p x)}} \right) \tag{8}$$

This control law can be saturated to any arbitrary value $\delta_{max}$ by tuning K.

## HEADING ESTIMATION.

The main problem we had to face was the heading estimation. The only information available from a single antenna CP-DGPS receiver are:

- the 3D position of the antenna

- the 3D velocity vector of the antenna

The control law makes use of both lateral deviation and heading of the vehicle. We present two methods to estimate the heading thanks to the later information. We first planed to estimate $\phi$ from raw velocity measurements. After thorough study of experimental results, we investigated the use of a Kalman state reconstructor.

## VELOCITY BASED APPROACH

First of all, one must notice that one need a relative heading, i.e. relative with respect to the reference path. Moreover, under the previous pure rolling and non slipping assumptions, one can infer the heading thanks to the velocity vector $\overrightarrow{V}$. And last, as the ground is supposed to be almost flat, a two dimensional vector is enough. According to the GPS receiver manufacturer, raw velocity are computed thanks to Doppler measurements.

Open loop experiments have been conducted on the combine harvester (figure 2) while the thresher was running. The driver followed a straight line on the ground, insuring zeroed experimental heading. We checked the estimated heading at various velocities. The estimated heading mean $\mu_\phi$ and standard deviation from the mean $\sigma_\phi$ are tabulated at four different velocities (table 1). One can notice that the standard deviation from the mean decreases as velocity increases. Fortunately, this heading is almost unbiased.

| velocity $(km.h^{-1})$ | 2.5 | 5.2 | 7.3 | 9.3 |
|---|---|---|---|---|
| $\mu_\phi$ $(degrees)$ | 0.13 | -0.25 | -0.14 | 0.15 |
| $\sigma_\phi$ $(degrees)$ | 3.3 | 1.6 | 1.1 | 1.1 |

Table 1: Open loop velocity based $\phi$ measurements

## KALMAN STATE RECONSTRUCTOR APPROACH

As this approach led to a noisy heading, we decided to design another heading estimator. The control law will remain unchanged. Two solutions among many can be proposed. On one hand, one can smooth raw velocity measurements using a Kalman filter. This is a signal processing approach. On the other hand, one can use a state reconstructor. This is a control approach. Once the combine harvester has been discretized, the velocity disappear, and one can use a Kalman state reconstructor based upon this model. The whole state vehicle $\underline{X} = (x, \phi)^T$ can be reconstructed in this way.



Figure 2: Combine harvester and base station

We have chosen the second approach as it seems easier to justify from a control point of view.

First of all, we must carefully state the purpose of this second approach. It was aimed at estimating the heading $\phi$ while reducing heading noise. This is the reason why we did not thoroughly developed the non linear and velocity independent model. We just wanted to compare both methods. In this paper, we will use an approximated model for the Kalman reconstructor, the tangent linearized of model (1).

We then transform the continuous model (1) into discrete time (at sampling period $T$):

$$\begin{cases} \underline{X}_{k+1} & = & A_d \underline{X}_k & + & B_d \delta_k \\ y_k & = & C \underline{X}_k \end{cases} \quad (9)$$

with $A_d = \begin{pmatrix} 1 & vT \\ 0 & 1 \end{pmatrix}$, $B_d = \begin{pmatrix} \frac{-v^2 T^2}{2l}, & \frac{-vT}{l} \end{pmatrix}^T$ and $C = \begin{pmatrix} 1 & 0 \end{pmatrix}$.

Using the following Kalman recontructor [7]:

$$\begin{cases} \overline{\underline{X}}_{k+1} & = & A_d \widehat{\underline{X}}_k & + & B_d \delta_k \\ \widehat{\underline{X}}_{k+1} & = & \overline{\underline{X}}_{k+1} & + & \underline{L}(y_{k+1} - C \overline{\underline{X}}_{k+1}) \end{cases}$$
$$(10)$$

One can use $\widehat{\underline{X}}$ instead of $\underline{X}$. Vector $\underline{L}$ as been computed for a $8km/h$ velocity, assuming sensor and model noise are known. We used the standard deviation from mean of the measured lateral deviation for sensor noise. Moreover, we assumed the model noise could be considered as a control noise. Both are supposed to have a gaussian distribution.

## EXPERIMENTAL RESULTS

All the trials have been carried out with a Dassault-Sercel, dual frequency GPS 5002 system. This realtime kinematic carrier-phase differential GPS outputs data (position and

Doppler based velocity) at 10 Hz. The control law was running on a laptop computer. The guidance system has been implemented and succesfully tested on a CLAAS Dominator combine-harvester. All the tests have been conducted on an almost flat ground.

## VELOCITY BASED EXPERIMENTS

During all the experiments, the whole state vector $\underline{X}$ was constructed from the GPS data as mentioned above.
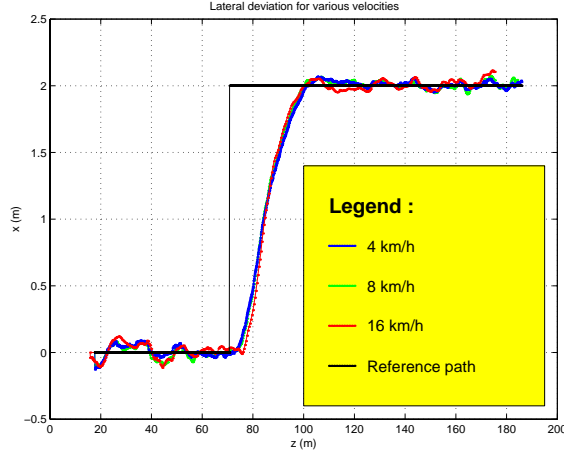


Figure 3: Closed loop system results at various velocities

We proposed an experimental setup to check the velocity independence property of the control law. The closed loop harvester has been tested with velocities ranging from 4 km/h to 16 km/h. Although 16 km/h is not realistic for a combine harvester in farming applications, it allowed us to validate this theoretical property. One can notice on figure 3 the harvester follows the reference path. Standard deviation from the mean of the lateral deviation is lower than 5 cm, which is a very low value. As a matter of fact, one must keep in mind the measured lateral deviation only reflects the antenna lateral position. The control point of the farm vehicle is about 3.5 meters below the antenna.

One can infer this approach proved to be efficient, even though $\phi$ is embedded in noise. Unfortunately, the control law is mostly related to the vehicle heading, so the computed $\delta$ is also noisy. From an experimental point of view, this leads to a very noisy and changing $\delta$. The low level system, including the valves, are strongly actuated. We could sum up these notes by:

- the control law has nice theoretical and practical properties
- the estimated heading is too noisy

## KALMAN STATE RECONSTRUCTOR EXPERIMENTS

The heading is now estimated thanks to the Kalman reconstructor. The same non linear control law is still used.

First of all, one can notice reconstructed heading (see figure 4) is far smoother (and thus realistic with respect to the vehicle dynamic).
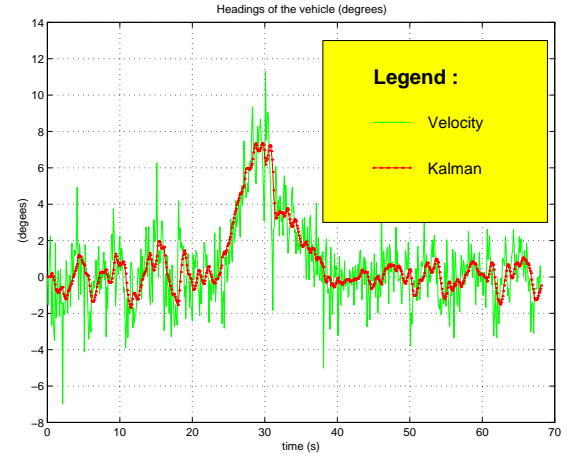


Figure 4: Kalman and velocity based heading

Moreover, the control $\delta$ is also smoother (figure 5). And last, the overall results (the cartesian trajectories) are similar for both estimators (figure 6).

The control is also smoother, insuring a more "comfortable" behavior of the vehicle. The standard deviation from mean of the lateral deviation is about the same, i.e. lower than 3.5 cm at the antenna location. The whole system is not velocity independent any more. It has also lost some of its non linear properties. As we mentioned earlier, this approach was a first step aimed at reducing the heading noise. One can think about a velocity independent Kalman state reconstructor relying, for instance, on equations 4.
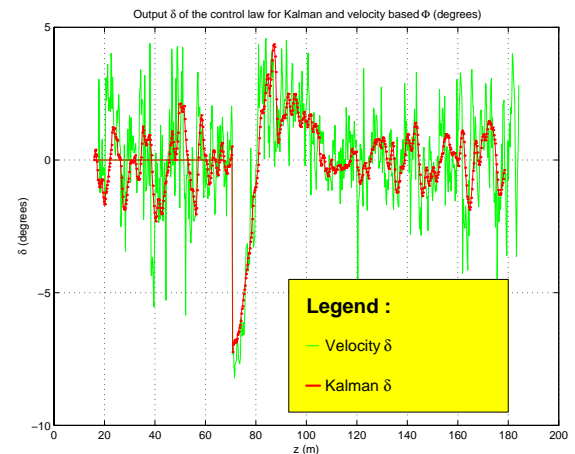


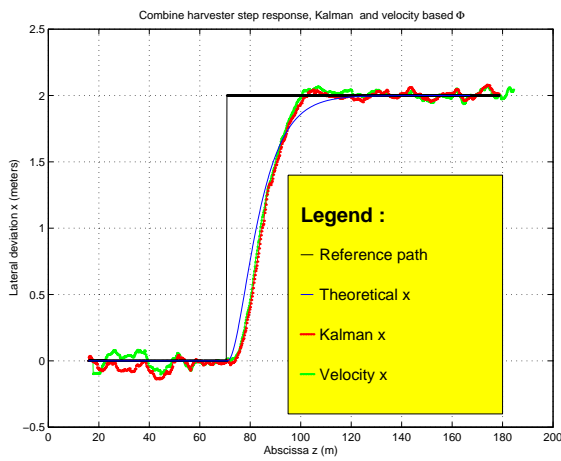Figure 5: Control variable $\delta$ for both Kalman and velocity heading estimators at 8 km/h

Figure 6: Step response for both Kalman and velocity heading estimators at 8 km/h

## CONCLUSION

This work was aimed at controlling a combine harvester without any attitude measurement unit.

A non linear, bounded control law has been presented. Its velocity independence property is particularly useful in agriculture. Two heading estimation methods have been proposed and thoroughly tested. A simple one, based upon CP-DGPS velocity measurements, proved to be efficient. A control approach, relying upon a Kalman state recontructor, showed nice lowpass filtering properties.

Further work has to be done to keep the reconstructor velocity independent as well as non linear. Moreover, one has to take into account for sloppy and sliding ground.

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