Nonlinear Model Predictive Trajectory Control in Tractor-Trailer System for Parallel Guidance in Agricultural Field Operations

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Abstract: So called automatic guidance systems are becoming more common in agricultural tractors, so that a driver does not need to steer the vehicle. The systems are mostly relying on GPS with correction. However, these systems usually steer only the tractor itself, despite the fact that the implement is the one that has to be run side by side with the previous swath. With towed implements, or trailers, it is not easy to keep the position of implement on track if the angle of the steering wheels of a tractor is the only resource under control. In this paper, a system with a standard tractor with front steering wheels and an active joint in the drawbar of the trailer are both controlled by the automatic guidance system. Besides, the positioning is not only based on GPS, but also with a local sensor that detects an edge of the previous swath; and this sensor is installed on the trailer. To control this system with two inputs and two outputs with nonlinear kinematics, a multivariable controller is needed for trajectory control. In the paper, an approach to the trajectory control in case of the tractor-trailer system with nonlinear model predictive control (NMPC) is studied. The test results show that the performance is better than with linear model predictive control that was tested in earlier study. Tests were done in driving speeds 8, 10 and 12 km/h. In a curved path, the tractor following error was typically less than 12 cm and in the implement less than 8 cm. The constant control cycle is achieved by alternating the prediction horizon length. By that way, the best possible solution is always gained at the limits of computation time.

Keywords: Path tracking, Predictive control, Navigation, GPS

1. INTRODUCTION

So called automatic guidance systems are becoming more common in agricultural tractors, so that a driver does not need to steer the vehicle. These parallel guidance systems definitely improve a precision of the farming, as overlapping of the operations is minimized and this reduces amount of inputs delivered to the field for instance. Most of the parallel guidance systems are relying on GPS positioning with some correction signal. Some other systems use only local sensors, like ultrasonic rangers, LIDAR, or camera vision to detect the position of parallel swath or the tracks of the previous operation in the field.

However, these commercial systems usually steer only the tractor itself, despite the fact that the implement is the one that has to be run side by side with the previous swath. With towed implements, or trailers, it is not easy to keep the position of implement on a track if the angle of the steering wheels of a tractor is the only resource under control. In a curved trajectory the trailer cuts corners and a deviation from the target trajectory increases due to kinematics. The other common reason why the trailer is not following tracks of the tractor is happening in inclined terrain where the trailer slides downgrade.

The objective of the research that is partially presented in this paper was to improve the path tracking accuracy of the trailer with the help of developed methods.

This paper presents a control system to guide both the tractor and the trailer along the trajectory generated from the previous swath. The system combines two sensors systems used in commercial parallel guidance systems, both GPS and local sensors. Here the GPS positioning device is installed on tractor and the local sensor in the trailer, which is seed drill. The local sensor detects an edge of the adjacent swath. The hypothesis is that a nonlinear model predictive control (NMPC) is powerful approach to realize the trajectory following.

2. TEST CONFIGURATION

In this paper, the test configuration consisted of a standard tractor and towed trailer. The test configuration was the same as reported by Backman et al. (2009). The tractor was a *Valtra T190*, with added *ISOBUS Class 3* facilities, and the trailer was a *Junkkari Maestro 3000* seed drill, also with *ISOBUS* controller. The drawbar of the seed drill was modified by an extra controllable joint, which gave an extra degree of freedom for controlling the position of the seed drill.

The goal of this case was to control the position of the seed drill and to keep it close to the adjacent driving line. Especially in the curves, the seed drill does not follow the same track as the tractor does and the tractor alone navigation system would produce gaps and overlaps.

The adjacent driving line was recognised locally by using a 2D laser scanner. The seed drill had a small plough mounted into a following harrow in the rear right corner of the seed drill. The plough produced a small furrow, which was identified from the field profile measured by the laser scanner. The local measurement and the global position information were merged with the help of the Extended Kalman filter (EKF) and the kinematic model of the system.

Because there were two actuators which affected the position of the seed drill, the problem was a multivariable control problem. Nonlinear Model Predictive Controller (NMPC) is a natural way to accomplish these kinds of tasks (Maciejowski 2002). NMPC was also seen as the best approach to the path tracking problems according to previous publications (Vougioukas 2007; Lenain et al. 2005).

2.1 Kinematic model of the tractor-trailer system

The model of the tractor-trailer system is needed for the estimation and the control purposes. The NMPC uses the kinematic model to estimate the future in the optimization process. The EKF uses the same model to estimate the current state of the controlled system.

In the derivation of the kinematic model, it is assumed that the ground is ideal and slipping affects only the front wheels sideways. By these assumptions, the kinematic model of the tractor is similar to the well-known bicycle model. The difference is the added slipping factor. The differential equation of the tractor's kinematic model is:

$$\begin{bmatrix} \dot{x}_R \\ \dot{y}_R \\ \dot{\theta} \\ \dot{\delta} \end{bmatrix} = \begin{bmatrix} v_t \cos\theta \\ v_t \sin\theta \\ v_t \frac{\tan\delta\alpha_t}{a} \\ 0 \end{bmatrix}, \quad (1)$$

where (x_R, y_R) is the centre position of the rear axle, θ is the heading angle, δ is the slip ratio, α_t is the realized steering angle, v_t is the realized vehicle speed and a is the wheelbase (Figure 1). The calculation of the realized control values are modelled with first order low-pass filter:

$$\begin{bmatrix} v_t(k+1) \\ \alpha_t(k+1) \end{bmatrix} = \begin{bmatrix} k_v v_t(k) + (1-k_v) v_d(k) \\ k_\alpha \alpha_t(k) + (1-k_\alpha)\alpha_d(k) \end{bmatrix}, \quad (2)$$

where k_v and k_α are the filter coefficients and the desired control values are v_d and α_d .

If it is assumed that trailer does not slide sideways, the kinematic behaviour can be modelled with only the angle between the trailer and the tractor. The differential equation for the freely moving joint can be derived to be:

$$\dot{\beta} = \frac{-av_t\sin(\beta+\gamma_t) + v_t(d + c\cos\beta + b\cos(\beta+\gamma_t))\tan\alpha_t - ad\dot{\gamma}_t}{a(d + c\cos\gamma_t)}, \quad (3)$$

where β is the angle between the tractor and the trailer, γ_t is the realized angle of the controlled joint, d is the distance to the seed coulters from the drawbar, c is the length of the drawbar and b is the distance to the attachment point from the rear axle (Figure 1). The realized control value is modelled again with first order low-pass filter:

$$\gamma_t(k+1) = k_\gamma \gamma_t(k) + \left(1-k_\gamma\right)\gamma_d(k), \quad (4)$$

where $k_\gamma$is the filter coefficient and γ_d is the desired joint angle. Because the derivative of the joint angle is needed in the Equation 3, the optimized control value is actually $\dot{\gamma}_d$ and γ_d is obtained by integrating it.

There are also auxiliary states for the optimization and the estimation process. Because the controlled point of the trailer (x_E, y_E) is at the centre point of the seed coulters, it is modelled in the kinematic equations. Also, the position of the laser scanner (x_L, y_L) is in the model.

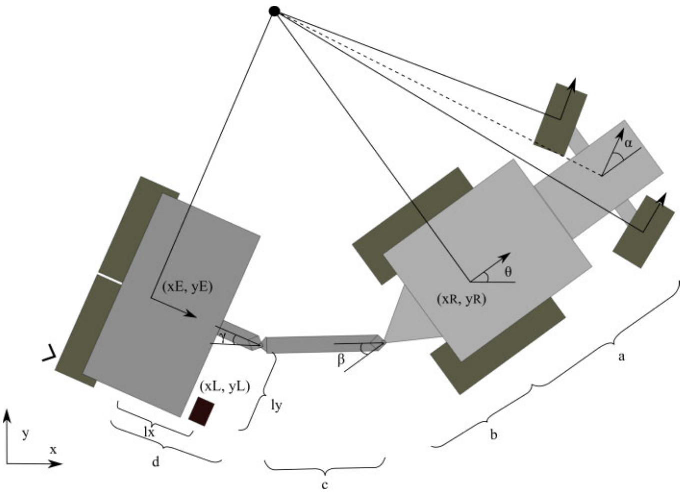

Figure 1. State variables and parameters of the kinematic model

2.2 Real world disturbances

Ideally, all the state variables should be measurable and the kinematic equations would describe the behaviour of the system perfectly. Unfortunately, this is possible only in the simulations and in the real world all kinds of disturbances are accumulated into measurements.

The position of the tractor and the trailer as well as the realized steering angle and speed are directly measurable. However, these measures include disturbances which are not pure Gaussian white noise. Even the most accurate non-military GPS receivers with the correction signal have a roaming error of few centimetres. This error cannot be filtered out without any external local measurement (Oksanen et al. 2005).

It was assumed that the ground is ideal and slipping affect only the front wheels sideways, in the derivation of the kinematic model. This is not true in the real world. The ground is not flat and homogenous. The tractor-trailer system does not follow the kinematic route and especially in the curves the difference could be remarkable. That difference is tried to correct with the slipping factor. This factor cannot be directly measured or beforehand tuned and for that reason it must be estimated continuously.

For bicycle kinematics, slip modelling is reported by (Leinain et al. 2006). Modelling of the slip is extremely challenging in a case of the agricultural fields, as the properties are largely varying. The soil and terrain properties are key factors affecting the slip, including slope, soil type and soil moisture. Also the parameters varying in tractor-trailer system affect the slip; like weight change, tire pressure, weight distribution, amount of additional counterweight installed on the tractor and the up/down state of the implement. In practice it is not possible to measure all these variables and for this model only the front wheel sideway slip is modelled and the rest are handled through estimation and feedback control.

3. METHODS

In the recent survey, different existing path tracking methods has extensively compared (Snider 2009). The path tracking methods were classified to three different groups: the geometric approach, the kinematic controller and the optimal control. The evolution of the path tracking methods has also gone roughly in that order. The NMPC was seen in that survey as a next logical step of the evolution.

In the past research with the same test configuration, a linear Model Predictive Controller (MPC) was used (Backman et al. 2009). As reported in the paper, the performance of that controller was not sufficient especially in tight corners. In addition, the linearization caused delays to the control system.

Vougioukas et al. (2007) have used Nonlinear Model Predictive Tracking (NMPT) to control the steering angle and the speed of the vehicle. The criterion was the difference between the desired trajectory and the actual predicted trajectory. The experiments were done completely in a simulator, but still good results were achieved and the advantage of this approach was shown.

Lenain et al. (2005) have used MPC in the real-time control of the steering angle of the tractor. The desired steering angle was still calculated by a nonlinear control law. MPC was used to reject the delays phenomenon of the actual steering system.

3.1 The Nonlinear Model Predictive Controller

The basic idea of the NMPC is to predict the future and to minimise the cost function. The future is predicted with the mathematical model of the controlled system. The general form of the prediction equations are:

$$x_{k+1} = f(x_k, u_k)$$
$$y_k = h(x_k) \quad , \qquad (5)$$

where x is the state vector, u is the control vector, y is the measurement vector and $\cdot_k$ is the time index. The function f is the state transition function and the function h is the measurement function. In this case, the model of the controlled system is the combined kinematic and dynamic model of the tractor-trailer system as presented in the previous section.

The cost function is a weighted quadratic sum of the state and control values. The general form of the cost function is:

$$J = \sum_{j=k}^{k+M} \left[(x_j - x_{r,j})^T Q (x_j - x_{r,j}) + (u_j - u_{r,j})^T R (u_j - u_{r,j}) \right], \quad (6)$$

where M is the length of the prediction horizon, x_r is the reference trajectory and u_r is the reference control vector. Q and R are positive definite weighting matrices. In this case, the reference control vector is the steady-state controls. At certain time step the position of the tractor or the trailer is not defined beforehand. Instead, at every time step the closest point in the path is searched and the distance and the gradient to this point are calculated. These are used as reference trajectory in the cost function Equation 6. By this way, the cost function in the test configuration is the difference between the controlled points and the desired path (Figure 2). Because the reference trajectory is not defined beforehand, the driving speed can be selected freely and deviation from the path does not induce changes in driving speed.

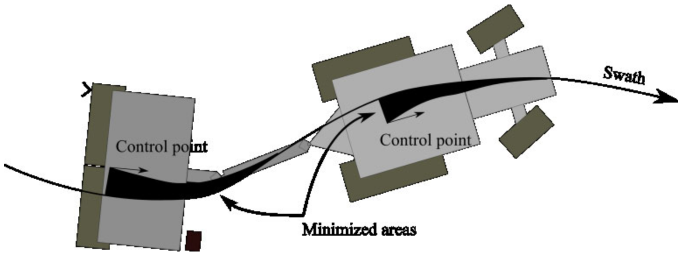

Figure 2. The cost function is the calculated area between the desired path and the realized trajectory.

3.2 The state estimation

The state variables presented in section 2 is summarised in Table 1 together with the measurement devices related to those.

Table 1. State variables

Symbol	Variable	Measurement
(x_R, y_R)	The centre position of the tractor rear axle	RTK-GPS
θ	The heading of the tractor	RTK-GPS + IMU
δ	The slipping factor	
v_t	The realized driving speed	wheel sensors
α_t	The realized steering angle	Potentiometer
β	The angle between the tractor and the trailer	Potentiometer
γ_t	The realized joint control	Potentiometer
(x_E, y_E)	The centre position of the seed coulters	
(x_L, y_L)	The centre position of the laser scanner	The distance to the adjacent driving line

Most of the state variables are directly measurable. However, the measurements are delayed at certain time and the measurements include noise. Therefore the current state must be estimated with the help of EKF.

The estimation procedure follows the standard EKF equations. The tricky part is to include the local measurement of the laser scanner into the equations. In order to do that, the route of the seed drill is recorded. The estimated position of the plough and produced furrow can be calculated from the estimated position and orientation of the seed drill geometrically. The laser scanner measures the lateral distance to the adjacent swath by fitting the prototype of the furrow to the measured field profile (Backman et al. 2009). The same distance can be calculated from the recorded furrow positions and the difference of those distances tells how much current and past estimations differs laterally at the angle of perpendicular to seed drill current heading (Figure 3). To correct both estimates, it would require calculating all recorded estimates again in every estimation step. Because it would require too much computation time, only the current estimate is corrected through the EKF. The correction equation or measurement residual is:

$$\Delta x_L = (\mathrm{L_{meas}} - \mathrm{L_{est}})\cos(\theta - \beta - \gamma_t)$$

$$\Delta y_L = (\mathrm{L_{meas}} - \mathrm{L_{est}})\sin(\theta - \beta - \gamma_t)\ , \qquad (7)$$

where $\mathrm{L_{est}}$ is the estimated lateral distance calculated based on recorded furrow positions and $\mathrm{L_{meas}}$ is the measured lateral distance.

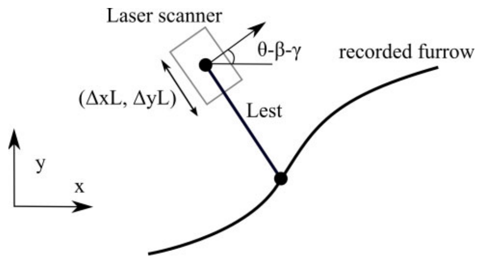

Figure 3. Laser scanner measurement estimation

Also the slipping factor of the front wheel angle cannot be directly measured. It is assumed that it stays almost constant in state prediction. The difference between predicted and measured transition and rotation of the tractor is assumed to occur from incorrect slipping factor. However, the position and heading measurement includes disturbance, so the EKF corrects the slipping factor together with the estimate of tractor position and heading.

3.3 Computational solution to the optimization problem

Solving the NMPC problem is computationally heavy. Usually, the nonlinear problem is transformed into linear one and solved with existing linear optimization methods. The solution of the linear problem is recursively repeated until the solution of the original nonlinear problem is feasible and close enough to the optimal one. In other words, the solution does not get better in one optimization step. The first control values of the solution (u_k) are used and the optimization is repeated with the updated state estimates.

In this research, a modified version of the NMPC tool called HQP (Huge Quadratic Programming) was used (Franke et al. 1996). It solves nonlinearly constrained problems with a sequential quadratic programming (SQP) algorithm as previously described. Convex quadratic sub problems are solved with an interior-point method. The original interface of the tool is modified in order to fulfil strict time limits. The first order derivatives of the discrete-time equations are analytically solved and the Jacobian matrix is manually built. For real-time purposes, an interrupt feature is added to ensure constant control cycle time. In case of the interrupt, control values to this time instant that were calculated in previous control cycle (u_{k+1}) are used and the prediction horizon size is reduced.

3.4 Parameters of the controller

The controller was preliminary tested and tuned in simulation environment. The final tuning was performed with real world environment and with actual hardware.

Based on previous publications (Vougioukas 2007), the prediction horizon has to be more than 25 steps in order to be better than traditional control algorithms. Naturally, the amount of steps required depends on the dynamics and on selected control cycle time; thus it depends. In this case the prediction horizon was set to be 30 steps at maximum and 10 steps at minimum, while the control cycle time is 100 ms.

The dimensions of the test equipment (Figure 1) are following:

$a = 2.8\ [m]$	$d = 3.3\ [m]$
$b = 1.7\ [m]$	$lx = 2.7\ [m]$
$c = 2.3\ [m]$	$ly = 1.48\ [m]$

The physical limitations of the control variables and joint angles are:

$max\lvert\Delta v\rvert = 1\ [m/s^2]$	$max\lvert v\rvert = 5\ [m/s]$
$max\lvert\Delta\alpha\rvert = 0.7\ [rad/s]$	$max\lvert\alpha\rvert = 0.7\ [rad]$
$max\lvert\Delta\gamma\rvert = 0.33\ [rad/s]$	$max\lvert\beta\rvert = 1.57\ [rad]$
	$max\lvert\gamma\rvert = 0.33\ [rad]$

The standard deviations of the state variables and measurements were empirically fitted by filtering recorded measurements and manually fine-tuned to get satisfactory estimation results. The following standard deviations were used in the test drives:

$x_R = 0.002\ [m]$	$x_{R,meas} = 0.03\ [m]$
$y_R = 0.002\ [m]$	$y_{R,meas} = 0.03\ [m]$
$\theta = 0.00002\ [rad]$	$\theta_{meas} = 0.0035\ [rad]$
$v = 0.00007\ [m/s]$	$v_{meas} = 0.000067\ [m/s]$
$\propto = 0.009\ [rad]$	$\propto_{meas} = 0.0066\ [rad]$
$\delta = 0.00001$	$\beta_{meas} = 0.0055\ [rad]$
$\beta = 0.000001\ [rad]$	$\gamma_{meas} = 0.0002\ [rad]$
$\gamma = 0.000002\ [rad]$	$x_{L,meas} = 0.038\ [m]$
$x_L = 1 * 10^{-10}\ [m]$	$y_{L,meas} = 0.038\ [m]$
$y_L = 1 * 10^{-10}\ [m]$	

The measurement delays were identified concurrently with standard deviation measurements and the following delays were found:

$\tau(x_{R,meas}) = 300\ [ms]$ $\tau(\beta_{meas}) = 200\ [ms]$
$\tau(y_{R,meas}) = 300\ [ms]$ $\tau(\gamma_{meas}) = 200\ [ms]$
$\tau(\theta_{meas}) = 500\ [ms]$ $\tau(x_{L,meas}) = 0\ [ms]$
$\tau(v_{meas}) = 100\ [ms]$ $\tau(y_{L,mesa}) = 0\ [ms]$
$\tau(\propto_{meas}) = 100\ [ms]$

The weights of the NMPC controller were experimentally searched. The following weights were used in test drives:

$W(\Delta v) = 0.02$ $W((x_R, y_R)_e) = 0.1$
$W(\Delta\alpha) = 0.004$ $W((x_E, y_E)_e) = 0.005$
$W\ (\Delta\gamma) = 0.004$ $W(\theta_e) = 0.1$

$W(v) = 20$
$W(\alpha) = 0.04$
$W\ (\gamma) = 0.001$

Where $(x_R, y_R)_e$ denotes the lateral error of the tractor and $(x_E, y_E)_e$ denotes the lateral error of the implement. The variable θ_e denotes the heading error of the tractor. $W(v)$, $W(\alpha)$ and $W(\gamma)$ are weights for the steady state control values. $W(\Delta v)$, $W(\Delta\alpha)$ and $W(\Delta\gamma)$ are weights for the optimized control values changes.

4. RESULTS AND DISCUSSION

Several test drives were performed in driving speeds 8, 10 and 12 km/h in real varying field conditions. With the parameters presented in previous section, the following error of the tractor was typically less than 12 cm and in the implement less than 8 cm (Figure 4 and Figure 5). In the reported test drives, the path was curved with 50 meter wavelength and 4 meter amplitude. The first driving line was manually driven and the automatic steering was started after the first headland turning. After that, the automatic steering system guided the vehicle for the next four driving lines also executing the headland turnings.

The accuracy is the same order of magnitude as in Lenain et al. (2005) and in Backman et al. (2009). However, in the first mentioned study the minimized cost was calculated differently and only the tractor was controlled. Therefore only the accuracies of the tractor were compared. In the latter study the accuracy is good only in almost straight paths.

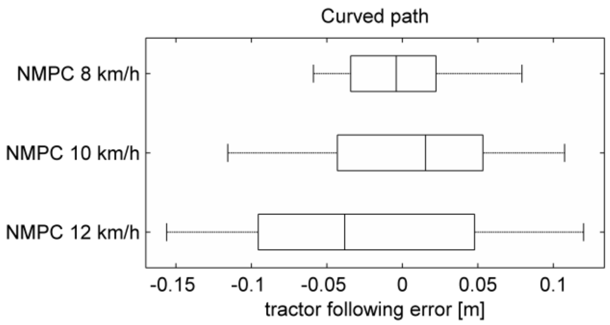

Figure 4. The box-and-whiskers plot of the following error of the tractor in curved path. The box presents the lower and upper quartiles, the band inside the box is the median and the whiskers are the minimum and maximum values.

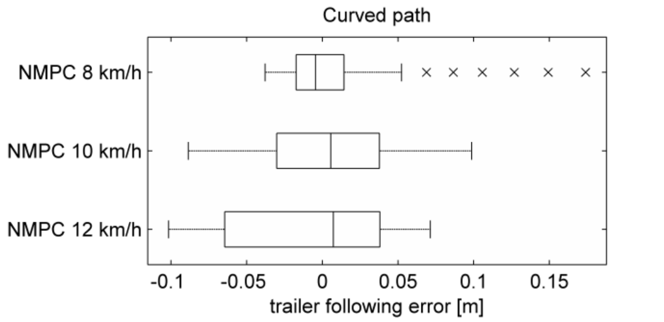

Figure 5. The box-and-whiskers plot of the following error of the trailer in curved path. The crosses are values that are considered to be outliers.

With the used navigation computer, which was powered with Core 2 Duo E8600 processor and 2GB memory, the prediction horizon was changing from 10 time steps to 30 time steps using 100 ms control cycle (Figure 6). Especially in the headland, the prediction horizon reduces to the minimal. The desired path is not feasible in the headland and the optimal solution is harder to calculate.

The path in the headland was calculated by the theorem of Dubins (1957). The theorem states that the time-optimal path between any locations can be calculated by using arcs with constant curvature. Between the arcs, the curvature changes instantaneously and because of the dynamic constraints the path is not feasible.

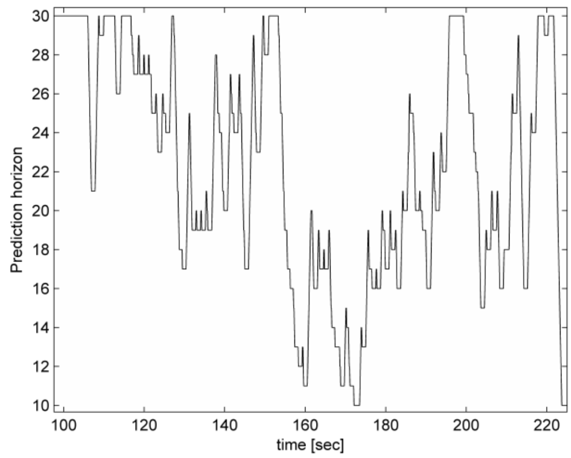

Figure 6. The evolution of the prediction horizon in a typical path. The path included a headland turning at the time between 160 and 180.

However, despite the fact that prediction horizon must be reduced, the control cycle time is still constant. That was not the case in Backman et al. (2009), where linear model was used and linearization made only when necessary. Also, Vougioukas mentioned in the conclusions of his study (Vougioukas 2007) that the prediction horizon is important parameter because it affects both the solution time and also the tracking quality remarkably. Real-time control was not achieved in that study.

In process control, even if the process in nonlinear, linear approximate MPC works often well enough due to the fact that the process is run around certain constant setpoints. In robotics and in control of vehicles, clearly better performance can be reached with NMPC algorithms due to the fact that a system is operated in whole workspace. This is also the case here. NMPC is well behaving solution for multivariable control. However, it is computationally quite heavy. In order to work well, it requires feasible path, which can be a bit difficult to assure in all situations. The reliability has to be tested and management of fault situations has to be carefully planned beforehand. In order to cope with all situations, the accurate NMPC has to be backed up with simpler reliable control law which is used when NMPC fails for some reason.

5. CONCLUSIONS

The objective of the research was to improve the tracking accuracy of the trailer. It has already reported (Backman et al. 2009) that the accuracy of the linear Model Predictive Control (MPC) together with trailer control is better than traditional tractor-alone navigation algorithm or separate controllers for tractor and trailer. In this paper, it is presented that Nonlinear Model Predictive Control (NMPC) work better than linear MPC in curved paths. It is also presented that by alternating the prediction horizon length, the computation time can be regulated to assure strict time limits.

The alternating prediction horizon length is not reported in other references that the author has found. Traditionally, the prediction horizon is one variable that is fixed in the tuning phase. The prediction horizon length is trade-off between computation time and tracking accuracy. To get the best performance, it must be as long as can be calculated in one control cycle time. By alternating it on-line, an optimal horizon size can be achieved.

The calculation of the cost (criteria) is implemented in this study in different way than in other references; the target position is not specified beforehand. The target position and target velocity are not coupled as in the case of fixed reference trajectory. By this way, the driving speed can be selected freely and deviation from the path does not induce changes in driving speed.

The problem with NMPC is that the tuning is case-specific. If the vehicle has different kind of kinematic model, the implementation has to be evaluated carefully again, even in principle it should work. For each case, the state estimation and control has to be retuned. It is difficult to invent proper a generic ‘rules of thumb’ for implementing NMPC. The weighs in the quadric criteria have to be find out and tested experimentally in order to reach ‘right’ driving response and sufficient accuracy in trajectory following.

The current and further developed control algorithms are tested experimentally with real, full scale machines in the ongoing Agromassi- research project.

ACKNOWLEDGEMENT

A part of this research is done in the project Agromassi that is part of FIMECC-program EFFIMA.

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