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Disturbance Estimation for Feedforward Control of Inland Vessels

B. Herzer * E. D. Gilles **

* *Max Planck Institute for Dynamics of Complex Technical Systems, Magdeburg, 39106 Germany (e-mail: herzer@isys.uni-stuttgart.de)*
** *Max Planck Institute for Dynamics of Complex Technical Systems, Magdeburg, 39106 Germany (e-mail: gilles@mpi-magdeburg.mpg.de)*

Abstract: The methods presented in this paper were designed to improve the performance of a control scheme for the automatic track-keeping of inland vessels. The performance of this control scheme heavily depends on the underlying models as it employs model inversion for the calculation of feedforward input signals and reference trajectories for feedback control. However, vessels on rivers are subject to model uncertainties as well as disturbances, such as cross currents or wind. Therefore, an estimation scheme was designed for the estimation of disturbances and their integration into the model inversion procedure. Simulation results show the usefulness of the presented methods for various disturbances and model uncertainties.

Keywords: disturbance estimation, track-keeping, model inversion, feedforward control

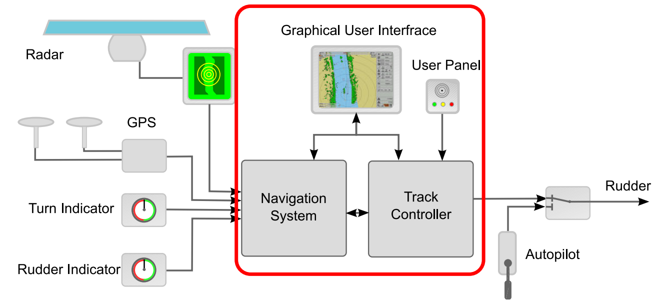


Fig. 1. Structure of the navigation system.

1. INTRODUCTION

The methods presented in this paper were designed for the integration into an existing navigation system for the automatic track-keeping of inland vessels. The structure of the navigation system, including the track-keeping functionality is depicted in Fig. 1. The graphical user interface consists of a computer screen, displaying the position of the ship in an electronic map overlaid with a radar image. The captain has the option, via a user panel, to select one of the displayed guiding lines(GL) stored in the system and activate the track controller. The track controller then actuates the rudder and keeps the vessel on the chosen track allowing the captain to focus on traffic. With the use of a joy stick, the captain has the option to parallel shift the desired track to avoid oncoming traffic, for example. Then the navigation system updates the desired track and generates a smooth transition from the current position to the newly set parallel distance to the guiding line. The data of various sensors, such as GPS or gyroscopes, is fed into the system were it is processed by a Kalman filter allowing for the estimation of the dynamic states. The structure of the controller is depicted in Fig. 2. It is based on a 2dof-design, with a feedforward component for the calculation

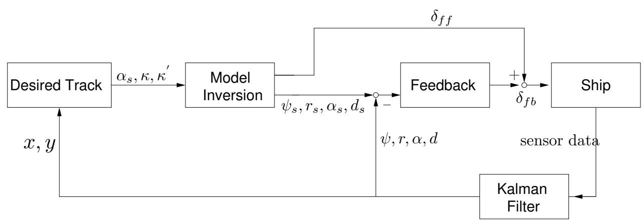
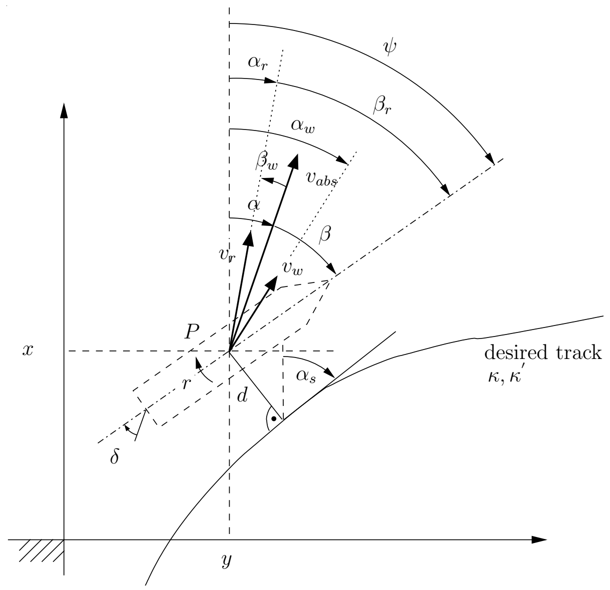


Fig. 2. Controller structure (variables see Fig. 3).

of the feedforward rudder angle δ_{ff} and reference states as well as a feedback component to compensate for model uncertainties and external disturbances. The feedforward controller is based on the dynamic inversion of the ship model, whereas the feedback controller is implemented as a Riccati controller based on the linearized model around the desired track. This control system has been proven to work well with various vessels and river conditions, thereby providing the captain an important aid in navigating safely. The methods presented in this paper aim to enhance control performance and robustness. To achieve this goal, external disturbances, which were unaccounted for in the existing control scheme, are now estimated and explicitly processed in the feedforward component of the control algorithm. Moreover, using model based control schemes, knowledge of the parameters of the underlying models is important for control performance. However, it is desirable to maintain control performance even in case of inaccurately set parameters. Therefore, it was also investigated whether an estimation of disturbances can compensate for model errors. In Do (2010) a disturbance observer for the estimation of unknown constant disturbances is integrated into the control design for track-keeping. The methods presented here are specifically tailored for the integration into the existing control scheme.

This paper is organized as follows. In section two the model and the model inversion procedure are introduced. Section



P..	Reference point	α..	Course angle (over ground)
ψ..	Heading	α_r..	Course angle (over water)
r..	Turning rate	α_w..	Angle of current
v_{abs}..	Speed over ground	β..	Drift angle ($\psi - \alpha$)
v_w..	Speed of water	β_r..	Rel. drift angle ($\psi - \alpha_r$)
v_r..	Speed over water	β_w..	Drift angle due to current $\beta - \beta_r$
κ..	Curvature of desired track	δ..	Rudder angle

Fig. 3. Variables involved in dynamics and control.

three describes estimation schemes for the estimation of disturbances in the drift angle β and the turning rate r and their incorporation in the control scheme. Simulation results demonstrate the usefulness of the presented methods for various disturbances and model uncertainties. Finally, the paper is concluded with a brief discussion of the advantages of the presented methods.

2. MODEL EQUATIONS AND INVERSION

In this section the model equations and the inversion procedure are introduced. The feedforward model consists of the states heading angle ψ, turning rate r and drift angle β which are depicted in Fig. 3, along with all other relevant variables. This section is finished by a brief description of the feedback model.

2.1 Model Equations

For the turning rate r a simple first order Nomoto model (see e.g. Fossen (2002)) is employed:

$$\dot{r} = -\frac{1}{T_r} r + b_r \delta. \tag{1}$$

The parameters T_r and b_r are assumed to be dependent on relative speed v_r according to Bolk (2004)

$$T_r = T_r^N \frac{v_r^N}{v_r}, \quad b_r = b_r^N \frac{{v_r}^2}{{v_r^N}^2}. \tag{2}$$

The differential equation for the drift angle β was originally derived in Bittner (2002). Here a slightly different approach is presented, which is based on Newton's law for the sway speed v_s in the reference point P. Assuming the center of gravity in P, the horizontal plane model results in

$$m(\dot{v}_s + u_s r) = F_{ad} + \sum F_y, \tag{3}$$

with the surge speed u_s and the added mass related force F_{ad} (Fossen (2002)):

$$F_{ad} = m_{ad} \dot{v}_s. \tag{4}$$

The drift angle β can be described as

$$\tan(\beta) = -\frac{v_s}{u_s}. \tag{5}$$

With $v_s \ll u_s$ the following assumptions can be made:

$$\beta = -\frac{v_s}{u_s}, \quad u_s = v_{abs}, \quad \dot{u}_s = \dot{v}_{abs} = 0 \tag{6}$$

and

$$\beta = -\frac{v_s}{v_{abs}}, \quad \dot{\beta} = -\frac{\dot{v}_s}{v_{abs}} \quad . \tag{7}$$

With (4),(6) and (7) $\dot{\beta}$ can be stated as

$$\dot{\beta} = -\frac{1}{(m + m_{ad}) v_{abs}} \sum F_y + \frac{m}{m + m_{ad}} r \quad . \tag{8}$$

The forces F_y consist of the following components:

- forces of the water acting upon the hull due to the angle β_r between hull and stream (Bittner (2002)):
$$F_y^\beta = c_\beta v_r^2 \beta_r = c_\beta v_r^2 (\beta - \beta_w). \tag{9}$$
- forces F_w due to wind
- rudder force F_δ

The rudder force F_δ is assumed to be small compared to F_y^β and is therefore neglected. The force F_w is not dependent on the states or the inputs and is therefore considered as disturbance.

For the drift angle β_w between the vector of absolute speed v_{abs} and the vector of relative speed v_r the following equation holds

$$v_r \sin(\beta_w) = v_w \sin(\alpha - \alpha_w). \tag{10}$$

Given that $|\beta_w| < \frac{\pi}{2}$, which is the case in track-keeping occurring under normal conditions, the following approximation can be introduced:

$$\beta_w \approx \frac{v_w}{v_r} \sin(\alpha - \alpha_w). \tag{11}$$

The drift dynamics model results in:

$$\dot{\beta} = -\frac{1}{T_\beta^N} \frac{v_r^2}{v_{abs}} (\beta - \frac{v_w}{v_r} \sin(\alpha - \alpha_w)) + K_\beta r. \tag{12}$$

2.2 Model Inversion

In Bittner (2002) the model inversion procedure for feedforward control of inland vessels was introduced. The task of model inversion consists of calculating a feedforward rudder angle δ_{ff} that keeps the vessel on the desired track under nominal conditions, as well as calculating reference trajectories for the model states of the underlying state feedback controller. For the reference states ψ_s, r_s and β_s the following relations can be stated

$$\psi_s = \alpha_s + \beta_s \tag{13}$$

$$r_s = \dot{\alpha}_s + \dot{\beta}_s \tag{14}$$

$$\dot{r}_s = \ddot{\alpha}_s + \ddot{\beta}_s \quad , \tag{15}$$

whereas α_s represents the known course of the desired track and $\dot{\alpha}_s$ and $\ddot{\alpha}_s$ can be calculated with the known curvature κ of the desired track:

$$\dot{\alpha}_s = v_{abs}\kappa \tag{16}$$

$$\ddot{\alpha}_s = v_{abs}\frac{\partial}{\partial s}\kappa \tag{17}$$

From eq.(1) it follows that

$$\delta_{ff} = \frac{1}{b_r}\dot{r}_s + \frac{1}{T_r b_r}r_s. \tag{18}$$

Equations (14) and (12) allow for the formulation of a differential equation for β_s,

$$\begin{aligned}\dot{\beta}_s = &-\frac{1}{T_\beta^N(1-K_\beta)}\frac{v_r^2}{v_{abs}}(\beta_s - \frac{v_w}{v_r}\sin(\alpha_s - \alpha_w)) \\ &+\frac{K_\beta}{1-K_\beta}\dot{\alpha}_s,\end{aligned} \tag{19}$$

which is only dependent on β_s and the known quantities α_s, α_w (see section two) and $\dot{\alpha}_s$ and can therefore be integrated. In system theoretic terms eq.(19) represents the zero dynamics of the system for the output $\alpha = \psi - \beta$. As $K_\beta < 1$ this equation is stable and can always be integrated.

Eq. (19), (13) and (14) allow for the computation of reference trajectories for the underlying state feedback controller. Eq. (19), (14), (15) and (18) allow for the computation of the feedforward rudder angle δ_{ff}.

2.3 Feedback Model

The Riccati controller in Fig. 2 is based on the linearized model equations around the reference trajectories for the respective states. As the goal is ultimately to control the distance d between the control reference point of the vessel and the desired track, the distance d needs to be incorporated into the feedback model, with

$$\frac{d}{dt}(d - ds) = v_{abs}(\alpha - \alpha_s), \tag{20}$$

with $d_s = 0$. Apart from that, the model is augmented by the state $i = \int d - d_s$, to guarantee for zero offset in the state d in case of disturbances. More information can be found in Bolk (2004).

3. DISTURBANCE ESTIMATION

In the following sections the algorithms for the estimation of disturbances in the turning rate r and the drift angle β are presented. The simulations were carried out for the parameters of a push tow with four empty barges (length = 180m), going downstream with $v_{abs} = 4.5m/sec$. The underlying model and control parameters can be found in table 1. Additionally, the employed simulation tool allows for the simulation of sensor data with their respective sample rates and measurement noise.

Table 1. List of parameters.

v_{abs}	v_r	T_r^N	b_r^N	v_r^N	T_B^N	K_β	T_{aw}	T_{rw}	K_{rw}
4.5	3.5	22.0	0.001	3.5	50.0	0.7	40.0	20	0.1

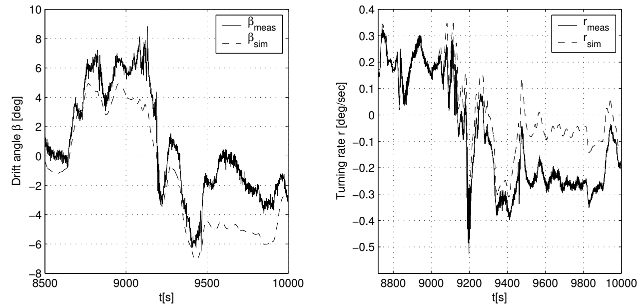


Fig. 4. Measured and simulated drift angle β and turning rate r.

3.1 Estimation of α_w

As stated above the integration of eq. (19) requires knowledge of the direction of current α_w. In previous applications of the presented control scheme, α_w was assumed to be parallel to the desired track and therefore set to $\alpha_w = \alpha_s$. This is a reasonable assumption when no additional information about the river is available, as generally no strong side currents are found on inland waterways. However, this is not true for certain scenarios, e.g.

- Desired tracks that are not perfectly parallel to the stream direction
- At places where there are actually significant side currents, for example close to inlets.

If the assumption for α_w is incorrect, the calculated reference trajectory for β_s is incorrect as well, leading to errors in the remaining reference trajectories and the calculation of δ_{ff}. Moreover, model errors as well as unmodeled forces on the hull, like wind forces or forces due to interactions with other vessels will lead to errors in the calculation of the desired states and inputs. Therefore, the disturbance estimation algorithm is designed to estimate disturbances acting on the hull, such as water currents and wind. To illustrate the necessity of disturbance estimation, in Fig. 4 on the left, the measured drift angle β_{meas} and the simulated drift angle β_{sim} are depicted for a push tow with four empty barges navigating on the Rhine river. As there is an offset between β_{meas} and β_{sim} for positive and negative drift angles, this offset cannot be compensated for by adjusting the model parameters of the underlying simulation.

Often times, the estimation of disturbances is integrated into the state estimation algorithm, which is a Kalman filter in this application. For this purpose, the model is extended by an additional state, representing the disturbance to be estimated. In our application this state $\alpha_{w_{fb}}$ represents the offset between the assumed direction of the current $\alpha_{w_{ff}}$ and the actual direction of current. The modified equations within the Kalman filter model are

$$\begin{aligned}\dot{\beta} = &-\frac{1}{T_B^N}\frac{v_{rel}^2}{v_{abs}}(\beta - \frac{v_w}{v_r}\sin(\alpha - (\alpha_{w_{ff}} + \alpha_{w_{fb}})) \\ &+ K_\beta r\end{aligned} \tag{21}$$

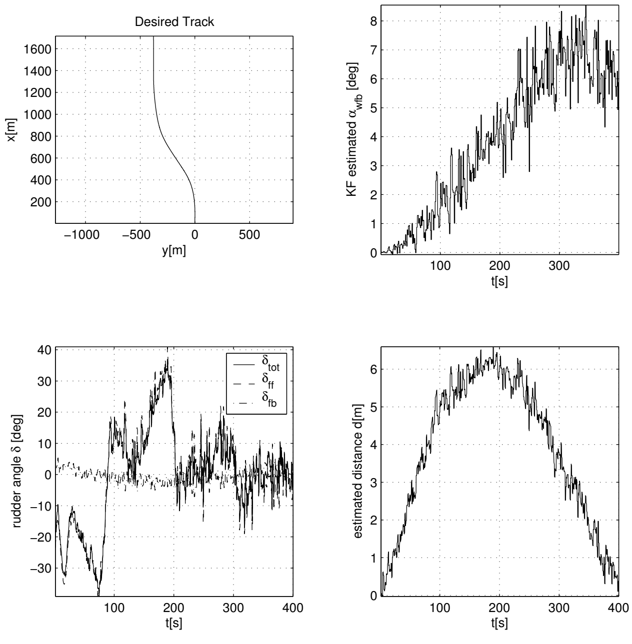


Fig. 5. Closed-loop simulation results for the KF-estimation of a constant disturbance $\Delta\alpha_w = 7°$ with $\alpha_w = \alpha_{GL} + \Delta\alpha_w$.

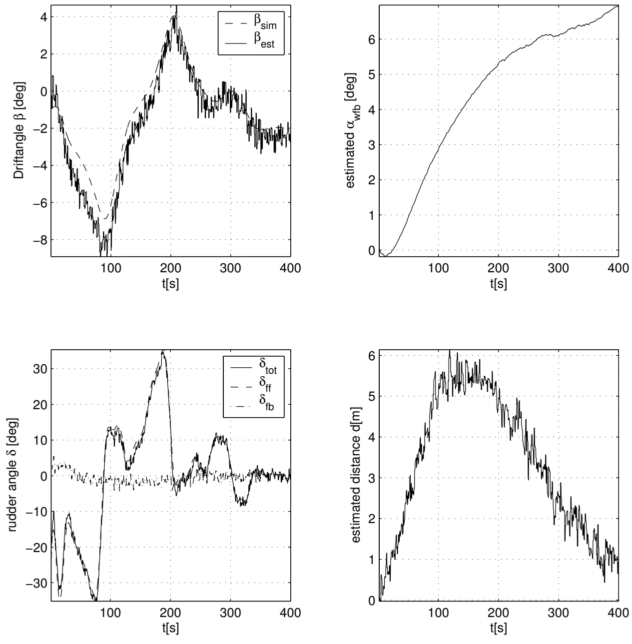


Fig. 6. Closed-loop simulation results for the estimation of a constant disturbance $\Delta\alpha_w = 7°$ with $\alpha_w = \alpha_{GL} + \Delta\alpha_w$.

$$\dot{\alpha}_{w_{fb}} = 0 \quad . \tag{22}$$

As no assumption can be made about the dynamics of $\alpha_{w_{fb}}$ it is modeled with trivial dynamics. The variable $\alpha_{w_{ff}}$ represents an input into the system. If no additional information about the river is available the best apriori guess for the direction of the current is $\alpha_{w_{ff}} = \alpha_{GL}$. The design parameters that determine the dynamic behavior of the Kalman filter are the elements in the covariance matrix Q of the associated state noise (see e.g. Pannocchia (2003)), for which a diagonal structure is usually assumed. In particular, the elements Q_β and $Q_{\alpha wfb}$, associated with the state noise for the respective states, determine how quickly changes in external disturbances can be traced and how noisy the resulting signals are. Fig. 5 shows the simulation results for the closed-loop simulation of the system with $\alpha_{w_{fb}}$ estimated within the Kalman filter and fed into the model inversion procedure for a constant disturbance. The value Q_β was left unchanged from the estimation without disturbance, $Q_{\alpha wfb}$ was chosen such that a constant offset in α_w could be traced adequately fast. It becomes obvious that the model inversion algorithm is very sensitive to noisy estimations of α_w, which produces unacceptably strong noise, especially in the signal for δ_{ff}. In fact, by choosing both Q_β and $Q_{\alpha wfb}$ to be very small it is possible to reduce the noise in the variable $\alpha_{w_{fb}}$ leading to a smoother signal. However, this design process is not intuitive, requiring tedious trial and error work. Moreover, if Q_β and $Q_{\alpha wfb}$ are chosen to be too small, there is an offset between the measured value β_{meas} and its estimated counterpart β_{est}, especially in the case of model errors.

Therefore, an alternative approach is presented here. As it is necessary to generate a smooth signal α_w to be fed into the model inversion procedure the following algorithm, which is part of the controller rather than the estimator, is employed:

$$\dot{\beta}_{sim} = -\frac{1}{T_B^N}\frac{v_{rel}^2}{v_{abs}}(\beta_{sim} - \frac{v_w}{v_r}\sin(\alpha - \alpha_w)) + K_\beta r \tag{23}$$

$$\alpha_w = \alpha_{w_{ff}} + \alpha_{w_{fb}} \tag{24}$$

$$\alpha_{w_{ff}} = \alpha_{w_{GL}} \tag{25}$$

$$\alpha_{w_{fb}} = \int_{to}^{t} -\frac{1}{T_{w_\alpha}}(\beta_{ref} - \beta_{sim})d\tau. \tag{26}$$

The estimation of α_w is based on an internal simulation of β based on the underlying model. The value α_w is adapted such, that the difference between the actual value β_{ref} and the internally simulated value β_{sim} becomes small. The signal β_{ref} can either be the measurement itself or the estimated value β_{est}. As above, the estimated value of α_w consists of an apriori or "feedforward" estimation $a_{wff} = \alpha_{GuidingLine}$ which is extended by a "feedback"-component α_{wfb}. The terms "feedforward" and "feedback" are also chosen to indicate the analogy of the algorithm to a control scheme with β_{sim} as the output variable, β_{ref} as the desired variable and α_w as the manipulated variable. The desired smoothness of the signal for α_w is achieved by merely integrating the "control error" ($\beta_{ref} - \beta_{sim}$). Fig. 6 shows the closed-loop simulation results for the previously introduced scenario and the presented estimation scheme. Due to the smoothness of the signal $\alpha_{w_{fb}}$ no additional noise is introduced by the estimation scheme. The dynamics of the estimation of $\alpha_{w_{fb}}$ is tuned with the single parameter T_{w_α}, representing the time constant for the integration. This allows for adjusting the dynamics of $\alpha_{w_{fb}}$ in a transparent way in contrast to the estimation via Kalman filtering, making the estimation scheme well suited for online tuning.

Ideally, the estimation scheme should not only be able to compensate for additional external forces but should also be able to improve control performance by compensating

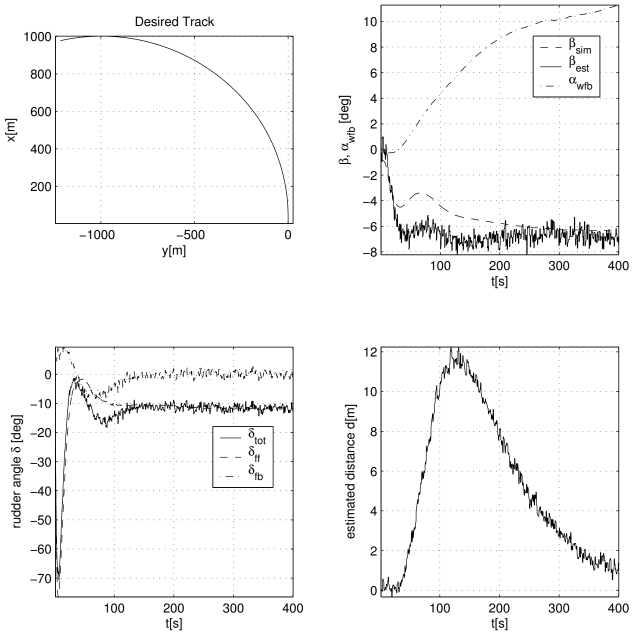


Fig. 7. Closed-loop simulation results for $T_B^N = 100sec$.

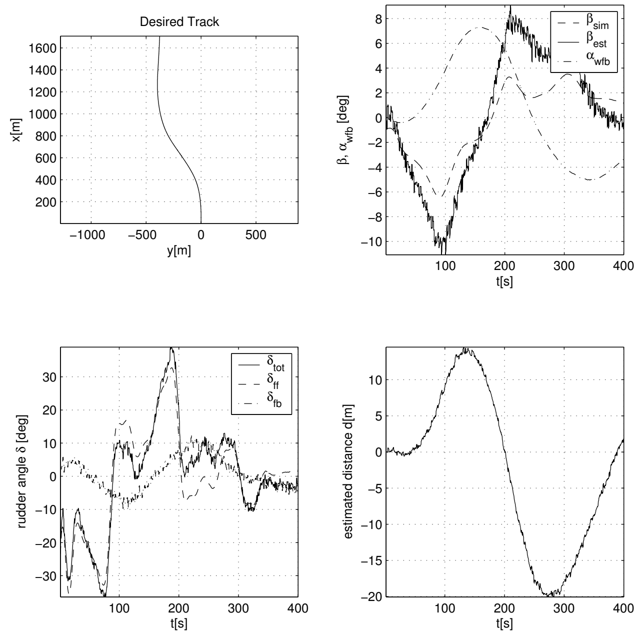


Fig. 8. Closed-loop simulation results for $T_B^N = 100sec$.

for model uncertainties. For the drift dynamics equation, these uncertainties are mostly related to the time constant T_B^N, as identification experiments with data from various inland vessels revealed. In Fig. 7, the simulation results are shown for a large error in the assumed value for T_B^N. The parameter in the plant model was set to $T_B^N = 100$, whereas the assumed value within the controller was left at the value listed in table 1. The desired track in this simulation is a section of a circle, similar to the large curves of the Rhine river with slow changing curvatures.

Due to the wrongly set value for T_B^N the desired calculated value β_s is too small in the long curve compared to the actually required value β_s. The estimation scheme reacts to this difference, by adapting $\alpha_{w_{fb}}$ such that the vessel can be kept on its track, even though the error in β_s is not due to a large angle between α and α_w. However, compensating for model uncertainties is only possible for tracks with slow changing curvatures κ, as the resulting estimated value $\alpha_{w_{fb}}$ is dependent on β. This is true for most stretches on the Rhine river. For some stretches of the Rhine river, or in case of aggressive avoidance maneuvers, this condition is violated, leading to larger distances d to the desired track. This situation is illustrated in Fig. 8, which shows the closed-loop simulation results for the previously introduced S-shaped track. The simulation results in Fig. 8 reveal that for large model uncertainties in the time constant T_B^N and a desired track with quick changing curvature an estimation of T_B^N is necessary to achieve good control performance. In Fig. 9 the closed-loop simulation results are shown for an estimation of T_B^N within the Kalman filter whose model was augmented by an additional state ΔT_B^N representing an offset in the assumed value T_{Bmod}^N:

$$T_{B_{est}}^N = T_{Bmod}^N + \Delta T_B^N. \tag{27}$$

The value $T_{B_{est}}^N$ was then fed into the inversion procedure. It becomes obvious that the control performance is improved by the estimation of ΔT_B^N. However, as pointed out

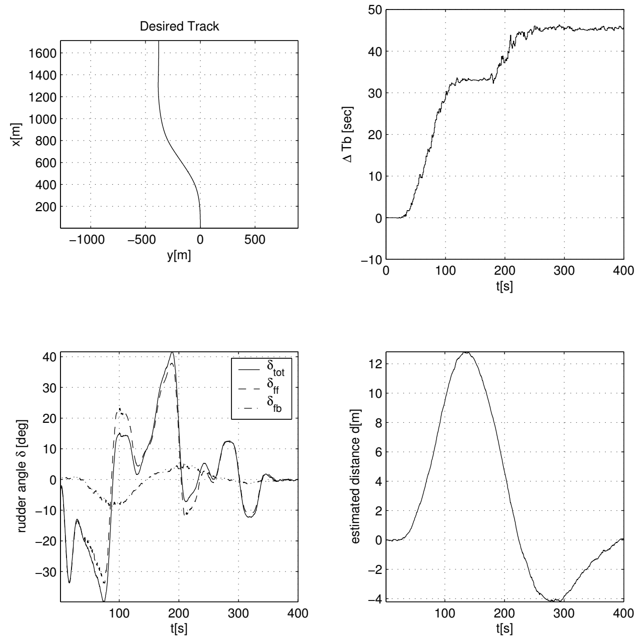


Fig. 9. Closed-loop simulation results for $T_B^N = 100sec$ and estimation of ΔT_B^N.

above, this requires careful calibration of the Kalman filter matrix Q. The employment of simultaneous disturbance and parameter estimation is subject to current research.

3.2 Estimation of r_w

The dynamics of the turning rate r is subject to external disturbances in the same way as the drift angle β. The currents in rivers are strongly variable, especially in case of high water, leading to additional forces not covered by the model in eq.(1). Moreover, offsets in rudder forces are a common phenomenon if the control system is not carefully calibrated. For example, if the output of the control system

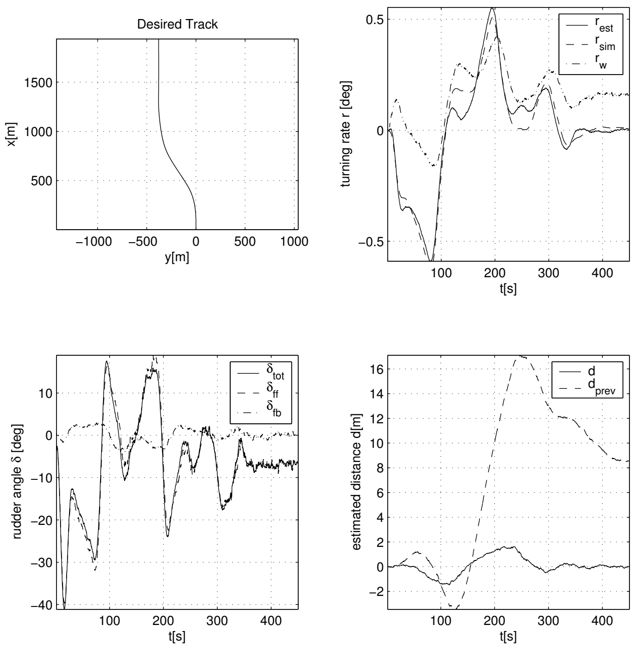


Fig. 10. Closed-loop simulation results for $\delta_{off} = 10$ and $T_r^N = 44$, d_{prev}..distance without estimation of r_w.

is $\delta_{out} = 0$, the actual rudder angle is $\delta = \delta_{off}$. Therefore, a disturbance estimation algorithm is introduced to account for these phenomena. Moreover, this estimation scheme allows for improving control performance in case of model uncertainties, as well. The model of eq. 1 is extended by an additional term r_w, representing the influence of unmodeled forces or model errors. It can be interpreted as the stationary turning rate, due to disturbances with $\delta_{out} = 0$:

$$\dot{r} = -\frac{1}{T_r}(r - r_w) + b_r\delta. \quad (28)$$

The algorithm for the estimation for r_w is set up similarly to the one for the estimation of α_w:

$$\dot{r}_{sim} = -\frac{1}{T_r}(r_{sim} - r_w) + b_r\delta_{out} \quad (29)$$

$$r_w = \int_{to}^{t} \frac{1}{T_{r_w}}(r_m - r_{sim})d\tau + K_{r_w}(r_m - r_{sim}). \quad (30)$$

Again, the value r_w is adapted such, that the difference between the internally simulated value r_{sim} and the measured value r_m becomes small. In contrast to the previously introduced estimation scheme for α_w, r_w consists of an integral component and a proportional component, much similar to a conventional PI-controller. The introduction of a proportional component is made possible by the fact that the disturbance r_w is incorporated in the model inversion procedure only at the very end, in the calculation of the feedforward rudder angle δ_{ff}, with

$$\delta_{ff} = \frac{1}{b_r}\dot{r}_s + \frac{1}{T_r b_r}(r_s - r_w), \quad (31)$$

making the inversion much less sensitive to noise in the term r_w and allowing for a more aggressive estimation. Fig. 10 shows the closed-loop simulation results for a constant disturbance $\delta_{off} = 10$ and a time constant for the plant model of $T_r^N = 44$, representing a model error of 22sec. As the estimation algorithm can be tuned more aggressively, the control performance is increased strongly, even in case of the previously introduced S-shaped track.

4. CONCLUSION

These results suggest that the methods presented here help to enhance the performance of the investigated control scheme. In fact, recent experimental results for a push tow on the Rhine river confirm these results.

One important consequence of the employment of the presented estimation schemes for disturbances is that it makes the incorporation of an integrating component in the feedback-controller obsolete. As pointed out in section 2.3, this integrating component was originally incorporated to avoid steady state offsets in the output variable d, in the presence of disturbances. In Pannocchia (2003) rigorous conditions are presented for the design of disturbance models and their incorporation into the control scheme that guarantee for offset-free control, in the presence of constant disturbances and arbitrary model mismatch. An important result in Pannocchia (2003) states that the number of estimated disturbances should be equal to the number of measurements to guarantee for zero-offset. As we assume all states to be measurable, but only incorporate two disturbances we hereby violate this condition. However, the two differential equations for the two states ψ and d, which we do not augment by integrating disturbances merely represent kinematic relations and are therefore not subject to disturbances or model errors. Therefore, an estimation of disturbances in these states is not necessary. In general, apart from enhancing control performance, the employment of disturbance models is considered to be advantageous over the employment of an output-error integrating feedback component as no anti-windup code is necessary. This is due to the fact that model error is integrated, rather than output-error.

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