Semi-automatic Tuning of NMPC Based Trajectory Control System in Agricultural Machine

Juha Backman*. Timo Oksanen*. Arto Visala*

**Aalto University, Dept. of Automation and Systems Technology,*
Otaniementie 17, 02150 Espoo, Finland (Tel: +358 9 470 25154; e-mail: juha.backman@tkk.fi).

Abstract: Currently, the most advanced method to realize trajectory control is to use Nonlinear Model Predictive Control (NMPC). The NMPC also needs an accurate estimate of the state of the controlled system. An Extended Kalman filter (EKF) is the best choice to realize the state estimation. Normally the tuning of these methods requires high expertise from the control engineer as well as knowledge of the controlled system. With the methods proposed in this paper, the tuning phase of the control system can be automated. The proposed methods were tested with a simulator and a full scale agricultural machine with an experimental control system. The methods did not give absolutely correct parameters values, but sufficiently good for EKF and NMPC to work properly.

Keywords: Tuning, Navigation, Trajectory following, Guidance system

1. INTRODUCTION

The Global Positioning System (GPS) was a driving force to create navigation systems for several kinds of vehicles. Agricultural working machines on the field are one of the applications of the navigation technology; the objective is to help a driver to keep a tractor with a tool parallel with the previous swath. Commercial products to keep a tractor on line have been available for more than 10 years. For guidance, an improved GPS positioning is used, with a differential GPS or real-time kinematic GPS (RTK-GPS).

However, the actual objective is to cover the entire field with an operation, so that neither overlaps nor gaps exist in swaths and the field is operated in minimum time. Therefore it is not enough that a tractor follows a certain trajectory, but the implement (an agricultural tool) also follows the trajectory. With a trailer type implement and curved trajectories there is a significant difference.

Agricultural machines are genuine modular systems as a tractor is used with several kinds of implements and the parts of the system are manufactured by more than one company. Historically the modularity has required standardization, and there exists international standards that define the mechanical interface between a tractor and implements. Recently more attention has been paid to electrical, electronical and communication interfaces, and this work has produced another international standard, ISO 11783.

True modularity sets high demands for integrated control systems. An implement may contain a control system that commands tractor resources, or vice versa, but in any case the other part in the system contains uncertainty: with regard to geometrical parameters and dynamics. In order to create a commercially valid and robust control system, a tuning procedure is required. This can be done by either identifying the system from the data with auxiliary sensors, or by setting assumptions and identifying the parameters that cannot be measured by a farmer.

This paper discusses challenges related to a situation, where a farmer has a tractor, an implement of trailer type and a NMPC (Nonlinear Model Predictive Controller) based navigational system that all are able to communicate with each other. The navigational system does not contain any prior information about the physical, geometrical nor dynamic parameters of the tractor or the implement. The objective of the research was to examine how the system can identify the system parameters that cannot be easily measured in order to apply NMPC based trajectory following, or to be adaptive. In this paper an approach to solve the tuning problem in a farm environment is presented for the case of an NMPC based trajectory following system.

2. STATE OF THE ART

Nonlinear Model Predictive Controllers are widely used in industry plants and in process control, where it is used to optimize the operation point of the controlled process. It is easier to implement NMPC in these environments due to longer time constants. If the time constants of the system are small as in vehicle trajectory control, the controller must run with a higher control cycle. This demands high computing capacity in real-time control.

The usage of NMPC in trajectory control has been researched recently (e.g. Vougioukas, 2007; Lenain et al., 2005; Kühne et al. 2005). Kühne et al. (2005) presents nonlinear MPC and linear MPC methods to solve a path-tracking problem with a nonholonomic wheeled mobile robot. In the research, the computational effort required to solve the optimization problems has been studied and the performance of both controllers compared. It was found that, at that time, the Nonlinear Model Predictive Controller was computationally too demanding to be solved in real-time and the linear MPC had a good performance with lower computational effort. But they also noted that the linear model is valid only near the reference trajectory.

Wojsnis et al. (2003) has proposed a practical approach for tuning MPC in process control. The proposed approach is based on four steps: (i) design the process model; (ii) establishing controller generation parameters; (iii) test controller response and behaviour in simulations; and (iv) perform online adjustment. The process is modelled in a Black-box manner using FIR and ARX-models. The controller generation parameters are the prediction and control horizons and penalty matrices on the controlled output error and on the control moves. According to Wojsnis et al., horizon parameters are not suitable to use for tuning or setup. The control and prediction horizons are selected to be long enough considering the process time constants. Also, the ratio between weights is more important than absolute values. For that reason, the penalty matrix on the controlled output error is assumed to be a scalar one. Wojsnis et al. has derived an experimental formula to calculate the penalty matrix on control moves from the process model. In that way, the process model is the most important parameter to be tuned or estimated.

The problem of implementing NMPC trajectory control in a real system is to have a representative model of a system and a proper state estimate. The Kalman filter is a natural choice for the state estimator. The tuning of the Kalman filter involves designing the model of the estimated system and establishing the covariance matrices of the measurement noise (usually symbol *R*) and system internal noise (usually *Q*). Again in chemical process control, Odelson et al. (2006) has researched a method to estimate the covariance matrices automatically with the autocovariance least-squares technique. Especially in GPS and INS integration, Mohamed et al. (1999), Congwei et al. (2003) and Weidong et al. (2007) have all studied covariance matching methods to estimate *Q* and *R* matrices from innovation terms. The drawback of these methods is that they work only for a linear system model.

Jetto et al. (1999a) have proposed an algorithm to update noise covariance matrices with the nonlinear Extended Kalman filter. In the proposed algorithm the *Q* and *R* matrices are assumed to be diagonal matrices. The components of the diagonal matrices are updated based on the innovation terms as in the linear case. There exist also algorithms based on Fuzzy logic to calculate weighting values for covariance matrices (e.g. Jetto et al. 1999b and Sasiadek et al. 2000).

The stability of the NMPC controller depends on the correct model of the controlled system, as well as on the correctness and stability of the state estimate.

3. PRELIMINARY KNOWLEDGE

3.1 System model

The methods presented in this paper are applied in a real control system and full scale agricultural vehicle. The controlled vehicle consists of standard tractor and a towed trailer with an active joint (Figure 1).

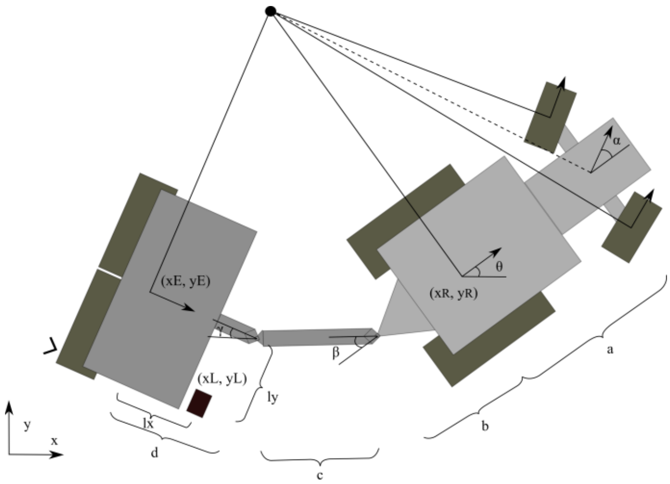

Figure 1. State variables and the parameters of the kinematic model (Backman et al. 2010).

The controlled system is modelled in two phases: (i) the kinematic model of the vehicle and (ii) the dynamics of the actuators. In the derivation of the kinematic model, it is assumed that slipping sideways does not occur except in the front wheels. The front wheel slipping is assumed to be linearly dependant on the wheel angle. The kinematic equation of the controlled vehicle is hence

$$\begin{bmatrix} \dot{x}_R \\ \dot{y}_R \\ \dot{\theta} \\ \dot{\beta} \\ \dot{\delta} \end{bmatrix} = \begin{bmatrix} \hat{v}\cos\theta \\ \hat{v}\sin\theta \\ \hat{v}\dfrac{\tan\delta\hat{\alpha}}{a} \\ \dfrac{-a\hat{v}\sin(\beta+\hat{\gamma}) + \hat{v}(d + c\cos\beta + b\cos(\beta+\hat{\gamma}))\tan\hat{\alpha} - ad\dot{\hat{\gamma}}}{a(d + c\cos\hat{\gamma})} \\ 0 \end{bmatrix}, \quad (1)$$

where (x_R, y_R) is the global position of the centre of the tractor rear axle, θ is the heading angle of the tractor, β is the angle between the tractor and the trailer and δ is the slipping factor of the front wheels. a, b, c and d are the physical parameters of the system; wheelbase, attachment point, length of the drawbar and distance to the centre of the seed coulters from the drawbar respectively (Figure 1).

The Dynamical models of the actuators are first order difference models. The dynamical model of the speed is

$$\hat{v}(t_{k+1}) = k_v \hat{v}(t_k) + (1 - k_v) v(t_k) \quad (2)$$

where $\hat{v}$ is the actual speed, v is the control value of the speed and k_v is the dynamic parameter. Similarly, the dynamical model of the steering is

$$\hat{\alpha}(t_{k+1}) = k_\alpha \hat{\alpha}(t_k) + (1 - k_\alpha) \alpha(t_k), \quad (3)$$

where $\hat{\alpha}$ is the actual steering angle, α is the control value of the steering and k_α is the dynamic parameter. Finally, the dynamical model of the controlled joint is

$$\hat{\gamma}(t_{k+1}) = k_\gamma \hat{\gamma}(t_k) + (1 - k_\gamma) \gamma(t_k), \quad (4)$$

where $\hat{\gamma}$ is the actual joint angle, γ is the controlled joint angle and k_γ is the dynamic parameter.

3.2 Parameter types

The parameters in the navigation system can be classified into four categories: (i) the parameters than cannot change during the operation and can be directly measured by measuring tape; (ii) the parameters that usually do not change during the operation time but cannot be directly measured; (iii) the parameters that can change during the operation time; and (iv) the parameters of the actual control algorithm that usually are kept constant.

The first class of parameters is trivial. Those parameters can be measured once and then left untouched. The parameters that belong to this class are listed in Table 1.

Table 1. Constant physical parameters

Symbol	Unit	Description
a	m	The wheelbase of the tractor
b	m	The distance to the attachment point from the rear axle
c	m	The length of the drawbar
d	m	The distance to the seed coulters from the drawbar
lx	m	Lateral distance to the laser scanner from the centre of the seed drill
ly	m	Longitudinal distance to the laser scanner from the drawbar
$\max\lvert v\rvert$	m/s	Maximum speed
$\max\lvert\alpha\rvert$	rad	Maximum steering angle
$\max\lvert\beta\rvert$	rad	Maximum angle of the free joint
$\max\lvert\gamma\rvert$	rad	Maximum angle of the controlled joint

The second class of parameters must be estimated using some kind of estimator. The estimation process must be repeated every time when something is changed; for example different implements. Parameters that belong to the second class are in listed in Table 2.

Table 2. Constant estimated parameters

Symbol	Unit	Description
$\tau(x_{R,meas})$	ms	Delay of the position measurement (RTK-GPS)
$\tau(y_{R,meas})$	ms	Delay of the position measurement (RTK-GPS)
$\tau(\theta_{meas})$	ms	Delay of the heading measurement (Fiber Optic Gyroscope)
$\tau(v_{meas})$	ms	Delay of the speed measurement
$\tau(\alpha_{meas})$	ms	Delay of the steering measurement
$\tau(\beta_{meas})$	ms	Delay of the joint angle measurement
$\tau(\gamma_{meas})$	ms	Delay of the joint angle measurement
$\max\lvert\dot{v}\rvert$	m/s²	Maximum acceleration
$\max\lvert\dot{\alpha}\rvert$	rad/s	Maximum steering angle rate
$\max\lvert\dot{\gamma}\rvert$	rad/s	Maximum joint angle rate
$\sigma(\theta_{meas})$	rad	Standard deviation of the angle measurement noise
$\sigma(v_{meas})$	m/s	Standard deviation of the speed measurement noise
$\sigma(\alpha_{meas})$	rad	Standard deviation of the steering measurement noise
$\sigma(\beta_{meas})$	rad	Standard deviation of the joint angle measurement noise
$\sigma(\gamma_{meas})$	rad	Standard deviation of the joint angle measurement noise

The third class of parameters must be initialized before the operation can be started, but also updated during the operation. Parameters that belong to the third class are listed in Table 3.

Table 3. Time-varying estimated parameters

Symbol	Unit	Description
$\sigma(x_{R,meas})$	m	Standard deviation of the GPS position measurement
$\sigma(y_{R,meas})$	m	Standard deviation of the GPS position measurement
k_v	-	Dynamics of the speed
k_α	-	Dynamics of the steering
k_γ	-	Dynamics of the joint control
δ	-	Slipping factor of the front wheels

The fourth class of parameters cannot be measured or estimated. Some rules of thumb can be derived to tune these parameters, but generally these parameters are manually tuned once and then left constant.

Table 4. NMPC parameters

Symbol	Description
m	NMPC control horizon
p	NMPC prediction horizon
$W(\dot{v})$	Weight for the speed change
$W(\dot{\alpha})$	Weight for the steering change
$W(\dot{\gamma})$	Weight for the joint control
$W(v)$	Weight for the steady state speed
$W(\alpha)$	Weight for the steady state steering
$W(\gamma)$	Weight for the steady state joint
$W((x_R, y_R)_e)$	Weight for the tractor lateral error
$W((x_L, y_L)_e)$	Weight for the trailer lateral error
$W(\theta_e)$	Weight for the tractor angular error

Later, the focus is how to estimate the second class of parameters and to initialize the third class of the parameters. The same methods can be used partially in the operation time to update the third class of the parameters.

4. METHODS

At the beginning of the tuning process, it is assumed that there is no knowledge of the parameters, and therefore the state estimator and closed loop control cannot be used; it is not possible to guarantee the stability of the controlled system. Only the parameters of class 1 can be set according to manual measurements. It is also assumed that the process model presented in Section 3 is correct and the unmodelled disturbances are random white noise with zero mean.

The input and output signals for parameter estimation are generated using open loop control. The input signals are assumed to be rich enough to produce sufficient information about the controlled system. For example, stepwise changes in the input signals with varying amplitudes can be used. The parameters of the navigation system are estimated offline from these recorded input and output signals. The estimation procedure contains four steps:

1. Estimating the dynamics of the actuators and the delays of the actuator measurements
2. Estimating the delays of the heading and the position measurement and estimating the average of the slipping factor of the front wheel
3. Simulating the remaining measurements and calculating the delays of the remaining measurements
4. Calculating the standard deviations of the measurement noises

These four different steps are described separately in the following subsections.

4.1 Estimating the dynamics of the actuators and the delays of the actuator measurements

The behaviours of the actuators are modelled using first order difference models and discrete time delays. The change of the input signal is also limited using rate limit values.

The delays and rate limit values of the controls are estimated iteratively. One step of the iteration contains two phases: limiting the change of the control value and estimating the dynamics of the actuator with several different delay values. The rate-limit and delay-time pair with minimum MSE is chosen and the corresponding dynamic parameter is used.

The changes of the input control values are limited as follows:

$$u_l(t_{k+1}) = \begin{cases} u_l(t_k) - T\max|\dot{u}| & \text{if } u(t_{k+1}) - u_l(t_k) < -T\max|\dot{u}| \\ u(t_{k+1}) & \text{if } |u(t_{k+1}) - u_l(t_k)| \le T\max|\dot{u}| \\ u_l(t_k) + T\max|\dot{u}| & \text{if } u(t_{k+1}) - u_l(t_k) > T\max|\dot{u}| \end{cases}, \quad (5)$$

where u_l is the limited control value, u is the original unlimited control value (v, α or γ), $\max|\dot{u}|$ is the maximum change of that control value and T is the sampling time ($t_{k+1} - t_k$).

The parameters of the dynamic models (2-4) are estimated using least-squares estimate

$$\hat{\theta} = \left(\mathbf{\Phi}^{\mathrm{T}}\mathbf{\Phi}\right)^{-1}\mathbf{\Phi}^{T}\mathbf{Y}, \quad (6)$$

where $\hat{\theta}$ is the parameter estimate (k_v, k_α or k_γ). $\mathbf{Y}$ and $\mathbf{\Phi}$ matrices are arranged as follows:

$$\mathbf{\Phi} = \begin{bmatrix} y(t_\tau) - u_l(t_1) \\ \vdots \\ y(t_{N-1}) - u_l(t_{N-\tau}) \end{bmatrix} \quad (7)$$

$$\mathbf{Y} = \begin{bmatrix} y(t_{\tau+1}) - u_l(t_1) \\ \vdots \\ y(t_N) - u_l(t_{N-\tau}) \end{bmatrix}, \quad (8)$$

where y, u_l and τ are corresponding measurement, limited control and delay values.

4.2 Estimating the delays of the heading and the position measurement and the slipping factor of the front wheel

The estimation of the delays of the heading and the position measurement and the slipping factor of the front wheel are all based on the heading angle.

The change of the heading angle is estimated using kinematic equation (1) and setting the slipping factor of the front wheels to one:

$$\hat{\dot{\theta}} = \hat{v}\frac{\tan\hat{\alpha}}{a}, \quad (9)$$

where $\hat{\alpha}$ is the steering angle filtered using the dynamic equation of the steering (3) and $\hat{v}$ is the speed filtered using the dynamic equation of the speed (2). The parameters for the dynamic equations (k_α and k_v) are gained from the previous step.

The delay of the heading measurement is estimated by minimizing the squared difference between the measured ($\dot{\theta}_{meas}$) and estimated ($\dot{\hat{\theta}}$) change of heading:

$$\tau(\theta_{meas}) = \min_{\tau} \sum_{k} \left(\dot{\hat{\theta}}(t_k) - \dot{\theta}_{meas}(t_{k+\tau}) \right)^2 . \tag{10}$$

The position measurement delay is estimated similarly by minimizing the squared difference between the measured heading and the derived heading from the position measurement:

$$\begin{aligned} &\tau(x_{R,meas}) = \tau(y_{R,meas}) = \\ &\tau(\theta_{meas}) + \min_{\tau} \sum_{k} \left(\theta_{meas}(t_k) - \theta_{pos}(t_{k+\tau})\right)^2 \end{aligned} \tag{11}$$

The heading is derived from position measurement as follows:

$$\theta_{pos} = \operatorname{atan2}(\dot{y}_{R,meas}, \dot{x}_{R,meas}), \tag{12}$$

where $\dot{y}_{R,meas}$ and $\dot{x}_{R,meas}$ are changes of the position measurement.

Finally, the slipping factor of the front wheels is estimated by taking the average of the ratio between the estimated steering angle and the hypothetical steering angle from the heading measurement:

$$\delta = \frac{1}{N} \sum_{k=1}^{N} \left(\frac{\arctan\left(a \dfrac{\dot{\theta}_{meas}(t_{k+\tau(\theta_{meas})})}{\hat{v}(t_k)} \right)}{\hat{\alpha}(t_k)} \right), \tag{13}$$

where N is the total number of used sample points.

4.3 Simulating remaining measurements and calculating the delays of the remaining measurements

As in the previous step, the delays of the remaining measurements can be estimated using filtered control values and kinematic equations.

The only measurement that is left is the freely moving angle between the tractor and the trailer. The change of the freely moving joint is estimated:

$$\dot{\hat{\beta}} = \frac{-a\hat{v}\sin(\beta + \hat{\gamma}) + \hat{v}(d + c\cos\beta + b\cos(\beta + \hat{\gamma}))\tan\hat{\alpha} - ad\dot{\hat{\gamma}}}{a(d + c\cos\hat{\gamma})} . \tag{14}$$

The delay of the joint angle measurement is estimated by minimizing the squared difference between the measured ($\dot{\beta}_{meas}$) and the estimated ($\dot{\hat{\beta}}$) change of the angle:

$$\tau(\beta_{meas}) = \min_{\tau} \sum_{k} \left(\dot{\hat{\beta}}(t_k) - \dot{b}_{meas}(t_{k+\tau}) \right)^2 . \tag{15}$$

4.4 Calculating the standard deviations of the measurement noises

In the previous steps, all measurements are estimated using kinematic and dynamic equations and the parameter estimates gained from the measurements. Also the delays of the measurements are estimated. It was assumed that all the remaining difference between the measurement and the estimate is white noise. Therefore, the measurement noises are calculated:

$$\sigma(y) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left(y(t_k) - \hat{y}(t_{k+\tau(y)})\right)^2} , \tag{16}$$

where y is the measurement, $\hat{y}$ is the estimate of the measurement and $\tau(y)$ is the discrete time delay of that measurement.

5. RESULTS

The input signals of the calibration sequence were left undefined in Section 4 due to differences between the hardware capabilities of different vehicles. With the test equipment used in this research, the calibration sequence contains a step response test for all controls separately with different step sizes (Figure 2). The step response tests for steering and joint control are realized at nominal driving speed (2 m/s).

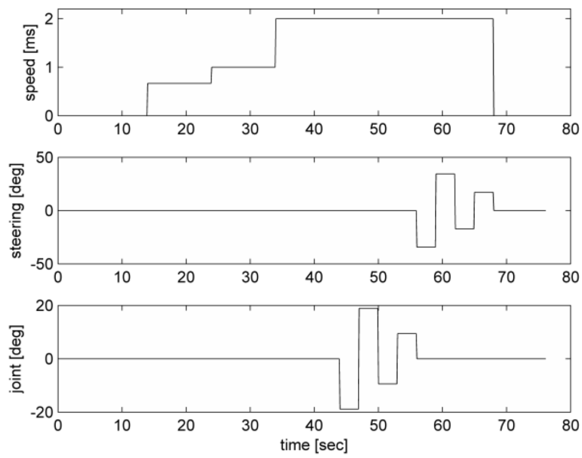

Figure 2. Input control signals for identification.

The proposed methods were tested both in a simulator, where the parameters are known, and with real equipment, where the parameters are unknown. The simulator test consisted of two different sets of test. The parameters of the simulator were modified between the test sets. Both test sets contained ten different calibration sequences. The results of the calibrations are listed in the Table 5, which contains the means and the standard deviations of each parameters together with the true values.

Table 5. Test results in the simulator

Symbol	Test 1		Test 2	
	Est.	True	Est.	True
$\tau(x_{R,meas})$ $\tau(y_{R,meas})$	630 (245)	400	590 (233)	500
$\tau(\theta_{meas})$	340 (52)	300	390 (32)	400
$\tau(v_{meas})$	440 (51)	300	510 (57)	400
$\tau(\alpha_{meas})$	360 (52)	300	410 (32)	400
$\tau(\beta_{meas})$	660 (52)	500	660 (52)	600
$\tau(\gamma_{meas})$	1320 (63)	500	1720 (79)	600
$\max\lvert\dot{v}\rvert$	0.5 (0.0)	0.5	0.7 (0.0)	0.7
$\max\lvert\dot{\alpha}\rvert$	0.5 (0.0)	0.48	0.79 (0.03)	0.72
$\max\lvert\dot{\gamma}\rvert$	5.41 (1.77)	2.2	6.6 (0.0)	2.2
$\sigma(\theta_{meas})$	0.003097 (0.002567)	0	0.009196 (0.001206)	0.01
$\sigma(v_{meas})$	0.022341 (0.001409)	0.02	0.024166 (0.000768)	0.02
$\sigma(\alpha_{meas})$	0.012944 (0.000827)	0.01	0.013791 (0.001971)	0.01
$\sigma(\beta_{meas})$	0.075294 (0.002587)	0.045	0.113412 (0.005169)	0.063
$\sigma(\gamma_{meas})$	0.057122 (0.004257)	0.032	0.066766 (0.001791)	0.045
k_v	0.880474 (0.006740)	0.9	0.712917 (0.024116)	0.8
k_α	0.544548 (0.082713)	0.67	0.441449 (0.095754)	0.4
k_γ	0.821790 (0.016349)	0.9	0.770314 (0.033090)	0.9
δ	0.895788 (0.021277)	1	0.786503 (0.020340)	0.8

With the real equipment described in the third section, the proposed method was tested several times under different conditions. The results of the three different tests are listed in Table 6. The first calibration test was performed in a grass field and the seed drill was in transport state. The second calibration test was performed in a threshed crop field and the seed drill was in working state. The third calibration test was performed in a harrowed field and the seed drill was again in working state.

Table 6. Test results with the real system

Symbol	Test 1	Test 2	Test 3
	Est.	Est.	Est.
$\tau(x_{R,meas})$ $\tau(y_{R,meas})$	200 [ms]	300 [ms]	300 [ms]
$\tau(\theta_{meas})$	100 [ms]	200 [ms]	200 [ms]
$\tau(v_{meas})$	500 [ms]	600 [ms]	100 [ms]
$\tau(\alpha_{meas})$	100 [ms]	100 [ms]	200 [ms]
$\tau(\beta_{meas})$	200 [ms]	200 [ms]	100 [ms]
$\tau(\gamma_{meas})$	100 [ms]	200 [ms]	200 [ms]
$\max\lvert\dot{v}\rvert$	0.5 [ms/s^2]	0.4 [ms/s^2]	0.4 [ms/s^2]
$\max\lvert\dot{\alpha}\rvert$	0.4 [rad/s]	0.4 [rad/s]	0.4 [rad/s]
$\max\lvert\dot{\gamma}\rvert$	1.9 [rad/s]	2.2 [rad/s]	2.2 [rad/s]
$\sigma(\theta_{meas})$	0.005672	0.005553	0.004272
$\sigma(v_{meas})$	0.065747	0.106305	0.123000
$\sigma(\alpha_{meas})$	0.019499	0.011546	0.018715
$\sigma(\beta_{meas})$	0.038527	0.029015	0.036244
$\sigma(\gamma_{meas})$	0.012112	0.009382	0.012608
k_v	0.871893	0.915468	0.944871
k_α	0.657935	0.508497	0.573319
k_γ	0.851840	0.837685	0.826468
δ	0.750245	0.743750	0.741343

6. DISCUSSION

The results show that the proposed methods give reasonably accurate parameter estimates for the controlled system. Usually, however, the estimate is greater than the true value. This is natural especially with the noise parameters, because the model is assumed to be perfect and no internal noise of the process is present (Q-matrix is zero). In reality, the noise is divided between measurement and process noises. However, the ratios between the different measurement noises are more important than the absolute values.

Other drawbacks of the proposed methods are that the estimated delay-times are multiples of the sampling time and the calibration sequence demands quite a large open area. However, the driver is usually present to make sure that the calibration is safe to perform and there are usually some fields in the farm that can be used. The discrete delay-time steps seemed to be sufficient for the control system to work properly. More details about the following accuracy can be found in Backman et al. (2010).

The topics for further investigations would be the estimation of the process noise covariance (Q-matrix), the tuning of the weight matrices, online adaptation and the usage of different kinds of kinematic types.

7. CONCLUSIONS

With the methods presented in this paper, the advanced NMPC based trajectory control system can be introduced in any vehicle with similar kinematics without the expertise of the control engineering. The methods do not extract the absolutely correct parameters of the system, but they do give rough estimates that lead to stable and sufficient performance of the EKF filter and the NMPC control.

All the methods presented in this paper give "a priori" information about the controlled system. These methods do not exclude the possibility of using other adaptation methods as well to update, for instance, the noise covariance matrices online.

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