

Heave Motion Estimation of a Vessel Using Acceleration Measurements

S. Kuchler* J. K. Eberharder** K. Langer** K. Schneider**
O. Sawodny*

* *Institute for System Dynamics, University of Stuttgart, P.O. Box
801140, D-70511 Stuttgart, Germany (e-mail:
kuechler@isys.uni-stuttgart.de).*

** *Liebherr Werk Nenzing GmbH, P.O. Box 10, A-6710 Nenzing,
Austria.*

Abstract: Ocean waves continuously disturb every vessel resulting in horizontal and vertical motions. Especially the vertical motion has a significant effect on certain marine applications like subsea lifting operations. Subsea lifts are required for underwater installations on the seabed. Since such operations are normally performed from vessels using offshore cranes, the vertical vessel motion results in excessive dynamic loads acting on the crane structure. Furthermore, an accurate positioning of the load on the seabed is nearly impossible during harsh sea conditions. To avoid these problems active heave compensation systems can be used. These systems actively compensate for the vessel's vertical motion and therefore reduce the dynamic loads acting on the crane structure and enable precise positioning of the load. However, active heave compensation systems always require the knowledge about a vessel's heave motion. This article presents an observer based method to estimate the heave motion of a vessel from accelerometer signals without requiring any vessel specific parameters. The observer model is formulated by a sum of periodic components that approximate the heave motion of a vessel. The parameters of these components are identified online. The identified model is used with an extended Kalman filter to estimate the heave motion with high accuracy. The proposed method is evaluated with simulation and measurement results from an experimental setup.

Keywords: Extended Kalman filters, Observers, Position estimation, Marine systems, Ship control

1. INTRODUCTION

Every vessel on the ocean is continuously disturbed by waves, wind, and ocean currents. These disturbances cause the vessel to move both horizontally and vertically. While horizontal motions are often controlled with dynamic positioning systems (Fossen and Strand, 2001; Fossen and Perez, 2009), the vessel still moves vertically. However, there are many marine applications that also require a compensation of the vertical vessel motion excited by ocean waves and thus an exact knowledge about the vertical motion. Examples for such applications are safe aircraft landing on vessels (Marconi et al., 2002) and hydrographic seabed mapping with an echo sounder mounted on a vessel. To improve the quality of seafloor maps, the vertical vessel motion has to be considered when a map is generated (Hopkins and Adamo, 1981).

Another example for such an application are subsea lifting operations required for underwater installations on the seabed like pipelines and conveying systems for oil and gas. Since these lifts are carried out with offshore cranes attached on a vessel, the vertical motion due to ocean waves has a significant effect on the involved crane system. Especially during harsh sea conditions immense dynamic loads act on the overall crane structure and the ropes which the load is attached to. Furthermore, the load mo-

tion can be hardly controlled by the crane operator. Hence, it is possible that the load gets damaged or even lost. To avoid these problems, there are passive and active heave compensation systems. Such systems decouple the vertical load motion from the vertical vessel motion. Thus, they decrease dynamic loads acting on the crane structure and enable precise positioning of the load also during harsh sea conditions. However, all active systems have in common that they require exact knowledge of the vertical motion that should be compensated, as described in the literature (Kuchler et al., 2011; Do and Pan, 2008; Messina and Serrani, 2009).

Fig. 1 shows a ship together with an offshore crane. Due to the ocean environment the vessel moves in six degrees of freedom, which are surge, sway, and heave in the translational directions and roll, pitch, and yaw in the rotational ones. As depicted, all six degrees of freedom can be measured with an inertial measurement unit (IMU) that has three accelerometers for the translational directions and three rotation rate sensors for the rotational directions. To obtain the relative position and attitude of the vessel, the accelerometer signals have to be integrated twice and the rotation rate signals once. However, a simple integration of these signals would result in an infinite drift due to typical sensor errors like noise, bias, and misalignment. A widely-used approach for eliminating the resulting drift terms

of the estimated position and attitude is to aid the IMU signals with GPS measurements as it is done by Godhavn (2000) or Fossen and Perez (2009). But aiding IMU signals with GPS measurements results in higher costs and an additional dependency on GPS availability.

However, from Fig. 1 follows that the three most important parameters for obtaining the vertical motion of a certain point on a vessel are roll, pitch, and heave. Thus, to obtain the vertical position it is only necessary to estimate the roll and pitch angles and the heave position without any drift. Using signal conditioning, these parameters can be determined with respect to the current sea level only from IMU signals without any external aiding; however it must be distinguished between estimating the roll and pitch angles and the heave position. While the roll and pitch angles can be obtained by fusing the rotation rate sensors with the measured accelerations of the IMU to compensate for the errors of the rotation rate signals (Kim and Golnaraghi, 2004; Metni et al., 2006; Setoodeh et al., 2004), a model of the vessel or the current sea state is required to estimate the heave position without any drift. Triantafyllou et al. (1983) use a simplified hydrodynamic model of a vessel to estimate the heave, pitch, and roll motion without aiding from any external signals. However, their approach requires a specific model of a certain vessel. Thus, it is not applicable if the method should be applied to different kinds of vessels, since an adaption to every type would be necessary. Godhavn (1998) presents an approach for determining the relative heave position of a vessel from measured heave accelerations without using any specific vessel model. The author proposes an integrating bandpass filter with a cut-off frequency chosen in accordance to the current sea state. Due to changing sea states, the cut-off frequency is continuously adapted. The necessary parameters for determining the optimal cut-off frequency are obtained from an online identification procedure in the frequency domain. Another method that does not require any model of a vessel and external aiding is proposed by Weiss (1977). In this article a dynamic model of the vessel motion is derived. The presented model is based on parameters that are obtained from the spectral density of the measured acceleration signals of the heave motion. The model is used to formulate a Kalman filter estimating the current heave position of a vessel.

This article derives an observer for estimating the heave position of a vessel during subsea lifting operations. The proposed scheme utilizes a low-cost IMU (ADIS 16365, 2009) from Analog Devices as a stand alone motion sensor without aiding from external sensor sources like a GPS receiver. The IMU has three accelerometers and three rotation rate sensors. The dynamic model used for the observer design describes the heave motion of a vessel without using any vessel-specific parameters. For this, the heave motion is approximated as a sum of overlaying sine waves. The number of sine waves that is required for an accurate approximation is identified together with the corresponding frequencies via a Fast-Fourier Transform (FFT) in a first step. The identified parameters are used to build an observer model estimating the heave motion online. The estimation itself is performed with an extended Kalman filter (EKF). To guarantee the validity of the observer model also after changing sea states, it is adapted from time to time.

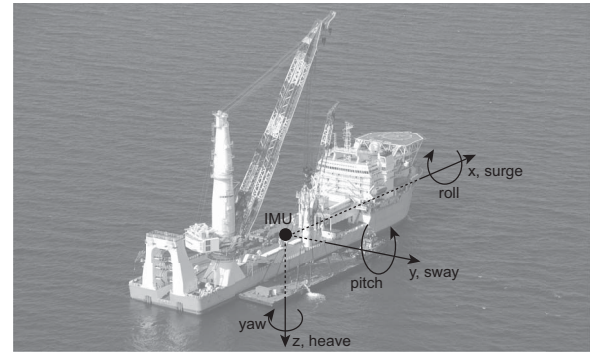


Fig. 1. Vessel with offshore crane.

The paper is organized as follows. In Sec. 2 the model describing the periodic components of the heave motion is derived. Furthermore, the implementation of the observer is explained together with the adaption to changing sea states. The proposed method for heave estimation of a vessel is evaluated in Sec. 3 using simulation and measurement results from a test bed. Concluding remarks are given at the end of the paper.

2. HEAVE ESTIMATION

In the following the vessel is considered as a rigid body with six degrees of freedom (DOF). As depicted in Fig. 1 all six DOF are measured in the vessel's coordinate frame using an IMU located in the vessel's center of gravity. Furthermore, it is assumed that one accelerometer points towards the vertical z -axis of the vessel's coordinate frame and measures the heave acceleration directly together with an additional offset due to the earth's gravitational constant and sensor errors. Since the scope of the contribution is heave estimation, only measurements of this accelerometer signal and not of all signals of the IMU are taken into account. Additional IMU signals would be required to determine the vertical motion of a certain point on a vessel in the earth fixed coordinate frame using kinematic transformations. Furthermore, the effects of the roll and pitch angles on the measured acceleration are neglected. This is a suitable assumption, as the roll and pitch angles of a vessel are normally small.

2.1 Heave Motion Model

To derive a model for the heave motion of a vessel, one has to consider the form of sea waves that excite the vessel motion. The random motion of sea waves is generally described through an energy density spectrum (Faltinsen, 1993). The wave energy spectrum depicts the energy content of an ocean wave and its distribution over a frequency range of the random wave. It can be approximated by so-called wave groups describing a sum of periodic functions that depend on time and the position in the horizontal x, y -plane (Chakrabarti, 2008). Thus, the wave motion on a certain position in the x, y -plane only depends on time and can be expressed as a set of N sine waves, so-called modes, and an additional term $v(t)$:

$$z(t) = \sum_{j=1}^{N_m} \underbrace{A_j \cos(\omega_j t + \varphi_j)}_{z_j(t)} + v(t) \quad (1)$$

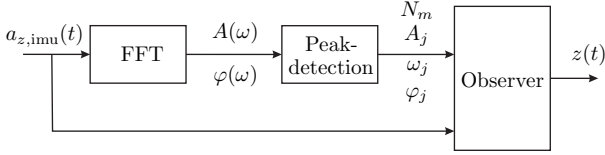


Fig. 2. Structure of the proposed estimation method for a vessel's heave motion.

with $j = 1, \dots, N_m$, where A_j , φ_j and ω_j denote the amplitude, phase, and eigenfrequency of mode j , respectively. The additional term $v(t)$ accounts for slow varying effects like the tidal range.

The resulting motion of a vessel due to the current sea state can be obtained from the energy density spectrum of the sea waves together with its response amplitude operator (RAO). Since the RAO normally acts as a low-pass filter, the resultant heave motion of a vessel that stays at a fixed position on the ocean can also be approximated using (1). However, the accurateness of the approximation depends on the number of significant modes N_m used for the model description. Since only the relative heave motion of a vessel due to the waves is of interest, the term $v(t)$ describing slow varying effects is neglected in the following.

2.2 Identification

To approximate the heave motion of a vessel accurately enough, the number of significant modes N_m considered for the observer design is identified online. Therefore, an FFT is applied to the measured acceleration signal of the IMU $a_{z,imu}$ in a first step. The window length and the sampling time of the FFT are chosen in a way that the highest frequency of the known wave spectrum (e.g., JONSWAP, Pierson Moskowitz, etc.) (Chakrabarti, 2008) can be detected and a desired resolution in the frequency domain is reached. Obviously, the FFT yields the phase and amplitude spectrum of the current heave acceleration, while (1) describes the heave position. However, the amplitude and phase spectrum of the position $A(\omega)$ and $\varphi(\omega)$ follow directly from the ones of the acceleration $\ddot{A}(\omega)$ and $\ddot{\varphi}(\omega)$ and are given by

$$A(\omega) = \frac{\ddot{A}(\omega)}{\omega^2}, \quad \varphi(\omega) = \ddot{\varphi}(\omega) - \pi, \quad \omega > 0, \quad (2)$$

where $\ddot{A}(\omega)$ and $\ddot{\varphi}(\omega)$ follow from the FFT.

Afterwards, a peak-detection algorithm is used to extract the peaks from the amplitude $A(\omega)$ of the position's frequency response obtained by (2). The number of detected peaks is equal to the number of significant modes N_m required to approximate the heave motion. The corresponding eigenfrequency, amplitude and phase of each mode are also obtained from the peak-detection algorithm using the frequency response. The identified modes and parameters are used to initialize an observer model estimating the heave motion of a vessel. Fig. 2 shows the general structure of the heave estimation method consisting of the identification via an FFT and an observer estimating the heave motion online. The observer is required, since the FFT only provides mean values over a certain time horizon that cannot be used for an estimation of the heave motion from acceleration signals.

2.3 Observer Design

To design an observer for heave estimation without using any vessel specific parameters, the approximated form of the heave motion (1) is transformed to a state space model in the following. Therefore, every identified mode of (1) is considered as the time domain solution of an undamped oscillator that is given by

$$z_j(t) = A_j \cos(\omega_j t + \varphi_j), \quad j = 1, \dots, N_m. \quad (3)$$

So the ordinary differential equation for a single mode can be written as

$$\ddot{z}_j + \omega_j^2 z_j = 0, \quad t > t_0, \quad z_j(t_0) = z_{j,0}, \quad \dot{z}_j(t_0) = \dot{z}_{j,0}, \quad (4)$$

where t_0 denotes the time point of a mode's identification. To adapt the observer model to changing sea states, the eigenfrequency of each mode ω_j is modeled as a random-walk parameter for the observer design. Such a random-walk modeling of uncertain parameters is a common technique for online estimation of uncertain parameters. With the state vector $\mathbf{x}_j = [z_j, \dot{z}_j, \omega_j]^T$ the ODE of a single mode (4) can be written in state space form as follows:

$$\dot{\mathbf{x}}_j = \underbrace{\begin{bmatrix} x_{2,j} & -x_{3,j}^2 x_{1,j} & 0 \end{bmatrix}^T}_{\mathbf{f}_j(\mathbf{x}_j)} \quad (5)$$

$$y_j = -x_{3,j}^2 x_{1,j}, \quad j = 1, \dots, N_m$$

with $t > t_0$ and $\mathbf{x}_j(t_0) = \mathbf{x}_{j,0}$. The output y_j denotes the acceleration of the corresponding mode and follows from (4). The initial conditions $\mathbf{x}_{j,0}$ are obtained from the identified parameters A_j , φ_j , and ω_j of each mode (see 2.2) together with (3).

To implement the observer on a real-time system, the derived continuous model of a single mode given by (5) has to be discretized in time. In the following, $[\bullet]_{[\bullet],k} = [\bullet]_{[\bullet]}(t_k)$ holds with $t_k = k\Delta t$ and $k \in \mathbb{N}$, where Δt denotes the discrete sampling time. From the continuous state space model for a single mode the discrete-time form follows directly with the transition function $\Phi_j(\mathbf{x}_{j,k-1}, \Delta t)$ by solving the ODE of $x_{3,j}$ first, as it is decoupled from the rest of the system. Afterwards, the resulting linear system can be solved using the matrix exponential function. Hence, the discrete observer model of the j -th mode can be written as follows:

$$\underbrace{\begin{bmatrix} x_{1,j,k} \\ x_{2,j,k} \\ x_{3,j,k} \end{bmatrix}}_{\mathbf{x}_{j,k}} = \Phi_j(\mathbf{x}_{j,k-1}, \Delta t), \quad y_{j,k} = y_j(t_k) \quad (6)$$

with $j = 1, \dots, N_m$ and $t_k > t_0$. The initial conditions are the same as for the continuous model.

The measured IMU acceleration used to estimate the heave motion is given by the sum of each mode's acceleration, the earth's gravitation, an unknown offset due to sensor errors and some sensor noise. It can be expressed as

$$a_{z,imu} = \underbrace{\sum_{j=1}^{N_m} \ddot{z}_j}_{\ddot{z}} - \cos(\phi) \cos(\theta) g + b_z + \xi_z, \quad (7)$$

where g is the earth's gravitational constant and b_z and ξ_z denote the offset of the sensor and some sensor noise, respectively. The angles ϕ and θ stand for the vessel's pitch and roll angles. The earth's gravity is considered negative,

since the z -axis of the vessel is directed downwards to the center of the earth (see Fig. 1). In the following, the effect of the earth's gravity on the measured acceleration is assumed to be constant. This is a suitable assumption, since the roll and pitch angles of a vessel are normally below 10 degrees, which results in $\cos(\phi)\cos(\theta) \approx 1$. To take g and b_z for the observer design into account an additional offset state is introduced to the discrete state space model. The dynamics of the offset state are modeled as a random walk process. Thus, for the offset state

$$\begin{aligned} x_{\text{off},k} &= x_{\text{off},k-1}, & x_{\text{off},0} &= -g, \\ y_{\text{off},k} &= -g + b_{z,k} + \xi_{z,k}, & t_k &> t_0 \end{aligned} \quad (8)$$

holds. Adding all modes and the additional offset state yields the complete discrete-time model to estimate the heave motion of a vessel

$$\begin{bmatrix} \mathbf{x}_{1,k} \\ \mathbf{x}_{2,k} \\ \vdots \\ \mathbf{x}_{N_m,k} \\ x_{\text{off},k} \end{bmatrix} = \begin{bmatrix} \Phi_1(\mathbf{x}_{1,k-1}, \Delta t) \\ \Phi_2(\mathbf{x}_{2,k-1}, \Delta t) \\ \vdots \\ \Phi_{N_m}(\mathbf{x}_{N_m,k-1}, \Delta t) \\ x_{\text{off},k-1} \end{bmatrix}, \quad (9)$$

$$\mathbf{x}_k = \underbrace{\begin{bmatrix} \mathbf{x}_{1,k} \\ \mathbf{x}_{2,k} \\ \vdots \\ \mathbf{x}_{N_m,k} \\ x_{\text{off},k} \end{bmatrix}}_{\mathbf{x}_k} = \underbrace{\begin{bmatrix} \Phi_1(\mathbf{x}_{1,k-1}, \Delta t) \\ \Phi_2(\mathbf{x}_{2,k-1}, \Delta t) \\ \vdots \\ \Phi_{N_m}(\mathbf{x}_{N_m,k-1}, \Delta t) \\ x_{\text{off},k-1} \end{bmatrix}}_{\Phi(\mathbf{x}_{k-1}, \Delta t)}$$

$$\mathbf{y}_k = y_{1,k} + y_{2,k} + \dots + y_{N_m,k} + y_{\text{off},k}$$

with

$$\mathbf{x}(t_0) = \underbrace{[\mathbf{x}_{1,0} \ \mathbf{x}_{2,0} \ \dots \ \mathbf{x}_{N_m,0} \ x_{\text{off},0}]^T}_{\mathbf{x}_0}. \quad (10)$$

For successful estimation of the heave motion, it is necessary that the proposed nonlinear observer model is globally observable (Zeitz, 1984). Simple algebraic calculation yields that (10) is globally observable, if the following conditions hold:

$$\begin{aligned} x_{3,j,k} &> 0, & \forall k, j &= 1, \dots, N_m, \\ x_{3,j,k} &\neq x_{3,i,k}, & \forall k, i, j &= 1, \dots, N_m, i \neq j. \end{aligned} \quad (11)$$

Obviously, (11) requires that the estimated eigenfrequency of each mode is greater than zero and that every mode of the observer model has a different eigenfrequency. As the eigenfrequencies of each mode are estimated online, situations can occur when (11) is not fulfilled and observability gets lost. However, it is possible to handle such situations with an adaption of the observer model. In order to do so, the estimated eigenfrequencies of each mode are checked at every time step. If a mode's eigenfrequency approaches zero, the corresponding mode is eliminated from the observer model given by (9). This way the updated state space model is reduced by the states of this mode. If the second situation occurs and the estimated eigenfrequencies of two modes approach the same value, these modes are merged together in the observer model. Again, the observer model is reduced by the states of one mode.

The observer itself is realized as a standard extended Kalman filter (EKF). The covariance matrix of the process noise required for the EKF is chosen in accordance to the dynamics of the different states penalizing the position and velocity $x_{1,j,k}$ and $x_{2,j,k}$ of modes with a higher eigenfrequency more than modes with a lower one. For the offset state $x_{\text{off},k}$ and the states for the eigenfrequencies $x_{3,j,k}$ a slow dynamic is assumed. The covariance of the measurement noise used for the EKF design is equal to the sensor noise (ADIS 16365, 2009).

To take changing sea states into account, the identification

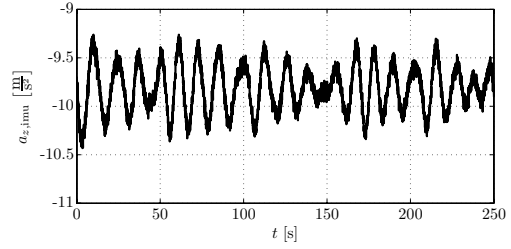


Fig. 3. Simulated acceleration measured by the IMU $a_{z,\text{imu}}$ towards the z -direction of the vessel's coordinate system.

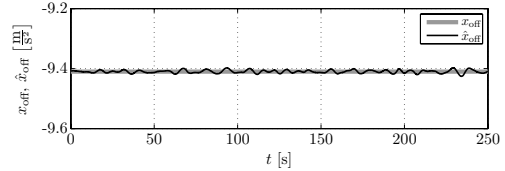


Fig. 4. Estimated offset state $\hat{x}_{\text{off}}$ together with its nominal value x_{off} used in the simulation.

procedure described in Section 2.2 is repeated after fixed time intervals. The results of the identification are used to check the observer model. If a newly identified mode does not exist in the current observer model, the observer model is extended by this mode and the EKF is re-initialized with the new model. To reduce the decay time after a re-initialization due to initial errors, only the states of the newly identified mode are initialized with the parameters obtained from the identification. All existing states are set to their estimated values.

3. RESULTS

In the following, the proposed observer for estimating a vessel's heave motion is evaluated. First, some simulation results are presented. The motion sequence used for simulation is obtained from a six DOF simulation of a vessel (MSS, 2010). The applied model corresponds to a vessel that is 175.0m long and has 24,609 tons of weight. The model is excited with a JONSWAP spectrum with a significant wave height of 7m. The resulting acceleration signal towards the vessel's z -axis used to estimate the heave motion is disturbed with an offset and sensor noise as well as the earth's gravity. Afterwards, measurement results from an experimental setup are shown.

3.1 Simulation

Fig. 3 shows the acceleration signal $a_{z,\text{imu}}$ measured by the IMU used to estimate the heave motion. Obviously, $a_{z,\text{imu}}$ oscillates around a constant value near the earth's gravitational constant $g = 9.81\text{m/s}^2$, as the sensor measures the sum of the heave acceleration, the earth's gravity, and some sensor offset and noise. The crucial point of the proposed method is that the observer correctly estimates the offset state $x_{\text{off},k}$ in (10) and decomposes the heave motion into its single modes as given by (1). Furthermore, the EKF has to suppress the sensor noise to obtain a smooth estimation signal required for active heave compensation systems as a reference. That the estimated offset state converges to the correct value can be seen in Fig. 4. Here,

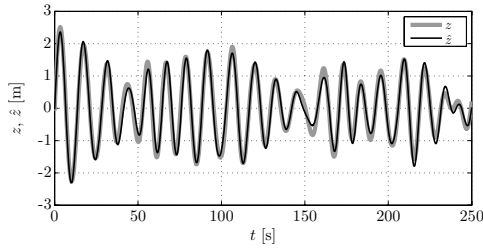


Fig. 5. Estimated heave position of the vessel $\hat{z}$ obtained during simulation together with the reference signal z .

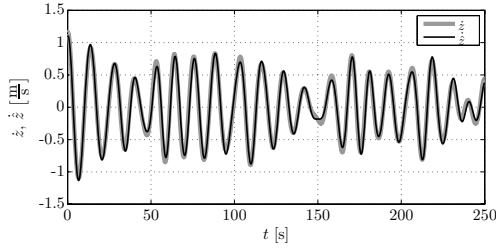


Fig. 6. Estimated heave velocity of the vessel $\hat{\dot{z}}$ obtained during simulation together with the reference signal $\dot{z}$.

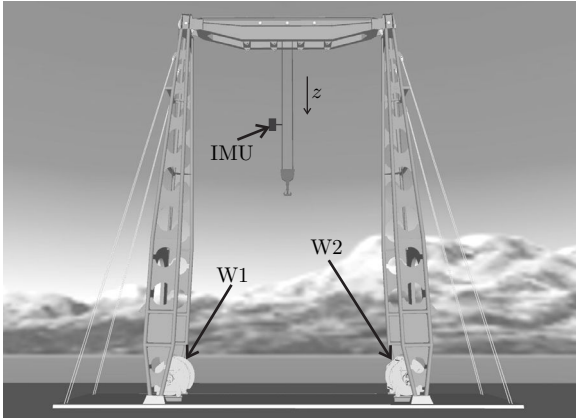


Fig. 7. Experimental setup.

$\hat{x}_{\text{off},k}$ is shown together with its nominal value used in the simulation. It clearly shows that $\hat{x}_{\text{off},k}$ slightly oscillates around the correct value $x_{\text{off},k}$. Since the offset state is correctly estimated, it is expected that the heave position and velocity are also estimated with high accuracy.

Figs. 5 and 6 show the estimated heave position and velocity $\hat{z}$ and $\hat{\dot{z}}$ obtained during simulation, respectively. Both figures show that the estimated values are in good accordance with their reference signals. However, the performance of the heave velocity is slightly better than the performance of the heave position. This is due to the fact that the acceleration signal has to be integrated only once for the velocity and twice for the position. So an error in the estimated offset state (see Fig. 4) has more influence on the position than on the velocity. Nevertheless, the position error stays in an acceptable range.

3.2 Experimental Setup

Fig. 7 shows the test bed used to validate the proposed observer during an experiment. The test bed has two

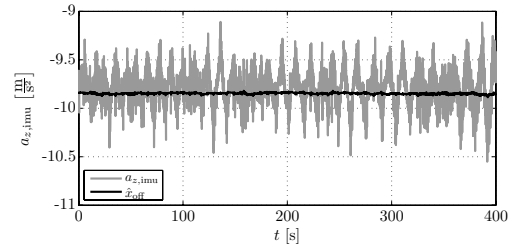


Fig. 8. Acceleration signal $a_{z,\text{imu}}$ measured at the experimental setup together with the estimated offset state $\hat{x}_{\text{off}}$.

winches and one hook. The rope is guided from the first winch W1 over the hook to the second winch W2. In order to test the complete active heave compensation system, the first winch imitates the heave motion of a vessel. To keep the hook at a fixed position, the second winch has to compensate for the motion of the first winch. The heave accelerations that are due to the first winch's motion are measured with an IMU attached on the rope as it is depicted in Fig. 7. The z -axis of the IMU is directed downwards to the ground and measures the heave acceleration directly. Thus no additional transformation of the IMU signals is required and the measured accelerations along the z -axis can be used directly to estimate the heave motion generated by the first winch. As the contribution only focuses on estimation of the heave motion, the second winch stands still and is not used for compensation in the following. Thus, only the first winch is excited using a simulated heave motion of a vessel as an input signal. The performance of the observer is evaluated using an incremental encoder attached to the first winch.

Fig. 8 shows the acceleration signal $a_{z,\text{imu}}$ measured by the IMU. The figure also illustrates the estimated offset state $\hat{x}_{\text{off},k}$ for this motion sequence. It clearly shows that $\hat{x}_{\text{off},k}$ is nearly a constant value and that the measured acceleration is the sum of the earth's gravity, the dynamic heave acceleration, and some sensor offset and noise. To evaluate the performance of the proposed method for estimating the heave position and velocity, $a_{z,\text{imu}}$ is used in the following to estimate $\hat{z}$ and $\hat{\dot{z}}$ online.

Fig. 9 depicts the estimated heave position $\hat{z}$ together with its reference z obtained from the incremental encoder attached to the first winch. It obviously shows that $\hat{z}$ and z are in good accordance with each other, especially during motions with high amplitude. The larger errors during motions with small amplitude are due to the fact that the first winch has some stick slip effect when its velocity approaches zero. This stick slip effect results in high accelerations measured by the IMU (see Fig. 8). These accelerations are not due to a dynamic heave motion and can therefore be seen as a disturbance signal causing some errors. The estimated heave velocity $\hat{\dot{z}}$ for this sequence is shown in Fig. 10. The figure also depicts the corresponding reference signal $\dot{z}$ obtained by differentiating the signal from the incremental encoder. As it can be seen, the estimated signal follows the reference signal with a small error. However, the error is less than the error of the estimated position. Again, this is due to the fact that the acceleration has to be integrated only once to obtain the velocity and twice for the position. Nevertheless, the overall performance of the proposed method is good

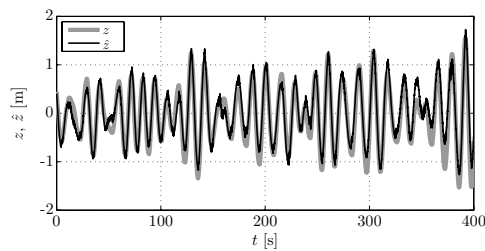


Fig. 9. Estimated heave position of the vessel $\hat{z}$ obtained from the experimental setup together with the reference signal z .

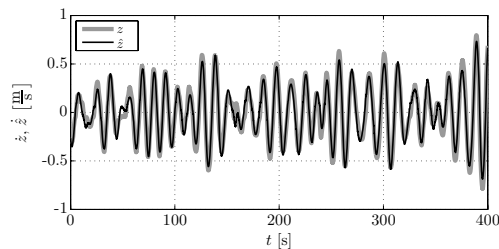


Fig. 10. Estimated heave velocity of the vessel $\dot{\hat{z}}$ obtained from the experimental setup together with the reference signal $\dot{z}$.

enough to use the estimated position and velocity as reference signals for an active heave compensation system.

4. CONCLUSION

The article has presented an approach for estimating the heave motion of a vessel from acceleration measurements of an IMU without using a vessel model or vessel specific parameters. For that the heave motion was decomposed into a sum of single modes and an ODE for every mode was formulated. The observer model was built out of the single modes and an offset state. The offset state was utilized to compensate for the earth's gravity and sensor errors that are measured by the accelerometers of the IMU additionally to the vessel's heave acceleration. The observer itself was designed as an EKF.

Through simulation and measurement results, the proposed method for heave motion estimation was validated. The heave velocity was estimated with a slightly better performance than the heave position. Nevertheless, both signals were in good accordance with their references and the estimation errors were always below an acceptable value. Thus, the results showed that the proposed method is applicable for marine applications and can be used to generate reference signals for active heave compensation systems.

REFERENCES

- ADIS 16365 (2009). *Six Degrees of Freedom Inertial Sensor*. Analog Devices.
- Chakrabarti, S. (2008). *Handbook of Offshore Engineering*. Elsevier, Amsterdam, 2 edition.
- Do, K. and Pan, J. (2008). Nonlinear control of an active heave compensation system. *Ocean Engineering*, 35(5-6), 558 – 571.

- Faltinsen, O. (1993). *Sea Loads on Ships and Offshore Structures*. Cambridge University Press, Cambridge, MA, 1 edition.
- Fossen, T.I. and Strand, J.P. (2001). Nonlinear passive weather optimal positioning control (wopc) system for ships and rigs: experimental results. *Automatica*, 37(5), 701 – 715.
- Fossen, T. and Perez, T. (2009). Kalman filtering for positioning and heading control of ships and offshore rigs. *IEEE Control Systems Magazine*, 29(6), 32 – 46.
- Godhavn, J.M. (1998). Adaptive tuning of heave filter in motion sensor. In *Proceedings of OCEANS*, 174 – 178. Nice.
- Godhavn, J.M. (2000). High quality heave measurements based on GPS RTK and accelerometer technology. In *Proceedings of MTS/IEEE OCEANS*, volume 1, 309 – 314. Providence, RI.
- Hopkins, R.D. and Adamo, L.C. (1981). Heave-roll-pitch correction for hydrographic and multi-beam survey systems. *Ocean Management*, 7(1-4), 85 – 97. Oceanology International "80.
- Kim, A. and Golnaraghi, M. (2004). A quaternion-based orientation estimation algorithm using an inertial measurement unit. In *Proceedings of Position Location and Navigation Symposium*, 268 – 272. Monterey, CA.
- Küchler, S., Mahl, T., Neupert, J., Schneider, K., and Sawodny, O. (2011). Active Control for an Offshore Crane Using Prediction of the Vessel's Motion. *IEEE/ASME Transactions on Mechatronics*, 16(2), 297–309.
- Marconi, L., Isidori, A., and Serrani, A. (2002). Autonomous vertical landing on an oscillating platform: an internal-model based approach. *Automatica*, 38(1), 21 – 32.
- Messineo, S. and Serrani, A. (2009). Offshore crane control based on adaptive external models. *Automatica*, 45(11), 2546 – 2556.
- Metni, N., Pfimlin, J.M., Hamel, T., and Soures, P. (2006). Attitude and gyro bias estimation for a vtol uav. *Control Engineering Practice*, 14(12), 1511 – 1520.
- MSS (2010). Marine systems simulator. <http://www.marinecontrol.org>. Viewed 20.11.2010.
- Setoodeh, P., Khayatian, A., and Frajah, E. (2004). Attitude estimation by separate-bias kalman filter-based data fusion. *The Journal of Navigation*, 57(2), 261–273.
- Triantafyllou, M., Bodson, M., and Athans, M. (1983). Real time estimation of ship motions using kalman filtering techniques. *IEEE Journal of Oceanic Engineering*, 8(1), 9 – 20.
- Weiss, I., D.T. (1977). Ship motion measurement filter design. *IEEE Journal of Oceanic Engineering*, 2(4), 325 – 330.
- Zeitz, M. (1984). Observability canonical (phase-variable) form for nonlinear time-variable systems. *International Journal of Systems Science*, 15(9), 949 – 958.