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Discrete Time Variable Structure Control for the Dynamic Positioning of an Offshore Supply Vessel

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Abstract: This paper presents a Discrete-Time Variable-Structure Control (DTVSC) for the dynamic positioning system of a marine supply vessel. The DTVSC guarantees robustness with respect to disturbances and parametric variations. Two wave-filtering approaches are employed: the Extended Kalman filter (EKF) and the multi-rate Kalman filter (MREKF) . The proposed solution is compared with a PID-based control and a passive non-linear wave filter. The reported simulations show that the proposed solution produces better performances and it is robust in the presence of input disturbances and model uncertainties.

Keywords: Automatic control system, Ship control, Positioning system, Filtering techniques, Nonlinear control

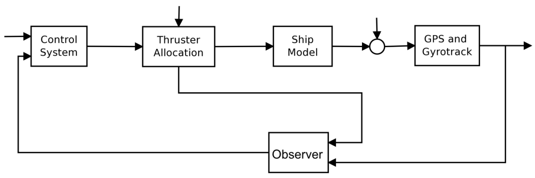

Fig. 1. Closed-loop DP system

1. INTRODUCTION

The number of vessels equipped with dynamic positioning (DP) systems has rosen in the recent years due to increasing oil and gas exploration at sea. The DP is an autonomous control system that acts as to maintain the vessel position and the angle of direction at a reference point by means of the vessel propulsion and manoeuvring thrusters. Knowledge of thruster allocation, combined with information from the sensors (GPS, gyroscopes, etc), is used to calculate the steering angle and the thrust for each thruster. The control action maintains the desired position and orientation according to a navigation path or a specific task (absolute or relative DP). The dynamic positioning system can be decisive in those situations in which the position of the unit is bound to a specific point on the seabed (absolute DP), or it is related to a moving unit, like when the ship is operating with other vessels or for remotely operated underwater vehicles.

Up to now, most dynamic positioning systems have been used for positioning drill ships in deep water, and other offshore operations, such as diving support and anchor handling. Furthermore, DP systems have been applied increasingly to shuttle tankers during offloading operation with a floating production storage and offloading (see Fossen (2011) and Sorensen (2011)). The first DP systems were designed using conventional PID controllers in cascade with low pass and/or notch filters to suppress the wave induced motion components. From 1980, a new model-based control concept, which is based on stochastic optimal control theory and Kalman filtering techniques, was employed to address the DP problem by Balchen et al. (1980). Later extensions and modifications of the latter work have been proposed by numerous authors, see Sorensen (2011) Fossen (2000), Strand and Fossen (1999) and Fang et al. (2011) and references therein. In Xia et al. (2005) and in Tannuri and Agostinho (2010) the sliding mode control is used with a Passive Nonlinear Observer for the DP problem.

This paper presents an innovative solution for the DP control system of a vessel which is based on the Discrete-Time Variable Structure Controller (DTVSC) and Wave Filtering using an (Multi-rate) Extended Kalman Filter. The block diagram of the control loop is shown in Figure 1. .The introduction of DTVSC allows to take into account the issue of control law digitalization directly. Moreover it ensures robustness with respect to model uncertainties and input disturbances acting on the actuators. An Extended Kalman filter (EKF) is designed in order to estimate the disturbances induced by the first order wave forces on the thruster. This is done to minimize the thruster efforts. The estimation is improved by means of a Multi-Rate Extended Kalman Filter (MREKF) which allows to take into account differences in working frequency of the sensors.

The paper is organized as follows. The kinematic and dynamic equations, the thruster allocation, the wave model and the measurement system are presented in Section 2. The control system, in particular the DTVS controller, is reported in Section 3. The filter techniques are discussed in Section 4. Simulation results are presented in Section 5. The paper ends with conclusions and comments.

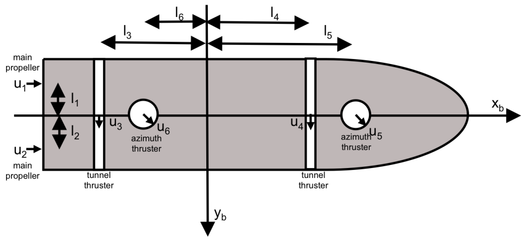

Fig. 2. Thrusters configuration for the offshore supply vessel

2. SHIP MODEL

2.1 Kinematic and Kinetics equations

Following Fossen (2011), the dynamics of marine vessels can be described using the following general model:

$$\begin{aligned} \dot{\eta} &= J(\eta)\nu \\ M_{RB}\nu + C_{RB}(\nu)\nu &= \tau_h + \tau_c + \tau_{env} \end{aligned} \tag{1}$$

where the vector variables η and ν represent the generalized displacement and body-fixed velocities, and τ_h, τ_c and τ_w represent the hydrodynamic, control and wave disturbance forces respectively. The term ν is defined with respect to a body reference frame b, fixed to the vessel. The term η is defined with respect to a local geographical frame n, fixed to the mean water level. Only movements of the vessel on the surface of the water are considered for DP systems. Therefore, movements on the vertical axis as well as pitch and roll movements can be neglected. Then, the horizontal motion of a ship is described by the motion components in surge, sway and yaw. The generalised position and velocity vectors are given by:

$$\begin{aligned} \eta &= [n, e, \psi]^T \\ \nu &= [u, v, r]^T \end{aligned} \tag{2}$$

The DP operations are *low-speed* applications, therefore the quadratic terms of the velocities can be neglected. Given the previous hypothesis and (1), the kinematics of the vessel can be characterised by the following rotation:

$$\dot{\eta} = R(\psi)\nu \tag{3}$$

where $J(\eta) = R(\psi)$ is the rotation matrix from body-fixed velocities to linear generalized displacement. The low-frequency dynamic equation from (1) is:

$$M\dot{\nu} + D\nu = \tau_c \tag{4}$$

where $M_{3\times3}$ is the inertia matrix, $D_{3\times3}$ is the damping matrix. The quadratic velocity terms are negligible in DP. Details about kinematic and dynamic equations can be found in Fossen (2011).

2.2 Thruster Allocation

For marine vessels with n DOF, the generalized control forces $\tau_c \in \Re^n$ are distributed among the actuators in terms of control inputs $u_c \in \Re^r$ (where r is the number of thrusters). A graphical representation is visible in Figure 2. The command forces and moments can be written as:

$$\tau_c = T(\alpha)Ku_c \tag{5}$$

where $f = Ku_c \in \Re^r$ is the thrust force vector. The thrust coefficient matrix K is a diagonal matrix of thrust coefficients. The actuator configuration matrix $T(\alpha)$ depends only on the location and orientation α of the actuators on the ship hull. The offshore supply vessel, which is used for testing the DP, has two main propellers, two tunnel thrusters and two azimuth thrusters, as shown in Figure 2. Hence we have 6 control variables for 3 DOF. Due to the symmetric disposition of the thrusters and propellers we can assume:

$$u_{c_i} = u_{c_{i+1}} \quad \text{for} \quad i = 1, 3, 5 \tag{6}$$

In case of input torque disturbances u_d on the actuators (5) becomes:

$$\tau_{c+d} = \tau_c + \tau_d = T(\alpha)K(u_c + u_d) \tag{7}$$

2.3 Enviromental disturbances

The environmental disturbances are due to both, slowly varying and high-frequency forces. Generally, the slowly varying environmental forces include the 2nd-order wave drift forces, the ocean current forces and the wind forces. These forces can be modelled as a bias:

$$\dot{b} = w \tag{8}$$

where w is a zero-mean Gaussian white noise, see Fossen (2011). The motion of an offshore supply vessel in a seaway is also affected by high-frequency disturbances caused by the 1-st order waves, which are random both in time and space. Therefore, the mathematical models for these wave components and their effects on the ship motion are depicted in a stochastic framework, Perez and Blanke (2002). Following Fossen (2011), it is possible to derive a linear approximation of the ship motion response to the 1-st order wave forces. Indeed the latter can be represented by a 1-st order transfer function driven by white noise:

$$h_w(s) = \frac{K_w s}{s^2 + 2\lambda_w \omega_0 s + \omega_0^2} \tag{9}$$

where $K_w = 2\lambda\omega_0\sigma_w$ is the gain constant, σ_w is a constant describing the wave intensity, λ_w is a damping coefficient and ω_0 is the dominating wave frequency. A linear state-space model can be obtained from (9) by defining $\dot{\xi}_1 = \xi_2$ and $\xi_2 = y_\omega$:

$$\begin{aligned} \dot{\xi} &= A_\omega \xi + E_\omega w_1 \\ y_\omega &= C_\omega \xi \end{aligned} \tag{10}$$

2.4 Measurement Systems

For conventional ships, only positioning and heading measurements are available. The position measurement is obtained by a GPS sensor and the heading measurement is obtained by a gyroscope sensor. In general, sensors work at different frequencies.

3. CONTROL SYSTEM

The DP control system, proposed in this paper, is based on the Discrete-Time Variable Structure Controller (DTVSC). The DTVSC is a state-feedback technique. Each state component can be equal to one of two state functions: the switching determines the discontinuity. For more details, see Utkin (1992), Furuta (1990), Corradini and Orlando (1997), Ciabattoni et al. (2010) and references therein. The introduction of DTVSC allows to take into account the issue of control law digitalization directly and to ensure robustness with respect to model uncertainties and input disturbances acting on the actuators. The control system scheme is shown in Figure 1.

We can discretize (4) using standard techniques considering a sampling time T_c as:

$$\nu(k+1) = \underbrace{e^{-M^{-1}DT_c}}_{F}\nu(k) + \underbrace{\int_0^{T_c} e^{-M^{-1}DT_c} M^{-1}T(\alpha)K\, d\sigma\, u_c(k)}_{G} \tag{11}$$

We can define the generalised force vector in the body-fixed frame to be imposed by the control law as:

$$\tau^*(k) = [\tau_u^*(k)\tau_v^*(k)\tau_r^*(k)]^T = G \cdot u_c(k). \tag{12}$$

As a consequence, the following discrete dynamic model can be obtained:

$$\nu(k+1) = F\nu(k) + \tau^*(k) \tag{13}$$

In order to take into account model uncertainties, we assume that the model parameters may differ from their nominal values for some unknown but bounded quantities:

$$F = \overline{F} + \Delta F \qquad G = \overline{G} + \Delta G. \tag{14}$$

Defining $\nu(k) = [u(k), v(k), r(k)]^T$ and the velocity reference $\nu^*(k) = [u^*(k), v(k)^*, r^*(k)]^T$, obtained using the inverse kinematic equation from (3) and a reference trajectory, we can define a reference error as:

$$\Delta\nu(k) = \nu(k) - \nu^*(k). \tag{15}$$

The control objective of the DTVSC is to let the state reach the intersection of two switching surfaces and to remain at their intersection, see Furuta (1990), Corradini and Orlando (1997). Using (15) we can define the two-steps sliding surfaces as:

$$s(k) = \Delta\nu(k) + \lambda_1\Delta\nu(k-1) + \lambda_2\Delta\nu(k-2) = 0 \tag{16}$$

where λ_1, λ_2 are tuning parameters which ensure that the zeros of (16) are inside the unit circle. The condition $\lim_{k\to\infty} s(k) = 0$ must be verified in order to reach the control objective, Furuta (1990). This requires

$$|s(k+1)| < |s(k)|, \quad \forall k. \tag{17}$$

From (17), defining $\Delta s(k+1) = s(k+1) - s(k)$, we can obtain the discrete sliding mode existence condition as:

$$s(k)^T\Delta s(k+1) < -\frac{1}{2}(\Delta s(k+1))^T(\Delta s(k+1)). \tag{18}$$

Let us consider the following control law:

$$\tau^*(k) = \tau_{eq}^*(k) + \tau_n^*(k) \tag{19}$$

. Using (13), (14) and (16), we can define:

$$\begin{aligned} \tau_{eq}^*(k) &= \nu(k) - \overline{F}\nu - s(k) \\ \tau_n^*(k) &= \begin{cases} \vartheta \cdot (|s(k)| - \rho) & if\ |s(k)| > \rho \\ -s(k) + \tau_n^*(k-1) & if\ |s(k)| \le \rho \end{cases} \end{aligned} \tag{20}$$

where the parameter $|\vartheta| \le 1$ and

$$\begin{aligned} \rho =& \Delta F\nu_{max} + \rho^* \\ \rho^* \ge& \mid \nu^*(k+1) - \nu^*(k)| \end{aligned} \tag{21}$$

Following Corradini and Orlando (1997), it can be demonstrated that (19) satisfies the condition in (18) outside a given sector defined by $|s(k)| > \rho$, where ρ is defined in (21). ρ depends on the model uncertainties defined in (14). Inside the sector defined by ρ, the sliding condition (18) can be imposed only approximately, using the approach of *Time Delay Control*. In order to obtain zero steady-state errors in surge, sway and yaw, it is possible to sum an integral action τ_I, appropriately discretized, to the control law of th DTVSC, see Fossen (2011):

$$\tau_I(k) = \tau_I(k-1) + K_I T_c e(k-1) \tag{22}$$

where $e(\cdot)$ is the error in surge, sway and yaw. The final control law u_c is given by resolving the set of equations which are obtained combining (6) and (12) with the DTVSC and integral actions.

$$\begin{aligned} \tau^*(k) + \tau_I(k) &= Gu_c(k) \\ u_{c_i}(k) &= u_{c_{i+1}}(k) \quad \text{for} \quad i = 1, 3, 5 \end{aligned} \tag{23}$$

4. WAVE FILTERING

Wave filtering is one of the most important aspects to take into account when designing ship control system. Only the slowly-varying disturbances are counteracted by the steering and propulsion systems. The oscillatory motion, due to the 1-st order waves, should be prevented from entering the feedback loop. This allows to prevent larger chattering phenomena in the control system. This objective can be reached by using a wave filter, which is usually a model-based observer, in the feedback loop.

4.1 Extended Kalman Filter

A commonly used technique, which enables the use of the Kalman Filter for non-linear systems, involves the linearisation of the system equations. This leads to the Extended Kalman Filter. In the case of the DP , 4) can be rewritten as

$$M\dot{\nu} + D\nu = T(\alpha)K\,(u_c + u_d), \tag{24}$$

where u_d is the vector of actuator disturbances. Also, considering (3) and (10), the resulting DP observer model is:

$$\begin{aligned} \dot{\xi} &= A_w\xi + E_w w_1 \\ \dot{\eta} &= R(\psi)\nu \\ \dot{b} &= w_2 \\ \dot{u}_d &= w_3 \\ M\dot{\nu} &= -D\nu + T(\alpha)K(u_c + u_d) + R(\psi)^T b + w_4 \\ y &= \eta + C_w\xi + v. \end{aligned} \tag{25}$$

The latter can be written in the following form:

$$\begin{aligned} \dot{x} &= f(x) + Bu_c + Ew \\ y &= H\hat{x} + v \end{aligned} \tag{26}$$

that is

$$\begin{aligned} \dot{x} = &\begin{bmatrix} A_w\xi \\ R(\psi)\nu \\ 0_{3\times3} \\ 0_{6\times3} \\ M^{-1}(-D\nu + T(\alpha)Ku_d + R(\psi)^T b) \end{bmatrix} + \\ &+ \begin{bmatrix} 0_{6\times3} \\ 0_{3\times3} \\ 0_{3\times3} \\ 0_{6\times3} \\ M^{-1}T(\alpha)K \end{bmatrix} u_c + \begin{bmatrix} E_\omega \\ 0_{3\times3} \\ I_{3\times3} \\ I_{6\times6} \\ M^{-1} \end{bmatrix} w \\ y = &\begin{bmatrix} C_\omega & I_{3\times3} & 0_{3\times3} & 0_{3\times6} & 0_{3\times3} \end{bmatrix} \hat{x} + w_m \end{aligned} \tag{27}$$

where $x = [\xi^T, \eta^T, b^T, u_d^T, \nu^T]$ is the state vector and $w = [w_1^T w_2^T w_3^T w_4^T]$ is the vector of the process white noise. The term $R(\psi)$ is non-linear, as a consequence it is necessary to linearise and discretize the system equation. In case of constant input disturbances acting on the actuators, the Kalman filter state u_d is reinitialized using an estimated disturbance value provided by an on-line detector module. See Fossen (2011) and Fu et al. (2010) for more details. The Extended Kalman filter equations are:

$$
\begin{aligned}
P_{k+1/k} &= \widehat{A}_d P_{k/k} \widehat{A}_d^T + E_d Q E_d^T \\
K_{k+1} &= P_{k+1/k} H^T (H P_{k+1/k} H^T + R)^{-1} \\
\widehat{x}_{k+1/k+1} &= \widehat{x}_{k+1/k} + K_{k+1}(y - H\widehat{x}_{k+1/k}) \\
P_{k+1/k+1} &= (I - K_{k+1} H) \\
\widehat{x}_{k+2/k+1} &= \widehat{A}_d \widehat{x}_{k+1/k+1} + f(x) - \widehat{A}_d \widehat{x}_{k/k+1} + \widehat{B}_d u_c(k).
\end{aligned}
\tag{28}
$$

4.2 Multi-rate Kalman Filter

Usually, sensors do not work at the same frequency, so not all measures are present at any instant of time. This can be modelled with different multi-rate techniques for time-varying model, such as the *delta-functions.* The introduction of the *delta functions* modifies the expression of the Kalman gain indicating the presence or the absence of measurements in every estimation instant. When there are no measurements available, matrices are zero and it is only necessary to run the prediction equations. When new measurements are available, matrices are unitary and all the Kalman filter equations can be run. This formulation changes the Kalman filter gain as follows:

$$K_{k+1} = P_{k+1/k} H^T (H P_{k+1/k} H^T + R)^{-1} \cdot \Delta_k \tag{29}$$

The Kalman filter gain is composed by a prediction and a correction, made through the sensor measurements. When measurements are not available, the multirate Kalman filter only predicts, placing a zero in the Δ_k matrix. For more details see Mora and Tornero (2008).

5. SIMULATION RESULTS

In this section we present the results of the simulations. The DTVSC is compared with a PID controller from Fossen and Perez (2010). Kalman filters based observers are tested against a Passive Nonlinear Observer from Strand and Fossen (1999). The *MSS* tollbox from Fossen and Perez (2010) has been used for the simulations. This toolbox provides a PID controller, whose parameters are chosen using an LQR algorythm (see Fossen (2011)) and a Passive Nonlinear Observer, whose notch frequency is tuned by Strand and Fossen (1999) to correspond to the wave peak frequency.

We use the dynamic model of the *CyberShip 2* (CS2) for simulations. This is a 1:70 scale model of an offshore supply vessel with a mass of 15 kg and a length of 1.255 m. The maximum surge force is approx. 2.0 N, the maximum sway force is approx. 1.5 N, while the maximum yaw moment is about 1.5 Nm. This ship is located in the *Marine Cybernetics Laboratory* (MCLab) at the Norwegian University of Science and Technology. For more details about the CS2 see Skjetne et al. (2004).

Simulations are run for a total period of 2000 s and separated in two successive stages. In the first stage the dynamic positioning system must maintain the vessel fixed to the initial position ($\eta_{ref} = \{0\text{m}, 0\text{m}, 0\text{deg}\}$), despite environmental disturbances from wave, wind and currents. In the second stage the dynamic positioning system must take the ship to a different position ($\eta_{ref} = \{20\text{m}, 20\text{m}, 50\text{deg}\}$). To avoid abrupt acceleration, due to the reference position change, we impose a smooth reference position change. The reference path and the two stage in the simulations are shown as black solid line in Figure 4. We refer to the first and second stages as *Costant References* and *Varying References* condition respectively.

We use the mean Integral of Squared Error (*ISE*), a commonly used performance index in control and estimation theory (see Grensted and Fuller (1965), to get a quantitative comparison between the results obtained in different simulations. For the DP system the indices depend on the error between the reference position and orientation and the position and orientation measured by the sensors, namely $e(t) = \eta_{ref}(t) - \eta(t)$. The mean ISE index expression, normalized with respect to the time follows:

$$ISE : \frac{1}{T} \int_{t_0}^{t_f} e(t)^2 dt. \tag{30}$$

Then we use the following expression as the percentage variation when comparing PID and DTVSC performances:

$$\%ISE : \frac{ISE_{DTVSC} - ISE_{PID}}{ISE_{PID}} \cdot 100. \tag{31}$$

5.1 CASE A: Filters comparison

In this case, the Extended Kalman filter, the multi-rate Kalman filter and the Passive Nonlinear Observer are compared, using the DTVS controller. The peak frequency of the wave disturbances is $\omega_0 = 0.8$rad/s and the Passive Nonlinear Observer is tuned up using 0.8 rad/s as the notch frequency. Results are shown in Figure 3. We compare the variances of control inputs in order to quantitatively evaluate the performance of the three filters , see Table 1.

The Passive Nonlinear Observer shows worse performance with respect to the other filters. Furthermore, the control efforts amplitudes, when using the Passive Nonlinear Observer are much larger (up to 55%) than the ones generated when using the EKF or MREKF filters, as is evident comparing the variances. Considering that the Kalman filters have comparable performances, but that the Multi-rate Kalman Filter can take into account differences among sensors sampling frequency, the latter is chosen as the reference filter for evaluating the controller performances in the next Section 5.2.

5.2 CASE B: Controllers comparison

In this second case, the PID and DTVS controllers are compared using the Multi-Rate Extended Kalman filter. Performances are compared both in the first and second

Table 1. Variances of generalized forces using different filtering techniques, Passive Nonlinear Observer (PNLO) used as reference value for percentage variation

	τ_u		τ_v		τ_r	
PNLO	0.0071		0.0371		$3.3797 \cdot 10^{-5}$	
EKF	0.0061	-14%	0.0249	-32%	$1.8808 \cdot 10^{-5}$	-55%
MREKF	0.0061	-14%	0.0251	-32%	$1.8658 \cdot 10^{-5}$	-44%

Table 2. ISE performance comparison between DTVSC and PID controller. In CASE C we consider a 20% increase of the inertia parameters of the vessel. In case D we consider a torque input disturbance affecting u_{c_1} with a magnitude equal to the 30% of the maximum value. Both the *Costant References* and *Varying References* conditions are considered. We use % ISE defined in (31) as percentage variation in the performance index.

	Constant References			Varying References		
	CASE B: Controllers comparison in nominal conditions					
	DTVSC	PID	% ISE	DTVSC	PID	% ISE
n	0.0291	0.0291	0%	0.0580	0.3570	-84%
e	0.0291	0.0291	0%	0.0582	0.7293	-92%
ψ	$6 \cdot 10{-}5$	$6 \cdot 10{-}5$	0%	0.0001	0.0623	-99%
	CASE C: Robustness to Parametric Variations					
	DTVSC	PID	% ISE	DTVSC	PID	% ISE
n	0.032	0.13	-75%	0.072	0.38	-81%
e	0.031	0.19	-83%	0.07	0.72	-90%
ψ	$7 \cdot 10^{-5}$	0.0007	-90%	0.0001	0.06	-99%
	CASE D: Robustness to toque input disturbance					
	DTVSC	PID	% ISE	DTVSC	PID	% ISE
n	0.0874	0.1285	-34%	0.1187	0.4771	-75%
e	0.0354	0.1841	-80%	0.0666	0.8056	-92%
ψ	0.0023	0.0028	-17%	0.0036	0.1226	-97%

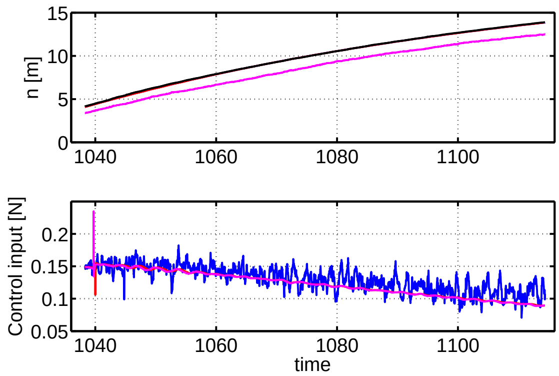

Fig. 3. *(Upward)* Zoomed plot showing the comparison between reference surge displacement (blue solid line) and measured surge displacement when using different observers: the Extended Kalman filter (red dotted line), the multi-rate Kalman filter (black dotted line) and the Passive Nonlinear Observer (purple dash-dotted line). *(Downward)* Zoomed plot showing the comparison of the first control input u_{c_1} when using different observers: the Extended Kalman filter (blue line), the multi-rate Kalman filter (red line) and the Passive Nonlinear Observer (purple line)

stage, when the references are constants and when the references are varying, respectively. The results are shown in Figure 4 and the performances index are reported in Table 2.

Simulations show that the DTVSC and the PID controller have the same performances when the dynamic positioning system is being used to maintain a fixed reference position. Still the DTVSC performs better than the PID control when the position reference changes, showing significantly smaller overshoots during the transition. This is reflected by a smaller ISE performance index, at least 50% less than PID, considering the second part of simulations with *Varying References*. Therefore lower tracking errors are obtained using the DTVSC for the DP system. Although the DTVS controller is usually more complex and computationally expensive than the PID controller, the latter suggest that more complex solutions for PID tuning, using more complex dynamical model can be used, see Lindegaard (2003).

5.3 CASE C: Robustness to Parametric Variations

In order to test the DTVSC robustness, we consider variations in the model parameters. An increase of the 20% of the parameters of the inertia matrix M in (4) is considered, which can be the result of a change in the load condition of the ship (e.g. moving cranes). The results are shown in Table 2. We can see that the DTVSC perform better than the PID controller, when the DP must hold the ship to the initial position. Results are even better when there is a position change in the references. Therefore the DTVSC has shown to be quite robust with respect to severe parametric variations, as a result of the inclusion of model uncertainties in (21).

Results suggest that PID tuning could be improved using gain scheduling approaches or acceleration feedback, see Lindegaard (2003).

5.4 CASE D: Robustness to toque input disturbance

In order to test the DTVSC robustness, we suppose to have a torque input disturbance affecting one actuator (u_{c_1}) with a magnitude equal to the 30% of the maximum value. In this case the Kalman filter state u_d is reinitialized using an estimated disturbance value provided by an online detector module. The results are reported in Table 2 and shown in Fig. 5.4. In this case, the DTVS controller performances are better then PID controller performances both when the references are constant and when the references are varying. Therefore DTVS controller has shown to be quite robust with respect to input disturbances.

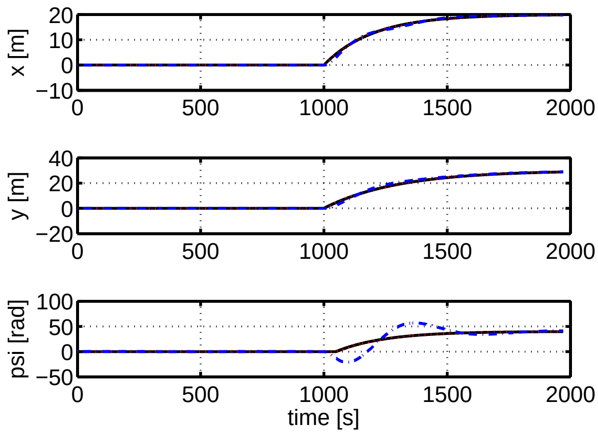

Fig. 4. Plot of the reference (black solid line) and estimated positions in the local geographical n frame using DTVSC controller (red dotted line) and the PID controller (blue dash-dotted line).

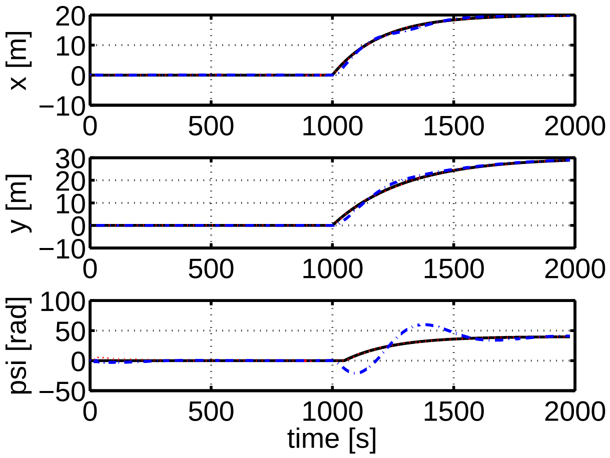

Fig. 5. Plot of the reference (black solid line) and estimated positions using the Multi-rate Kalman filter and the DTVSC (red dotted line) and the PID controller (blue dash-dotted line) in case of disturbances on the actuators

6. CONCLUSION

The problem of dynamic positioning plays a key role in all those cases in which it is not possible to anchor the ship at the seabed, or in which the ship position is bound to a specific point on the bottom. In this paper, an architecture for the autonomous dynamic positioning of an offshore supply vessel is identified using non-linear discrete control and wave filtering techniques for the resolution of the DP problem.

From a control perspective, it was shown that the DTVSC controller satisfies the sliding mode existence condition in a sector depending on the maximum uncertainties of the system. Simulations confirm the robustness of the control scheme in the presence of disturbances or parametric variations and show that DTVSC can show better performances than classic PID controllers especially when there is a change in the reference position for the DP system and in the case of uncertainties/actuator disturbances. From the point of view of filtering, we introduced two different techniques for filtering the 1-st order wave effects based on Kalman filtering techniques in the feedback loop. Simulations performed for the CS2 offshore supply vessel scaled-model showed that the Extended Kalman filter and the Multi-Rate Kalman filter have comparable performances. But they outperform standard Passive Nonlinear Observer in terms of variances of the controller efforts and drifts. The MREKF has been chosen because it is designed for GPS and gyrotrack signals which are acquired with different frequencies, maintaining comparable performances.

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