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Experimental Validation of Transverse Stability Monitoring System for Fishing Vessels

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Abstract: Active monitoring of transverse stability in fishing vessels is paramount due to its significant incidence in operational accidents. Access to systems for automatic detection of changes in vessel’s stability related parameters would better support the crew during fishing and navigation operations. The paper presents an initial experimental validation of a signal-based transverse stability monitoring system, which consists of an estimator-detector kernel that solely uses measurements of roll motion to identify changes in vessel’s metacentric height by estimating the roll natural frequency. Its performance is evaluated based on experimental data from a towing tank scale model test campaign. The proposed transverse stability monitoring system well performs by identifying the potential risks and changes in loading condition.

Keywords: Experimental validation, Transverse stability, Frequency estimation, Empirical mode decomposition, Generalized likelihood ratio test, Real-time monitoring

1. INTRODUCTION

The fishing sector is notorious for its high fatal injury rate. Most affected vessels are small and medium sized ones, which represent the largest percentage of the fleet (Krata, 2008; Gudmundsson, 2013), and stability-related accidents are among the most frequent ones. According to the Annual Overview of Marine Casualties and Incidents 2018 (European Maritime Safety Agency, 2018) human erroneous actions account for 54.4% of the 338 accidental events analyzed in the period 2011-2017, and loss of control is one of two main reasons of casualty events, the other being collision. Accidents are usually connected to the lack of safety culture on board and the insufficient training in seamanship, particularly for what concerns static and dynamic stability. Skippers subjectively assess the level of vessel stability based on previous experiences where no accidents have occurred (Wollson Unit, 2004).

To facilitate an objective stability evaluation by the skippers, on board stability guidance systems emerged in the form of paper based procedures and recommendations about the stability of the vessel. They also included safe loading conditions and warnings about potential risky situations. The earliest attempts were the stability poster and the loading matrix (Deakin, 2005; Womack, 2003), which are based on a colour code to indicate the level of safety of each loading condition. Over the past decade, the first computer-based stability guidance systems appeared. Their main features were the automatic estimation of the stability level of the vessel and the clear provision of information to the crew. The stability assessment relied on loading condition data manually entered by the crew to the system. Therefore, these systems are prone to provide erroneous information due to mistaken input data. Some examples of these kind of systems are those described in Tello et al. (2011) and Míguez González et al. (2012).

Recently, in an attempt to minimize the crew interaction/interference, a new generation of decision support systems has been proposed. The main goal of these systems is to provide an intelligent assessment of the vessel transverse stability in real-time. This evaluation is based on the estimation of the metacentric height (GM), a key parameter to characterize the stability level of the vessel that is directly related to the roll natural frequency.

A mathematical model that estimates the roll natural frequency and gyroradius from the vessel roll motion was proposed in (Terada et al., 2016) and further refined by using the Markov chain Monte Carlo method in Terada et al. (2018). The reliability of this procedure needs to be verified as there are some discrepancies in the peak frequency results. Another approach based on the spectral analysis
of the roll motion for estimating the roll natural frequency was developed by Santiago Caamaño et al. (2018b). This method was further improved in (Míguez González et al., 2017) by implementing a sequential application of FFT together with an averaging, smoothing and fitting process of the roll spectra. Although its performance was good, it largely relied on the accuracy of the frequency estimations.

To overcome the challenge of obtaining very accurate estimates of the roll natural frequency with limited vessel information, Santiago Caamaño et al. (2019) developed a novel vessel stability monitoring system that combines signal processing methods with probabilistic learning to detect in near real-time changes in the vessel metacentric height. This system also integrates an awareness indicator that informs the crew about the current stability level of the vessel and its proximity to a critical stability condition. Although the vessel stability was assessed based on the estimated roll natural frequency, the ultimate objective of this research line is to integrate this approach into the guidance system proposed in (Santiago Caamaño et al., 2018a), where other dynamical phenomena (surf riding/broaching, pure loss of stability, etc.) and bad weather sailing will be taken into account. The monitoring system achieved good detection performances across a wide operational profile; however the verification was carried out only on simulated data.

This paper contributes with the initial experimental validation of the stability monitoring system proposed in (Santiago Caamaño et al., 2019) exploiting data from a towing tank test campaign of a scale model of a medium sized stern trawler. Despite the limited operational profile (2 loading conditions, 2 sea states) the experimental data confirm the probabilistic model proposed in (Santiago Caamaño et al., 2019). Further, the stability monitoring system clearly detect the transition from safe to risky condition in the tested cases and it provides a clear and simple representation of how the transverse stability of the vessel changes over time.

2. TRANSVERSE STABILITY MONITORING SYSTEM

The main objectives of the proposed stability monitoring system are (i) to provide a near real-time estimate of the vessel’s roll natural frequency during navigation solely using the measured roll motion and (ii) to monitor changes in the estimated frequency as a mean to assess variations in stability level due to the altered loading condition of the vessel. The fulfillment of the second objective should occur within a maximum detection time, such that the crew can take preventive actions. For the vessel under analysis the maximum detection time is set to three minutes.

The developed method is vessel-independent and employs the Empirical Mode Decomposition (EMD) combined with the Hilbert-Huang Transform (HHT) to estimate the roll natural frequency. The generalized likelihood ratio test (GLRT) based on the Weibull distribution is adopted to discriminate between safe and unsafe loading conditions. In addition a stability awareness feature is built in the monitoring system to provide high-resolution consciousness about the ongoing variations in vessel stability.

Fig. 1. Architecture of the transverse stability monitoring system.

The proposed system architecture is illustrated in Fig. 1 and its main components are listed in the following:

- **DAQ** the data acquisition system measures and logs the vessel roll motion;
- **EMD** the signal is decomposed into its main oscillatory modes by applying the Empirical Mode Decomposition (Dätig and Schlurmann, 2004; Huang et al., 1998);
- **HHT** the Hilbert-Huang Transform is applied to each of the oscillatory modes to estimate their modal frequency (Dätig and Schlurmann, 2004; Huang et al., 1998). Among all of these frequencies, the vessel roll natural frequency is selected;
- **W-GLRT** the Weibull generalized likelihood ratio test evaluates the current estimate of the roll natural frequency and decides if the loading condition of the vessel is safe or not. When the safety threshold is crossed an alarm is triggered;
- **BPF** Band-pass filtering of the measured roll motion is applied when the wave encounter frequency is far from the roll natural frequency in order to attenuate the wave component.

2.1 Data acquisition

The function of the DAQ is to measure and store the vessel roll motion. To estimate the roll natural frequency in near real-time, the roll motion record should be sufficiently short as to ensure detecting changes in the ship stability condition and, at the same time, sufficiently long as to obtain a reliable estimate. According to the characteristics of the studied vessel, the above trade-off is achieved with a batch length of 3 minutes and a 75% overlap between consecutive batches.

2.2 Empirical Mode Decomposition

The Empirical Mode Decomposition is a time-domain method for decomposing a signal into its main oscillatory components (Intrinsic Mode Functions, IMFs). Each IMF is characterized by time-varying frequency and amplitude, and an equal number of extrema (maxima and minima) and zero-crossings (Dätig and Schlurmann, 2004; Huang et al., 1998).

IMFs are obtained through an iterative procedure called sifting, which decomposes the signal from high to low frequencies until a monotonic residual is obtained. Once the EMD is applied, the roll motion time series can be described as:
where \( R(t) \) is a monotonic function, \( N_{\text{IMF}} \) is the total number of IMFs extracted from the measured roll motion and \( \bar{t} \) is the current time.

2.3 Hilbert-Huang transform

The Hilbert-Huang transform (HHT) is a spectral analysis method that enables the computation of the instantaneous frequency \( \omega(t) \), amplitude \( a(t) \) and phase \( \theta(t) \) of a signal.

Let \( x(t) \) be the \( i \)-th IMF and \( y(t) \) its Hilbert transform, i.e.

\[
y(t) \triangleq \frac{1}{\pi} \text{p.v.} \int_{-\infty}^{+\infty} \frac{x(\tau)}{t - \tau} \, d\tau
\]

where p.v. in front of the integral denotes the Cauchy principal value, then the aforementioned parameters are calculated as (Dätig and Schlurmann, 2004; Huang et al., 1998):

\[
a(t) \triangleq \sqrt{x(t)^2 + y(t)^2}
\]

\[
\theta(t) \triangleq \arctan \left( \frac{y(t)}{x(t)} \right)
\]

\[
\omega(t) \triangleq \frac{d\theta(t)}{dt}
\]

In general each IMF is not a simple harmonic function, therefore the resulting \( \omega(t) \) is time varying within the time interval \([\bar{t} - 3 \text{ min}, \bar{t}]\). However, a constant frequency estimate is needed for the monitoring system; hence the mean instantaneous frequency is computed for each IMF (Xie and Wang, 2006):

\[
\hat{\omega}_i = \frac{\sum_{k=1}^{L_\omega} \omega_i(k) a_i^2(k)}{\sum_{k=1}^{L_\omega} a_i^2(k)}, \quad i = 1, \ldots, N_{\text{IMF}}
\]

where \( L_\omega \) is the number of samples contained in the time window \([\bar{t} - 3 \text{ min}, \bar{t}]\) for a given sampling frequency \( F_s \); \( \omega_i(k) \) and \( a_i(k) \) are the instantaneous frequency and amplitude of the \( i \)-th IMF. Once all mean instantaneous frequencies contained in the roll motion have been estimated, the roll natural frequency should be identified among them.

The roll natural frequency of the vessel varies during the fishing operations due to the changes in loading condition. However, the range of variation is limited within the interval \([\omega_{0,\text{min}}, \omega_{0,\text{max}}]\), where \( \omega_{0,\text{max}} \) is obtained from the largest GM condition contained in the vessel’s stability booklet and \( \omega_{0,\text{min}} \) is associated with the minimum stability level necessary to keep heel beyond 15 degrees under a 30 knot lateral wind (IMO, 2012).

According to the signal decomposition strategy the IMFs extracted from the original signal are ranked in relation to the frequency (from high to low) and to the power content associated with the different frequencies present in the signal. This implies that the first IMF is a narrow band signal that retains the higher frequencies of the original signal as well as most of its power.

When the wave spectrum is well within the roll spectrum most of the signal power is concentrated around the roll natural frequency. Therefore the first IMF is expected to contain most of the information related to the roll natural frequency. Conversely, when the wave spectrum falls at the boundaries of the roll spectrum most of the signal power is concentrated around the wave encounter frequency; hence the first IMF is not expected to be informative about the roll natural frequency. In these cases filtering is applied as discussed in Section 2.5 to significantly attenuate the impact of the wave spectrum and emphasize the part of the signal due to the roll natural frequency. Applying the EMD after filtering will ensure that the first IMF contains information about the roll natural frequency. Based on this estimated roll natural frequency is \( \hat{\omega}_0 = \hat{\omega}_1 \).

2.4 Weibull GLR detector

To trail changes in roll natural frequency, and thus in vessel’s transverse stability, a detection system is designed. Its function is to evaluate two competing hypotheses and it is based on a probabilistic approach. This requires to identify the parametric probability distribution that best characterize the roll natural frequency estimates \( \hat{\omega}_0 \).

Figure 2 shows the probability plots for two loading conditions of the vessel under analysis (see Table 2) and four probability distributions fitted against 42 roll natural frequency estimates. The probability distribution that most accurately describes the behaviour of \( \hat{\omega}_0 \) is the Weibull distribution, given by:

\[
W(\hat{\omega}_0) = \frac{\kappa}{\lambda} \left( \frac{\hat{\omega}_0}{\lambda} \right)^{\kappa-1} \exp \left( -\left( \frac{\hat{\omega}_0}{\lambda} \right)^{\kappa} \right)
\]

where \( \kappa \) and \( \lambda \) are the shape and scale parameters, respectively. Both parameters depend on the vessel loading condition.

The two hypotheses to be distinguished by the detector are defined as:
where $H_0$ represents a safe loading condition and $H_1$ a risky one. $\omega_0$ is the roll natural frequency of the critical loading condition, i.e. the one that corresponds with the minimum standard metacentric height ($GM = 0.350 \text{ m}$) (IMO, 2012), and the probabilistic median of the Weibull distribution is a robust estimator of $\omega_0$.

$$\hat{\omega}_0 = \lambda (\ln 2)^{\frac{1}{\hat{\xi}}}$$

Although according to IMO regulations the critical loading condition is accepted as a safe working scenario from a point of view, the detection problem is set up in a more conservative manner. To decide between the two competing hypothesis for a given set of roll natural frequency estimates, the generalized likelihood ratio test is applied. The GLRT is based on the Neyman-Pearson theorem and tries to maximize the probability of detection for a desired probability of false alarms (Kay, 1998).

Let $\Omega_0 = [\omega_0(j - N), \omega_0(j - N + 1), \ldots, \omega_0(j)]^T$ be the vector containing the latest $N$ estimates of $\omega_0$, then the GLRT decides that $\Omega_0$ belongs to $H_1$ if:

$$L_G(\Omega_0) = \frac{W(\Omega_0; \hat{\theta}_1, H_1)}{W(\Omega_0; \hat{\theta}_0, H_0)} > \gamma$$

where $\hat{\theta}_1$ is the maximum likelihood estimate (MLE) of the parameter vector $\theta = [\lambda, \kappa]^T$ under the hypothesis $H_1$ and $\gamma$ is the detection threshold for a chosen probability of false alarms, $\hat{\theta}_1$ is calculated maximizing $W(\Omega_0; \theta)$ under the hypothesis $H_1$; hence the parameters $\hat{\lambda}_1$ and $\hat{\kappa}_1$ are determined as

$$\hat{\lambda}_1 = \left[ \frac{1}{N} \sum_{i=0}^{N-1} \Omega_{0,i}^2 \right]^{\frac{1}{2}}$$

$$1 - \frac{1}{N} \sum_{i=0}^{N-1} \ln(\Omega_{0,i}) - \frac{\sum_{i=0}^{N-1} \Omega_{0,i}^2 \ln(\Omega_{0,i})}{\sum_{i=0}^{N-1} \Omega_{0,i}^{\hat{\kappa}_1}} = 0$$

Taking the natural logarithm of both sides of Eq. (10) and simplifying, the detector is obtained

$$N \ln \left( \frac{\hat{\kappa}_1 \lambda_0^\hat{\xi}}{\kappa_0 \lambda_1^\hat{\kappa}_1} \right) + (\hat{\kappa}_1 - \kappa_0) \sum_{i=0}^{N-1} \ln(\Omega_{0,i})$$

$$- \left( \frac{\sum_{i=0}^{N-1} \Omega_{0,i}^\hat{\xi}}{\lambda_1} \right) \hat{\kappa}_1 + \left( \sum_{i=0}^{N-1} \Omega_{0,i}^{\hat{\kappa}_1} \right) \kappa_0 > \gamma'$$

The threshold $\gamma' = \ln(\gamma)$ is computed according to the Neyman-Pearson theorem (Kay, 1998)

$$P_{FA} = \int_{\Omega_0 : L_G(\Omega_0) > \gamma'} W(\Omega_0; \theta_0, H_0) \, d\Omega_0$$

The GLRT raises an alarm when the risky stability condition is identified; however it cannot trail changes among different safe loading conditions. For this purpose and to provide the skipper with actionable information about how close the vessel is to the critical condition, a color coded indicator based on multiple deterministic thresholds has also been designed. This indicator compares the current probabilistic median of the Weibull distribution with $\omega_0$, and outputs a color that varies from dark green (safe situation) to red (critical condition). These different transverse stability conditions have been defined according to the following thresholds

$$\frac{\hat{\lambda}_1 (\ln(2))^{\frac{1}{\hat{\xi}}} \omega_0}{\omega_0} \geq 1.3 \rightarrow \text{dark green}$$

$$1.3 > \frac{\hat{\lambda}_1 (\ln(2))^{\frac{1}{\hat{\xi}}} \omega_0}{\omega_0} \geq 1.1 \rightarrow \text{green}$$

$$1.1 > \frac{\hat{\lambda}_1 (\ln(2))^{\frac{1}{\hat{\xi}}} \omega_0}{\omega_0} \geq 1.05 \rightarrow \text{yellow}$$

$$1.05 > \frac{\hat{\lambda}_1 (\ln(2))^{\frac{1}{\hat{\xi}}} \omega_0}{\omega_0} \geq 1 \rightarrow \text{orange}$$

$$1 > \frac{\hat{\lambda}_1 (\ln(2))^{\frac{1}{\hat{\xi}}} \omega_0}{\omega_0} \rightarrow \text{red}$$

2.5 Filtering

When the wave encounter frequency is significantly larger or smaller than the roll natural frequency, the EMD-HHT estimator has difficulties in identifying $\omega$. The frequency component with the highest energy content in the signal usually corresponds to the wave excitation, and the peak of the spectrum located at the wave encounter frequency tends to mask the other components. This issue is especially relevant when the roll motion has small amplitude.

In this scenario $\hat{\omega}_0$ falls outside the interval $[\omega_{0\min}, \omega_{0\max}]$, hence it is unlikely to be a correct estimate of the roll natural frequency. To avoid that the wave encounter frequency masks the roll natural frequency, a pass-band filter is applied. The filter is a 5th order Chebyshev Type II with an attenuation in the stop band of 20 dB, a lower cut-off frequency of 0.3 rad/s and an upper cut-off frequency of 0.95 rad/s. These values coincides with $\omega_{0\min}$ and a conservative choice of $\omega_{0\max}$.

The filtering action has changed in comparison to that one proposed in (Santiago Caamaño et al., 2019), where simulated roll motion time series were used for testing. This change is motivated as for the experimental data a low-pass filter has proved not to be suitable.

3. TEST AND VALIDATION

To validate the performance of the stability monitoring system, roll motion time series obtained from towing tank tests in regular beam waves for two different loading conditions and sea states have been used. The experiments were carried out at the University of A Coruña towing tank ($L \times W \times H = 56 \text{ m} \times 4.20 \text{ m} \times 1.80 \text{ m}$), which is equipped with an unidirectional wave generator capable of generating regular and irregular waves according to different wave spectra, a carriage and wave height measuring devices.

The vessel under analysis is a 1/30 scale model of a medium sized stern trawler (see Fig. 3), made in fibreglass and with adjustable weights for modifying the loading condition. The roll motion was measured using an inertial measurement unit with the sampling frequency $F_s = 50 \text{ Hz}$, and the obtained roll motion time series have been subsequently scaled to fit the real vessel size.
3.1 Test vessel

The test vessel is a mid-sized stern trawler, representing a typical unit from the Spanish fleet. Its main characteristics are shown in Table 1.

Table 1. Test vessel: main characteristics

| Parameter            | Value     |
|----------------------|-----------|
| Overall Length       | 34.50 m   |
| Beam                 | 8.00 m    |
| Depth                | 3.65      |
| Draft                | 3.34 m    |
| Hull Volume          | 448 m³    |
| Minimum Roll Natural Frequency \( (\omega_0,_{\text{min}}) \) | 0.300 rad/s |
| Maximum Roll Natural Frequency \( (\omega_0,_{\text{max}}) \) | 0.95 rad/s |

Two loading conditions are considered: LC 1 represents a safe condition (\( GM \) over the minimum required value) while LC 2 is the critical condition of the vessel (\( GM = 0.350 \) m). Details are provided in Table 2.

Table 2. Test vessel: loading conditions

| LC | \( \Delta (t) \) | d (m) | \( GM \) (m) | \( \omega_0 \) (rad/s) | \( k_{xx} \) |
|----|------------------|-------|-------------|------------------|------------|
| 1  | 489              | 3.484 | 0.503       | 0.691            | 0.395      |
| 2  | 448              | 3.340 | 0.350       | 0.563            | 0.411      |

3.2 Test conditions

The operation of this type of vessels is typically divided into two different stages: the cruising to and from the fishing grounds at moderate speeds; the fishing manoeuvre that consists of three phases, i.e. the letting out where nets are deployed, the trawling and the reeling in. The most dangerous phase is usually the last one, as the vessel is sailing at very low forward speed (close to zero) and with reduced course keeping capabilities. Under these conditions, the vessel may face beam waves which, together with possible appearance of roll resonance, reduced damping moments (due to low speed), opened doors and hatches and hanging weights, could easily lead to flooding and/or capsizing. To address these conditions, in which accidents could be most likely, regular beam waves and zero vessel forward speed have been chosen as test scenario. Noteworthy that the effect of the fishing nets on the vessel roll motion, and thus on the performance of the detector, has not been taken into consideration.

The test waves were selected taking into account the possible impact of the wave encounter frequency on the performance of the monitoring system. Thus, two cases can be distinguished: a sea state with a wave encounter frequency close to the vessel roll natural frequency and a sea state with a wave encounter frequency far from the roll natural frequency. The sea state parameters are detailed in Table 3, where \( H_s \) is the significant wave height, \( \omega_w \) is the peak frequency and \( S_w \) is the wave steepness. At zero speed the wave encounter frequency matches the wave peak frequency.

Table 3. Sea state parameters

| Sea state | \( H_s \) (m) | \( \omega_w \) (rad/s) | \( S_w \) |
|-----------|---------------|----------------------|---------|
| 1         | 1.95          | 0.563                | 0.01    |
| 2         | 3.03          | 1.008                | 0.05    |

3.3 Tuning of the condition monitoring system

The detector is designed under the assumption that the elements of \( \Omega_0 \) are independent and identically distributed (i.i.d.) random variables. If this assumption fails, then the theoretical performance of the detector cannot be guaranteed and \( \gamma' \) should be empirically determined. Figure 4 shows the auto-correlation function of \( \Omega_0 \) under \( H_0 \) and it can be appreciated that the data are uncorrelated and therefore the i.i.d. requirement is fulfilled.

Given a desired false alarm probability \( P_{FA} \) the threshold \( \gamma' \) is found by

\[
\gamma' = \lambda_0(-\ln(P_{FA}))^{\frac{1}{\kappa_0}}.
\] (15)

Setting the desired number of false alarms to one each three months and considering that the monitoring system outputs a value every three minutes, the probability of false alarms is \( P_{FA} = 0.000023 \), which results in the threshold \( \gamma' = 0.6281 \).

Furthermore, a second threshold \( \gamma'' \) has been defined as a return-from-alarm criterion. If an alarm is triggered by the detector, then it will be withdrawn when the detector’s output is lower than \( \gamma'' \). This threshold is set to \( \gamma'' = \gamma'/2 \) and it is added to ensure that possible stability overpredictions do not mask real alarms.

In the design of the GLRT detector it was assumed that the parameters of the \( H_0 \) hypothesis were known. This in
general is not true, because when the monitoring system starts operating, the loading condition of the vessel may have changed since the last time the system was used. For this reason, two operational stages are defined for the monitoring system:

**Estimation stage** When the vessel leaves the port and the system is started, roll natural frequency estimates are stored for a time window $T_{est}$. After that, an estimation of the parameter vector $\theta_0$ is done. If $\theta_0$ fulfills the condition of $A_0(ln2)^{\frac{1}{\kappa}} \geq \omega_0$, it is stored as the reference value. Otherwise, an alarm is given to inform the crew about the low stability level of the vessel. $T_{est} = 10$ min is chosen to generate sufficient estimates $\hat{\omega}_0$ to achieve a robust statistics of the Weibull distribution.

**Detection stage** Once the hypothesis $H_0$ is known, $H_1$ can be estimated and both values compared. The time window $T_{det}$ is set in order to have enough estimates of $\hat{\omega}_0$ to estimate $\theta_1$. $T_{det} = 4.5$ min and 33% overlap between consecutive batches of estimates have been selected to meet the detection requirement of the system.

### 3.4 Evaluation of the monitoring performance

Due to physical limitations of the towing tank facilities, in order to obtain sufficiently long roll motion time series to evaluate the performance of the proposed condition monitoring system, each wave case has been tested 4 times for each loading condition. Then, the roll motion time series have been stitched together removing the transient part and using a smoothing filter around the stitching points to avoid sudden fictitious variations within the signals. The first part of the time series corresponds to the safe loading condition (LC 1), while the second part corresponds to the loading condition with reduced stability level (LC 2). Further, the roll motion time series have been pre-processed with a low-pass filter with cut-off frequency of 1.75 rad/s to attenuate signal content related to possible rebound of the waves in the tank, wall effects, etc.

Figure 5 shows the results related to the experimental data gathered in Sea State 1. In this case the wave encounter frequency is close to the roll natural frequency for both loading conditions. In LC 2, where both the wave encounter frequency and the roll natural frequency coincide, the roll natural frequency is accurately estimated since the energy is largely concentrated around a single peak as result of the resonance condition. On the other hand, there is a clear underestimation of the roll natural frequency in LC 1. This fact is due to the proximity between the wave encounter frequency and the roll natural frequency that makes it harder to carry out an exact estimation. The largest difference between the median of the estimates of the natural roll frequency and its true value in LC 1 is 17% and in LC 2 is 1.2%. The monitoring systems performs rather well, displaying good sensitivity to changes in loading conditions. When the detector’s alarm is triggered it appears in red color. In LC 1 a false alarm appeared due to an erroneous estimation of $\omega_0$. LC 2 is correctly identified as a risky situation by the detector, which raises an alarm within five minutes from the appearance of the critical condition (there is one miss detection). The awareness indicator is also sensitive to variations in loading conditions as LC 2 is plotted in red while LC 1 is plotted in orange most of the time.

Figure 6 shows the results corresponding to the second wave condition. In this situation, the wave encounter frequency is far from the roll natural frequency ($\omega_w \gg \omega_0$) and the resulting roll motion amplitude is small. The roll natural frequency estimates present some dispersion for both LC 1 and LC 2. In this case, the largest difference between the median and the true value is 9.1% for LC 1 and 3.7% for LC 2. The overall performance is still quite good and the transition between the two loading conditions is detected most of the time. There are a few miss detections due to errors in the estimation of $\omega_0$. Noteworthy that in this scenario bandpass filtering was applied to the batches of measured roll motion.

Overall, the monitoring system shows a good and robust performance for both considered sea states and filtering has proven to be a viable way to limit the impact of environmental conditions when the wave encounter frequency is much larger than the roll natural frequency and resulting
4. CONCLUSIONS

Intelligent systems for the real-time monitoring of transverse stability variations in fishing vessels may be a solution to reduce the number of fatal accidents during fishing operations. This work presented the experimental validation of a novel data-driven stability monitoring system based on the integration of advanced signal processing with statistical change detection.

The experimental validation performed using data including safe and risky loading conditions confirmed the ability of the stability monitoring system to track variations in roll natural frequency, thereby raising an alarm whenever the risky loading condition is met.

The probabilistic modeling provides sufficient robustness to the monitoring system to overcome the uncertainty present in the estimation of the roll natural frequency. Further, the awareness indicator yields a detailed visualization of the underlying changes in the vessel's transverse stability; however it is more sensitive to estimation inaccuracies.

Although the obtained results showed a promising performance, further work is needed to verify the capability of the transverse stability monitoring system to correctly operate in conditions other than beam seas, with the vessel advancing in waves with a speed significantly different from zero and accounting for the effects of fishing gear deployed underwater.

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