Parallel guidance system for tractor-trailer system with active joint

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Abstract

Parallel tracking or auto guidance systems are becoming common in tractors. Auto guidance systems with accurate positioning allow driving very accurately in straight driving lines. If the driving lines include curves, however, it is mathematically much harder to keep the shortest distance to the adjacent driving line constant. And it becomes even harder if the vehicle is a tractor-trailer and a certain point in the trailer has to follow the curve. If the field has slopes, the trailer necessarily does not follow the kinematical route and more measurements are required to compensate for the error.

In this paper a developed path tracking system is presented. An ISO 11783 compatible tractor was used together with a towed combine seed drill. The drawbar of the seed drill was customized by adding a hydraulically controlled joint. The measurements used in navigation were: a RTK-GPS receiver in the tractor, a laser scanner in the seed drill to detect previous swath, and attitude estimation from the inertial and magnetometer measurements.

Two different algorithms were developed: a simple one which is based solely on tractor navigation with direct laser scanner based drawbar control; and an advanced one which is based on nonlinear Model Predictive Control (MPC). In MPC approach, a full kinematic model of the tractor-trailer system with active joint is utilized and the laser scanner measurement is in an auxiliary state. For testing purposes a simulator was also developed.

The active joint in the trailer drawbar was found to be valuable as the response from control to error is much quicker than from front wheel control. The laser scanner was found to be reliable to detect an edge of the previous swath when the produced small furrow at the edge is clear. The model predictive control also worked nicely and gave a smoother control curve than traditional control algorithms without affecting the response and settling time.

Keywords: navigation, path tracking, model predictive control, kinematics, agriculture

1 Introduction

In agricultural guidance systems the basic idea of path tracking has been to take some point of the followed path at a defined distance ahead of the tractor and to calculate the steering angle which would lead the tractor to that point. The idea is essentially the same, despite the algorithms, for how the control value is calculated. These algorithms do not take into account the position of the implement in general. The idea of this research is to try to keep both tractor and trailer in the followed path. Also because there are two controllable degrees of freedoms in the system, the problem statement becomes a multivariable control problem. Model Predictive Control (MPC) is a good choice for this kind of purpose. With that it is also possible to take into account more points along the followed path.

The test configuration consisted of a standard tractor and towed trailer. The tractor was a Valtra T190, with added ISOBUS (ISO 11783) Class 3 facilities. The trailer was a Junkkari Maestro 3000 seed drill, with also added ISOBUS facilities. The drawbar of the seed drill was also modified for this research by supplementing an extra controllable joint. This joint gives an extra degree of freedom for controlling the position of the seed drill. This test configuration is illustrated in Figure 1.

Figure 1 Test equipments in field.

2 The structure of navigation system

The navigation system can be divided roughly into three parts: path planning, path tracking and actuator control. In this paper, the focus is on path tracking and the other parts receive less detailed attention.

2.1 Basic path planning algorithm

Path planning is a challenging task as such. In this research, the adjacent driving line is used for two simple reasons: the limited measurement range of the laser scanner and ease of implementation. A laser scanner can measure land-marks accurately only two meters distance in both directions. This limits the usage of local positioning to only the adjacent driving lines. Also in the global positioning system, the path to be tracked is gained from the recorded GPS-positions of the trailer. The positions are shifted amount of one machine width away from already sowed area in order to gain the new adjacent driving line. More advanced path planning algorithms are considered, for example, in Oksanen (2007).

2.2 Path tracking algorithms

The purpose of path tracking algorithms is to keep a vehicle on the desired route. In this research there were two different types of path tracking algorithms developed: a Target Point –algorithm and a MPC –based algorithm. The developed Target Point –algorithm is similar to the Pure-pursuit –algorithm developed by Amidi (1990). In addition to Amidi's algorithm, an integration term was used to boost up steering in strict curves. Another similar type tracking algorithm is, for example, the Vector-pursuit –algorithm (Wit et. al., 2004).

As the basic path tracking algorithm did not cover the control of the active joint, the control values were calculated in a geometric manner from the distance to the path measured by the laser scanner. The transformation formula from the distance (L) to the desired joint angle (γ_{new}) is in Equation 1.

$$\gamma_{new} = \sin^{-1}(\sin(\gamma) + L/c) \quad , \tag{1}$$

where variable c is the length of the drawbar and γ is current joint angle measurement. It is noticeable that this transform does not take account of either the GPS-position or the recorded path. In this way, the system consists of two separate path tracking algorithms; a local positioning based algorithm for the trailer and a global positioning based algorithm for the tractor.

MPC –based algorithms are completely different, utilizing the followed path along a broader length, not just a single point like the previously mentioned algorithms. They can also give control values to several actuators simultaneously. The usage of real time MPC algorithms is becoming possible due to the development of the computational resources of computers. Lately, several researchers (Lenain et. al. 2005; Vougioukas, 2007) have used MPC for path tracking problems. In their research, however, there has been only one controlled variable: the steering angle of the front wheels of the tractor; and the position of the trailer is not considered.

2.3 Actuators

The ISOBUS defines the control interface of the steering angle. Control messages consist of curvature values so the implementation of the wheel angle controller is at lower level and stays at the responsibility of the tractor manufacturer. The navigation system gives setpoint values for this controller.

There are specified messages to control the hydraulic valve in the ISOBUS, but the control of the active joint is not considered. Therefore, the navigation system must include a low level controller which controls the valve of the hydraulic cylinders of the joint. The implemented controller was a standard PID-controller which uses the difference of desired and measured joint angle as an input value. With this controller the active joint worked in a way similar to a front wheel steering.

2.4 Localization

In this research, the tractor position was measured with a Trimble 7400MSi RTK-GPS receiver. It produces position measurements five times per seconds and horizontal accuracy is stated to be three centimetres. If the number of available satellites drops below five, however, the accuracy dramatically reduces. A Trimble 5700 VRS-GPS was used as a reference measurement for the trailer position. It was not used for any control purposes. Attitude estimation from inertial, magnetometer and GPS measurements was gained with the help of an Unscented Kalman filter. As mentioned before, in addition to the global positioning system based on RTK-GPS, also a local positioning system based on laser scanner is also utilized.

3 Model predictive control

The function of Model Predictive Control is based on predicting future changes in the states of the controlled model. Together with predicting, MPC also tries to find an optimal solution for the control problem. Optimality is judged from the quadratic cost function.

The prediction model is in Equation 2.

$$\begin{aligned} x(k+1) &= \mathbf{A}x(k) + \mathbf{B_u}u(k) + \mathbf{B_v}v(k) + \mathbf{B_d}d(k) \\ y_m(k) &= \mathbf{C_m}x(k) + \mathbf{D_{vm}}v(k) + \mathbf{D_{dm}}d(k) \\ y_u(k) &= \mathbf{C_u}x(k) + \mathbf{D_{vu}}v(k) + \mathbf{D_{du}}d(k) \end{aligned} , \tag{2}$$

where x is the process state vector, u the control vector, v the measured disturbances vector, d the unmeasured disturbances vector, y_m the measured outputs vector and y_u the unmeasured outputs vector. The cost function is defined in Equation 3.

$$\begin{aligned} J(\Delta u,\varepsilon) = \sum_{i=0}^{p-1} \Big(& [y(k+i+1|k) - r(k+i+1)]^T \mathbf{Q} [y(k+i+1|k) - r(k+i+1)] \\ & + \Delta u(k+i|k)^T \mathbf{R}_{\Delta\mathbf{u}} \Delta u(k+i|k) \\ & + [u(k+i|k) - u_{target}(k+i)]^T \mathbf{R}_{\mathbf{u}} [u(k+i|k) - u_{target}(k+i)] \Big) + \rho_\varepsilon \varepsilon^2 \end{aligned} \quad (3)$$

Where the y vector consist of y_m and y_u, r is the target vector and $\mathbf{Q}$, $\mathbf{R}_{\Delta\mathbf{u}}$ and $\mathbf{R}_{\mathbf{u}}$ are positive semidefinite square-matrices consisting weights. Variable ε is a slack variable, which is used to loosen the limits in state constraints. Constraints are in Equation 4.

$$\begin{cases} u_{\min}(i) - \varepsilon V_{\min}^{u}(i) \le u(k+i|k) \le u_{\max}(i) + \varepsilon V_{\max}^{u}(i) \\ \Delta u_{\min}(i) - \varepsilon V_{\min}^{\Delta u}(i) \le \Delta u(k+i|k) \le \Delta u_{\max}(i) + \varepsilon V_{\max}^{\Delta u}(i) \\ y_{\min}(i) - \varepsilon V_{\min}^{y}(i) \le y(k+i+1|k) \le y_{\max}(i) + \varepsilon V_{\max}^{y}(i) \\ \varepsilon \ge 0 \end{cases}, \quad (4)$$

where the vectors $u_{\min}$, $u_{\max}$, $\Delta u_{\min}$, $\Delta u_{\max}$, $y_{\min}$ and $y_{\max}$ are minimum and maximum values of the controls, control changes and measurements respectively. $V_{\min}^{u}$, $V_{\max}^{u}$, $V_{\min}^{\Delta u}$, $V_{\max}^{\Delta u}$, $V_{\min}^{y}$ and $V_{\max}^{y}$ are the loosening parameters for the minimum and maximum values.

Because the cost function is a quadratic type, the solution of the optimization problem is gained from the QP-solver (Quadratic Programming). This is automatically done by the Matlab Model Predictive Control –Toolbox. (Bemporad et. al., 2008)

4 Kinematic model of tractor-trailer system

As mentioned in the previous chapter, MPC requires an exact model of the controlled system. In this case, the model of the controlled system is the kinematic model of the tractor-trailer combination. In derivation of the kinematic model, it is assumed that the ground is ideal and sliding does not occur. With these assumptions, the kinematic model can be easily derived from two sets of constraints. The first set of constraints connects together the global positions of the centre point of the front (x_F, y_F) and rear (x_R, y_R) axles, the connection point of the drawbar (x_C, y_C), the point of the controlled joint (x_D, y_D), the centre point of the seed drill (x_E, y_E) and the position of the laser scanner (x_L, y_L). These constraints are in Equation 5.

$$\begin{cases} x_F = x_R + a\cos(\theta) \\ y_F = y_R + a\sin(\theta) \\ x_C = x_R - b\cos(\theta) \\ y_C = y_R - b\sin(\theta) \\ x_D = x_C - c\cos(\theta-\beta) \\ y_D = y_C - c\sin(\theta-\beta) \end{cases} \quad \begin{cases} x_E = x_D - d\cos(\theta-\beta-\gamma) \\ y_E = y_D - d\sin(\theta-\beta-\gamma) \\ x_L = x_D - l\cos(\theta-\beta-\gamma) \\ y_L = y_D - l\sin(\theta-\beta-\gamma) \end{cases}, \quad (5)$$

where a is the wheelbase, b is the distance from the rear axle to the connection point of the drawbar, c is the length of the drawbar, d is the distance from the drawbar joint to the centre point of the seed drill, l is the distance from the drawbar joint to the laser scanner, θ is the tractor heading, β is the angle between tractor and the drawbar and γ is the angle of the controlled joint. These above mentioned positions and parameters are also depicted in Figure 2.

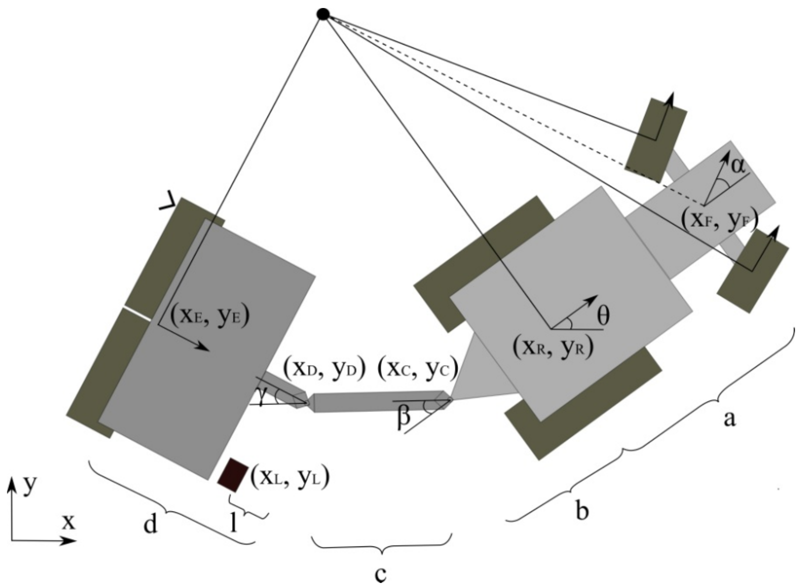

Figure 2 Variables and parameters of the kinematic model.

The second set of constraints includes the assumption that sliding does not occur. In other words, movement perpendicular to the heading is zero and movement of the rear axle along the heading direction equals the velocity of the tractor. These constraints are in Equation 6.

$$\begin{cases} \dot{x}_R \cos(\theta) + \dot{y}_R \sin(\theta) = v \\ -\dot{x}_R \sin(\theta) + \dot{y}_R \cos(\theta) = 0 \\ -\dot{x}_F \sin(\theta+\alpha) + \dot{y}_F \cos(\theta+\alpha) = 0 \\ -\dot{x}_E \sin(\theta-\beta-\gamma) + \dot{y}_E \cos(\theta-\beta-\gamma) = 0 \\ \dot{L} = -\dot{x}_L \sin(\theta-\beta-\gamma) + \dot{y}_L \cos(\theta-\beta-\gamma) \end{cases} , \tag{6}$$

where $\dot{s}$ denotes the time derivative of the variable s, L is the distance to the followed path measured by the laser scanner and α is the angle of the front wheels.

The centre point of the tractor rear axle, tractor heading, angle between the tractor and the drawbar and the distance to the followed path are considered to be the state variables. The steering angle of the front wheels and the angle of the controlled joint are considered to be control variables. The velocity of the tractor is considered to be a measured disturbance because it is controlled manually in this research. The state equations are derived from the two sets of given constraints in Equation 5 and Equation 6. The results are in Equation 7.

$$\begin{cases} \dot{x}_R = v\cos(\theta) \\ \dot{y}_R = v\sin(\theta) \\ \dot{\theta} = \dfrac{v\tan(\alpha)}{a} \\ \dot{\beta} = \dfrac{-av\sin(\beta+\gamma) + v(d + c\cos(\gamma) + b\cos(\beta+\gamma))\tan(\alpha) - ad\dot{\gamma}}{a(d + c\cos(\gamma))} \\ \dot{L} = \dfrac{(d-l)(v(\cos(\gamma)(a\sin(\beta) - b\cos(\beta)\tan(\alpha)) + \sin(\gamma)(a\cos(\beta + b\sin(\beta)\tan(\alpha))) - ac\cos(\gamma)\dot{\gamma})}{a(d + c\cos(\gamma)} \end{cases} \tag{7}$$

These state equations are highly nonlinear and, therefore, they must be linearized about an operating point in order to gain the linear state space model as in Equation 1. It turned out that the linearization and QP-solver reinitialization with the MPC Toolbox takes about three times longer than the control cycle time. Therefore, linearization is done only if the tractor heading is changed remarkably. In this research, linearization was done if the tractor heading was changed 45 degrees.

5 Laser scanner measurement handling

The seed drill marks its route on the field with a small plough which is mounted in the following harrow and is located rear left corner of the seed drill. The produced furrow is approximately 5 cm deep and 15 cm wide in dry ground and in wet ground even smaller. The furrow is located at the edge of the swath and it will be covered by the adjacent driving line. As seen in Figure 3, the furrow is not much larger than natural roughness in the field so any additional coverer is not needed.

The laser scanner is mounted one meter above the ground in the front right corner of the seed drill. The scanning direction is perpendicular to the ground and driving direction. In this research a Sick LMS221 2D laser scanner was used. It scans a 180 degree area with one degree resolution 77 times per second.

At first, the laser scanner measurements are transformed from polar coordinates to rectangular coordinates. From this the supposed ground level is found by fitting the first degree polynomial to the neighbourhood of last found mark position by minimizing the Mean Square Error (MSE). The instantaneous mark position is found by fitting the mark prototype to the residuals again by minimizing the MSE error. The found positions are filtered by a five sample averaging filter which leaves the leftmost and the rightmost measurements out. This reduces noise and prevents outliers from affecting the control. In Figure 3, the field profile and fitted ground level together with the mark prototype is drawn.

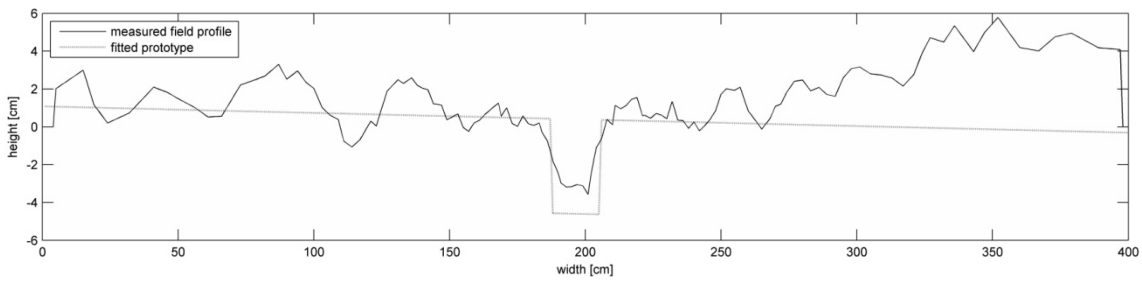

Figure 3 Laser scanner measurements and fitted mark prototype, note that the scales of x- and y-axis are different.

6 Results

The first tests were performed in a simulator where the kinematic model was utilized and noises were modelled. Final tuning was done under field conditions. The prediction horizon of the MPC algorithm was 60 steps and the control horizon was five steps, but the same control value was kept for three consecutive time steps so the control horizon was in total 15 time steps long. A single time step was 100 milliseconds long which was the same as the control cycle time of both algorithms. The followed point in the Target Point –algorithm was four meters ahead of the front axle of the tractor.

The laser scanner worked surprisingly well and distance to the followed path was recognized reliably 80% of the time. Sometimes the tractor front wheels went over the mark furrow and the mark was destroyed. Unfortunately, this happened mainly in tight curves where local positioning is required most. With a wider seed drill these events would be much more uncommon and the recognizing percent even better.

The developed path tracking algorithms were compared in four different cases. Tests were similar to those from Roth et al. (2002). These four different cases were: straight line following test, step response test, real world test and tight curve following test.

The first test - ‘straight line following’, did not shown much difference between the tested algorithms. The following accuracy was almost as good as positioning accuracy with the standard deviation of the errors being smaller than 10 cm.

The second test - ‘step response’, was realized by starting the navigation system at the desired speed when the tractor was manually driven two and a half meters beside the followed path. The function in the Equation 8 was fitted to the error values to gain some statistical information.

$$y = y_0 \exp(-t/\sigma)\cos(\omega t) + y_1 \quad , \tag{8}$$

where t is time since the discontinuity, σ is the exponential decay constant and ω is the oscillation frequency (Roth et al., 2002). Some of the results are listed in Table 1.

Table 1 Results from the second test at 8 km/h speed.

		Tractor			Trailer		
Method	v (km/h)	σ (s)	ω (s^{-1})	$\sum\lvert\varepsilon\rvert$	σ (s)	ω (s^{-1})	$\sum\lvert\varepsilon\rvert$
MPC	8	3.05	0.45	100	3.03	0.54	149
TargetPoint + active joint	8	4.37	0.78	130	2.98	0.73	190
TargetPoint	8	4.90	0.59	149	2.81	0.44	203

It can be seen in the results that the MPC –algorithm is slightly faster to settle down to a new path than the Target Point –algorithm. Nevertheless, changes in the control values were smoother as seen in Figure 4. This is due to the overshooting of the Target Point –algorithm. The same kind of results were achieved also with different speeds and step sizes.

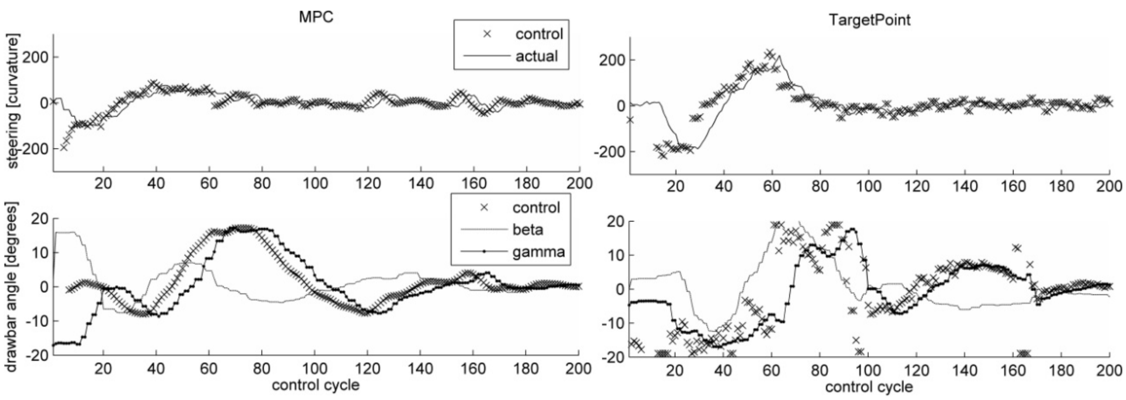

Figure 4 Control values of steering and joint angles using MPC and Target Point –algorithms in step response test.

The third test - ‘real world test’, consisted of several variable sizes curves. The results using either MPC or Target Point –algorithms were again similar. If active joint was not used, however, the error was much larger than with if the active joint was used. Especially in the last test - ‘tight curve test’, where path curvature was changed smoothly from a nine meter radius to a 20 meter radius, the trailer straightened curves being almost one meter distance to the followed path. In the same tests using active joint, the error was 0.40 m at most.

7 Summary and Conclusions

A navigation system with global and local positioning systems was developed. The global positioning system was based on RTK-GPS and the local positioning system was based on a laser scanner and driving marks on the field. The MPC based algorithm was implemented for path tracking purposes. Furthermore, a traditional path tracking algorithm was implemented together with a direct laser scanner based drawbar control for comparison.

The functionality was tested in four different types of field test. An active joint proved to be valuable and the MPC based algorithm produced a smoother control curve and was still able to be as effective as traditional control algorithms. The benefit of MPC is a capability to prepare for future changes in the followed path and a capability to control multiple devices.

Still further development is needed to achieve more precise path following. Also, the kinematic model needs to be enlarged to include the dynamics of actuators. With the help of true Nonlinear Model Predictive Control, the navigation system would also achieve better results.

References

Amidi, O., 1990. Integrated Mobile Robot Control. Carnegie Mellon University. Pittsburgh, Pennsylvania. 39 pp.

Bemporad, A, Morari, M and Ricker, N. L., 2008. Model Predictive Control Toolbox 2 User’s Guide. The MathWorks, Inc. 248 pp.

Lenain, R., Thuilot, B., Cariou, C. and Martinet, P., 2005. Model Predictive Control for Vehicle Guidance in Presence of Sliding: Application to Farm Vehicle Path Tracking. In: ICRA Proceedings of the 2005 IEEE International Conference on Robotics and Automation. Barcelona, Spain, pp. 885-890.

Oksanen, T., 2007. Path planning algorithms for agricultural field machines. Helsinki University of Technology, Espoo, Finland, 110 pp.

Roth, S.A and Batavia, P.H., 2002. Evaluating Path Tracker Performance for Outdoor Mobile Robots. Automation Technology for Off-Road Equipment. 10 pp.

Vougioukas, S.G., 2007. Reactive Trajectory Tracking for Mobile Robots based on Non Linear Model Predictive Control. In: ICRA Proceedings of the 2007 IEEE International Conference of Robotics and Automation. Roma, Italy, pp. 3074-3079.

Wit, J., Crane III, C.D., Armstrong, D., 2004. Autonomous Ground Vehicle Path Tracking. Journal of Robotic Systems 21: 439-449, Wiley Periodicals, Inc.