

Fig. 5: The upper plots show the yaw angle estimates of the onboard EKF, ψ_{EKF} , and the nonlinear observer, $\hat{\psi}$. The lower plot shows the difference between the estimates, $\tilde{\psi} = \psi_{EKF} - \hat{\psi}$.

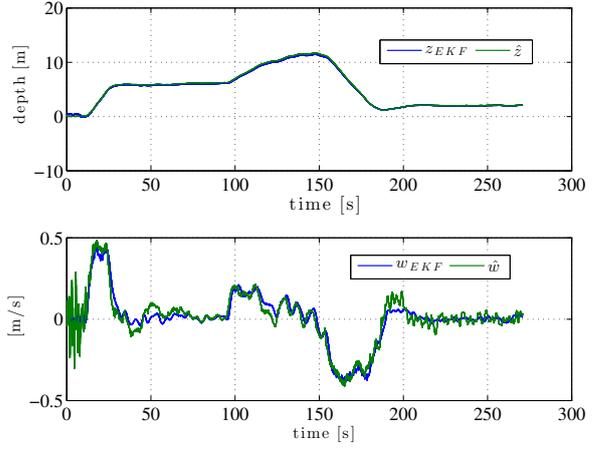


Fig. 7: Estimates of depth and heave velocity.

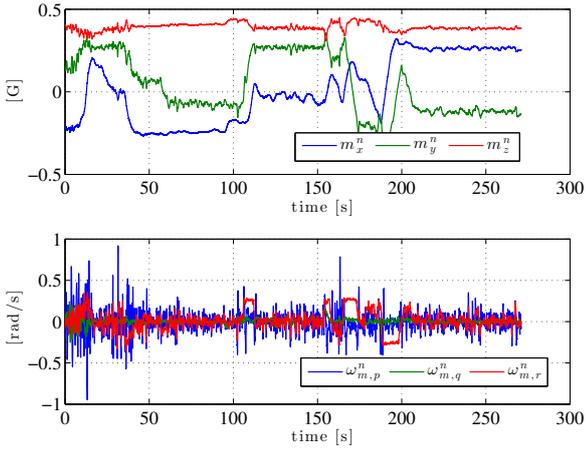


Fig. 6: The upper plots show the measured magnetic field strength, m^n . The lower plot shows the measured angular velocities, ω_m^n .

E. Assumptions Discussion

Figure 8 shows the Kalman filtered estimates of the acceleration in the x and y direction in the NED frame. It is evident that *Assumption 3* is not strictly valid throughout the experiment, since the horizontal accelerations deviate from zero. Even though the Seacon-1 vehicle's behavior does not strictly fulfill *Assumption 3*, the nonlinear observer still displays excellent performance in estimating attitude and heave position.

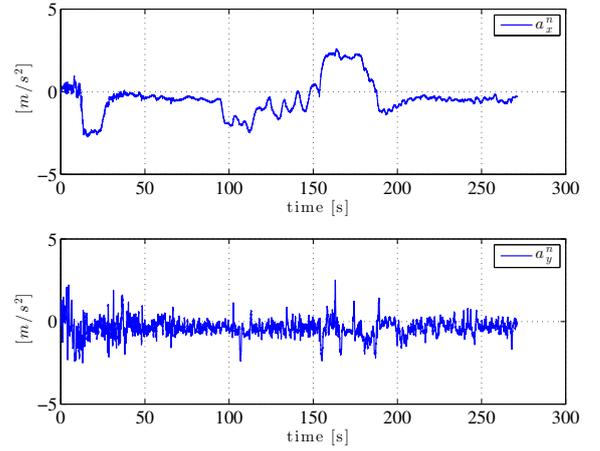


Fig. 8: The acceleration components of the horizontal plane in NED.

VI. CONCLUSION

In this paper the experimental results from testing a nonlinear observer on an AUV data set were presented. The nonlinear observer was modified by only utilizing a pressure sensor instead of GNSS position and velocity. The measured pressure was effectively treated as a measure of depth and the observer was therefore modified to only estimate the heave motion along with the attitude. The experimental testing showed excellent performance of the nonlinear observer, with performance comparable with the onboard Kalman filter. The nonlinear observer was global exponentially stable and it is much less computational demanding than the Kalman filter.

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APPENDIX

A. Pseudo Code for Nonlinear Observer

The Matlab code for a single iteration of the depth-aided nonlinear observer is given below. Prior to entering the observer loop the variables needed for operation are initialized, including the needed conversion from pressure measurements to depth. The code does not contain storage of variables needed for plotting, but only the basic mechanics of the nonlinear observer needed for implementation.

The variable n_depth handles the frequency difference from measurement updates and j_depth is an index

counter for the depth measurements. The overall observer loop iterates using i and i therefore also functions as the index variable for the IMU measurements.

The naming of variables have been attempted to be self-explanatory, e.g. z_{hat} is represented by z_hat , \hat{a}^n by a_hat_n . The gains K_{zz} , K_{wz} and $K_{\zeta z}$ are represented by K_zz , K_wz and K_zeta , respectively and have been chosen as $K_{zz} = 0.5$, $K_{wz} = 0.5$ and $K_{\zeta z} = 0.14$. The attitude estimation gains are $k_I = 1.0$, $\sigma = 1.0$ and K_p as a diagonal matrix with $K_{p,11} = 0.5$, $K_{p,22} = 2.0$, and $K_{p,33} = 0.5$.

The function `skew_sym(A)` represents the skew-symmetric operator $\mathbb{P}_a(A)$, the linear function `vex(A)` is represented by `vex(A)` and the skew-symmetric matrix $S(x)$ is represented by the function `space_iso(x)`. The functions are not included in the code below, but are straightforward to implement in Matlab.

```

if n_depth == 5; % Update depth measurements.
    z = z_meas(j_depth);
    j_depth = j_depth+1;
    n_depth = 0;
end

% Corrector for heave motion observer
z_hat = z_bar + K_zz*(z-z_bar);
w_hat = w_bar + K_wz*(z-z_bar);
zeta_hat = zeta_bar + [0 0 1]'*K_zeta*(z-z_bar);
a_hat_n = B*R_hat*a_b(:,i) + B*zeta_hat;

% Normalizing the vectors for the injection term J
a_hat_n_norm = a_hat_n/norm(a_b(:,i));
m_b_norm = m_b(:,i)/norm(m_b(:,i));
a_b_norm = a_b(:,i)/norm(a_b(:,i));

A_b = [m_b_norm space_iso(m_b_norm*a_b_norm) ...
        space_iso(m_b_norm)*space_iso(m_b_norm)*a_b_norm];

A_hat_n = [m_n_norm space_iso(m_n_norm)*...
            a_hat_n_norm space_iso(m_n_norm)*...
            space_iso(m_n_norm)*a_hat_n_norm];

J_hat = A_hat_n*A_b'-R_hat*(A_b*A_b');

% Saturation of values below and above -1,1
R_hat_s = max(min(R_hat,1),-1);

% Attitude estimator from eq. (4)
R_dot_hat = R_hat*space_iso(omega_b_imu(:,i)...
            -b_hat_b_gyro)+rho*K_p*J_hat;
b_dot_hat_b_gyro = projection(b_hat_b_gyro,...
            -k_I*vex(skew_sym(R_hat_rho'*K_p*J_hat)),M_b);

% Predictor
z_bar = z_hat + dt*w_hat;
w_bar = w_hat + dt*a_hat_n(3)+dt*g;
zeta_bar = zeta_hat - dt*rho*K_p*J_hat*a_b(:,i);

% Euler integration updates of attitude estimator
R_hat = R_hat + dt*R_dot_hat;
b_hat_b_gyro = b_hat_b_gyro + dt*b_dot_hat_b_gyro;

% Update depth counter
n_depth = n_depth+1;

```