Estimation of Directional Sea Spectra from Ship Motions in Sea Trials

R. Pascoal[3], L. P. Perera[2], C. Guedes Soares[1]

Centre for Marine Technology and Ocean Engineering (CENTEC), Instituto Superior Tecnico, Universidade de Lisboa, Lisbon, Portugal.

[1] Corresponding Author e-mail: c.guedes.soares@centec.tecnico.ulisboa.pt ; Tel: +351 218 417607
[2] Presently at the Norwegian Marine Technology Research Institute (MARINTEK), Trondheim 7052, Norway
[3] Presently at IEETA, University of Aveiro, 3810-193 Aveiro.

ABSTRACT

This paper compares the skill of two algorithms that enable real-time estimation of the directional wave spectra exciting a ship from its measured motions. One algorithm consists of a nonlinear optimization of a parametric or non-parametric spectral model and the other is a Kalman filter based observer. Sea trials have been conducted on an oceanographic vessel that was instrumented with a six degree of freedom fibre optic gyro, complemented with a rate gyro, several accelerometers, a dedicated GPS receiver and a bow mounted down-looking wave radar with motion compensation. The two algorithms are applied to the measured data and a discussion is provided on their skill to recover the properties of existing sea states.

Keywords: Wave spectra; Spectral estimation; Vessel motions; Kalman Filtering; Sea trials

1 INTRODUCTION

This paper concerns procedures that enable real-time estimation of the wave spectra exciting a ship by measuring its motions, in an extension of the principles that govern the use of wave-rider buoys to record sea surface height and derive wave spectra. The wave climate greatly influences marine operations and, therefore, this topic has deserved the attention of researchers and the maritime community. Improvements to vessel per-

formance, the avoidance of dangerous loading and stability conditions and minimizing seasickness and other health conditions related to the crew or passengers, can all benefit from on-board estimation of the wave conditions.

The research efforts specifically focused on the estimation of sea spectra from ship motions has extended for several decades, since the first post-WWII deployments to estimate the scalar spectrum with data recovered from moored ships, instrumented with accelerometers and pressure transducers (Darbyshire, 1961, Tucker & Pitt, 2001), to the more recent procedures enabling estimation of the directional spectrum under non-negligible speed of advance and in real-time. The estimation procedure has shifted from direct methods in the frequency domain to nonlinear optimizations or time domain procedures that require higher computational resources, which in the meanwhile have become available.

Estimation of sea spectrum from ship motions, with the explicit account for wave direction and ship speed of advance, appears to have been first presented in Japan during the 1970's, with well-structured published research produced by Takekuma & Takahashi (1973), as a result of work started in 1971 by the 108th Research Committee of the Ship-building Research Association of Japan. At the time they coined the procedure as a "Reverse Operational Method of Sea Spectrum" and were not focused on determining the directional spectrum but rather on taking into account the fact that ship response changes with incoming wave direction.

In the late 1970's, Pinkster (1978) proposed that the wave feedforward information could be used to achieve better performance in dynamically positioned vessels. During the 1980's there appears to be reduced interest in spectral estimation from ship motions, but Pinkster's work, though he did not go as far as to actually demonstrate the hypothesis on a real ship, seems to have motivated several proposals and experiments on spectral estimation that appeared in 1990's and early 2000's. In these publications there was a small detour from using ship motions alone to estimate directional wave spectra and wave staffs or laser probes around the hull were proposed as a means to measure relative elevations (Drennan & Donelan et al., 1994, Linfoot & Wright, 1995, Waals et al., 2002).

In the early XXI century there was a renewed interest on estimation of the directional spectrum from ship motions, with several publications addressing the problem from diverse perspectives. It is probably at this

time that most of the proposals appear and that researchers start to worry more explicitly about strategic positioning of the onboard sensors, mathematical details, real-time algorithms and speed of advance.

Focusing on the available methods to estimate wave spectra from ship responses, one will find, as with generic procedures designed for spectral estimation given the responses of an excited medium, that there exist parametric and non-parametric formulations, depending on whether or not an analytical shape is made available. There are many features in common with generic spectral estimation procedures designed to determine spectra, however, the single most important aspect, correctly emphasized back in 1970, is the fact that the predictions of full sensor dynamics (i.e. ship) are not negligible, requiring state of the art hydrodynamic calculations, and that, unlike the response of a spherical wave buoy, the response of a vessel is also a function of wave direction and not just of frequency.

Similar work has been published on wave spectrum estimation using parametric and nonparametric representations. The parametric formulation consists on giving a spectral shape with mathematical representation and unknown coefficients, such as the JONSWAP, while the nonparametric is a minimization where only a non-negativity constraint on the spectral amplitude is mandatory but the form is otherwise not specified (this is sometimes called hyperparametric representation) (Pascoal et al., 2007).

Iseki and co-workers (2000, 2001, 2002, 2004) proposed a non-parametric Bayesian formulation for estimating the directional sea spectrum. The Bayesian formulation is a formal path to obtain a constrained non-linear optimization problem. In the respective publications, he incrementally improves or at least suggests different procedures to estimate the motion cross-spectra, needed for the final step of the estimation of the wave spectrum. Iseki is probably the first, in this setting, to propose the use of multivariate autoregressive moving average filters in order to provide real-time cross-spectral estimates, but his contribution felt short, since real-time cross-spectra of ship motions did not result in real-time wave spectral estimation due to the computational bottleneck of the non-linear optimization that was still necessary to recover the wave spectrum.

Tannuri and co-authors (2001, 2002, 2003) proposed both parametric and non-parametric procedures for stationary vessels. After several numerical and physical experiments, Tannuri favoured the non-parametric formulation, which was written as a Bayesian problem, and explicitly arrived at a non-linear programming problem to optimize for the spectral ordinates. The computationally demanding procedure was signalled to be

a problem and there was great care in justifying which motions should be chosen for the optimization, as well as to why hydrodynamic calculations need to be carried out carefully.

Saito et al. (2000), Maeda et al. (2001), Masuda et al. (2001), also proposed non-parametric methods, formulated as non-linear programming problem, and suggested that results from the procedure could be used to provide guidance for ocean going ships.

Nielsen (2005, 2007, 2008) worked extensively on the Bayesian formulation of the same problem, reinstated the need to carefully handle the non-bijective nature of the encounter frequency, identified the need to carefully calculate ship responses and the need to refine the way that the tuning parameters are found, as they influence the shape of the estimated spectra. Furthermore, the proposed approaches were confronted with spectral estimation from radar backscatter images from full scale trials.

Pascoal et al. (2007, 2008, 2009) worked on several aspects of spectral estimation and proposed several alternatives of non-parametric and parametric formulations. In these publications, it was clearly stated that the computational bottleneck is at the final step of optimization, with execution times given for comparison, and therefore conditioning factors and ways to quickly find robust initial estimates were proposed. It was probably the first time, in this setting, that genetic algorithms were used to provide global search in the parametric formulation and that the Kalman filter was used to obtain estimates of the actual wave elevations in real time and without requiring any cross-spectral calculations. Those algorithms were verified only with numerical simulations and in this paper they are compared with experimental results obtained in sea trials conducted in 2009. It is interesting to note that around the same time the works of Tannuri and co-workers and of Nielsen have been validated with full scale motion data (Simos et al, 2010; Nielsen and Stredulinsky 2012). A recent limited validation has also been made of the parametric approach of Pascoal and Guedes Soares (2009) using a small patrol boat (Hinostroza and Guedes Soares 2016).

In the sections to follow, the formulations adopted in this study are briefly described and the results of a full scale experimental campaign are shown and compared with the estimates of the two main alternative methods, allowing conclusions about their relative capabilities.

2 FORMULATIONS FOR SPECTRAL ESTIMATION FROM SHIP MOTIONS

2.1 *Non-Parametric formulations*

There are several alternatives to obtain a non-parametric formulation and it is the one that is favoured by most authors. As mentioned in the Introduction, a formal way to reach the optimization problem is to use a Bayesian setting. However the Bayesian setting is most important if one is dealing with iterative schemes or with probabilistic error measures, where the conditional probabilities make explicit sense and otherwise it is just complicating the problem. Writing down the optimization problem is simple but not exempt of some pitfalls in what respects rates of convergence.

The Bayesian setting, as mentioned, is ideally used in the iterative schemes. In fact, the Kalman filter algorithm, last proposed to perform estimates of the wave elevation (Pascoal and Guedes Soares, 2009), is a result of a Bayesian analysis on the state variables and outputs corrupted by noise and modelling errors.

2.1.1 *Non-linear Optimization*

In case the problem is written as a non-linear minimization, which is eventually the case for any non-iterative scheme that disregards probabilistic measures, then one wishes to minimize the quadratic error between cross-correlation as estimated from the ship motions and the one calculated by using the vessel's hydromechanic response transfer functions and the estimated wave spectrum.

If wave elevation is written as

$$\eta(\vec{x},t) = \iint_D a(\sigma,\theta)e^{i(\vec{k}\cdot\vec{x}-\sigma t)}d\sigma d\theta \quad , \tag{1}$$

where $a(\sigma,\theta)$ is the complex wave amplitude as function of the intrinsic angular wave frequency and the wave direction, σ and θ respectively, i is the imaginary unit and $\vec{k}$ is the wave vector, then any response of the vessel can be expressed as

$$R_m(\vec{x},t) = \iint_D H_m(\sigma,\theta)a(\sigma,\theta)e^{i(\vec{k}\cdot\vec{x}-\sigma t)}d\sigma d\theta , \tag{2}$$

with $H_m(\sigma,\theta)$ representing the transfer function as function of incoming wave frequency and direction, and cross-spectra can be calculated as the Fourier transform of the cross-correlation $\overline{R_m(\vec{x},t)R_n(\vec{x}+\vec{r},t+\tau)}$, resulting in

$$\Phi_{nm}(\sigma,\theta) = \overline{H_n^*(\sigma,\theta)H_m(\sigma,\theta)a^*(\sigma,\theta)a(\sigma,\theta)}. \tag{3}$$

However, the sensors located inside the vessel cannot determine the direction of incoming waves and consequently in which direction the response exists. The equivalent of an integral for all directions is performed by the system, which can be written as:

$$C_{mn}(\sigma) = \int_{-\pi}^{\pi} \Phi_{mn}(\sigma,\theta)d\theta , \tag{4}$$

which in fact corresponds to the measured cross-spectra.

Then, because the cross-spectral matrix is Hermitian one may map the sub-indices as:

$$A_{kr} = H_m(\sigma,\theta_r)H_n^*(\sigma,\theta_r)$$
$$\text{combinations of } m, n \rightarrow k = 1,2,...,6 \tag{5}$$
$$r = 1,2,...,N_\theta$$

The numerical estimates of the cross-spectra in this work have been determined with Welch's method (Welch, 1967) and the Blackman Harris window (Harris, 1978), with two non-overlapping windows over 3 minute intervals. When the speed of advance is close to zero, one may establish an error for each frequency band and that results in a much faster optimization. Even if the zero speed condition is not satisfied at a given moment, but it is known that most energy lies within the single valued branch, it is still recommended to make

the initial estimates based on that hypothesis, allowing one to apply nonlinear least squares, and then to tune the result using the full non-linear optimization. The error at each band can then be expressed as

$$
e_k = \frac{W_k(\sigma)\left(\sum_{r=1}^{N_\theta} A_{kr}\Delta\theta K_r x_r - [C_k(\sigma)]\right)}{\sum_{j=1}^{6} W_j(\sigma)C_j(\sigma)},
$$

(6)

with the weighting factor

$$
W_k(\sigma) = \lambda \overline{|A_{kr}|}^{-1}, \text{ with } \lambda = \begin{cases} 2, \text{ if } k = heave \\ 1, \text{ otherwise} \end{cases}
$$

(7)

and K_r a matrix whose elements depend on the numerical integration scheme, identity if rectangular rule is used.

The cost function to be minimized is of the form:

$$
f = \sum_k e_k e_k^* + \frac{\alpha}{\iint_D S_w^e d\theta d\sigma} \iint_D \left(\nabla^2 S_w^e\right)^2 d\theta d\sigma,
$$

(8)

where the unknowns are the real valued spectral ordinates represented by S_w^e, and the last term, with $\alpha \geq 0$, is a smoothing constraint. Again, the first estimate should be performed as least-squares problem, in which case $\alpha = 0$, the solution of which becomes the initial estimate (Pascoal and Guedes Soares, 2008). By using the intrinsic wave frequency, speed of advance is also taken into account.

2.1.2 Kalman Filtering

The Kalman filter is used in many different settings where optimal linear estimation is sufficient to achieve a good estimate. In order to use the filter, one needs to establish a model of the process in the form of a first order linear, possibly time-varying, multivariate state space, the measuring equations and probabilistic information about errors in modelling and measurements.

The use of a Kalman filter to estimate wave elevations was initially envisaged as the solution to the problem even before the authors developed the parametric and non-parametric approaches. At the time, it was thought possible to use a time domain non-linear sea-keeping code (Fonseca and Guedes Soares, 1998) in closed loop with an Extended Kalman filter responsible for updating the wave elevations as function of the er-

ror between estimated and sensed motions, but that is a very complex configuration that would not run in real-time with reasonable computational effort and actually was never put into practice. It is also quite doubtful that one could manage provide a robustly convergent setup.

The assumption of linearity was then invoked and the wave elevations for a chosen set of frequencies were tagged as being the states. The model was then based on the fact that the measured responses are a combination of the incoming waves weighted by the corresponding transfer functions (Pascoal and Guedes Soares, 2009):

$$r(t) \cong \text{Re}\left(\sum_{j=1}^{n_f} \sum_{m=1}^{n_\theta} H_{jm} \times \left(X_{2j-1,m} + \sqrt{-1} X_{2j,m} \right) \left(\cos\left(\sigma_j t \right) + \sqrt{-1} \sin\left(\sigma_j t \right) \right) \right) \tag{9}$$

where the state variables, $X_{2j-1,m}$ and $X_{2j-1,m}$, represent the real and imaginary parts of the complex wave amplitude and σ represents the intrinsic frequency of a harmonic. Expanding, results in

$$r(t) \cong \sum_{j=1}^{n_f} \sum_{m=1}^{n_\theta} \left(\text{Re}\left(H_{jm} \right) \times \cos\left(\sigma t \right) - \text{Im}\left(H_{jm} \right) \sin\left(\sigma t \right) \right) \times X_{2j-1,m} -$$

$$\sum_{j=1}^{n_f} \sum_{m=1}^{n_\theta} \left(\text{Im}\left(H_{jm} \right) \times \cos\left(\sigma t \right) + \text{Re}\left(H_{jm} \right) \sin\left(\sigma t \right) \right) \times X_{2j,m} \tag{10}$$

and from which one can then identify the measurement matrix by writing the response as a matrix equation with size n_r by $n_\theta \times 2 \times n_f$

$$r_{jk} = C_{jk} \cdot X_k + \theta_k . \tag{11}$$

With respect to the transition matrix, each wave component was considered to evolve independently of others and at the same time the rate of change of wave amplitude is considered zero when compared to the time constants associated with the Kalman filter updating. Consequently, the transition matrix is the identity, so that the state equation is

$$X_{k+1} = X_k + \xi_k \tag{12}$$

and the time-varying measurement matrix is:

$$C_{jklm} = \begin{bmatrix} \mathrm{Re}(H_{jlm})\cos(\sigma_j kT) - \mathrm{Im}(H_{jlm})\sin(\sigma_j kT) \\ -\mathrm{Im}(H_{jlm})\cos(\sigma_j kT) - \mathrm{Re}(H_{jlm})\sin(\sigma_j kT) \end{bmatrix}' \tag{13}$$

The last terms of the equations, ξ_k and θ_k, are noise which are to account for modelling errors and measurement noise, respectively. Noise and errors have typical behaviour as function of frequency, with errors increasing and noise being typically band-limited.

The Kalman filter is applicable only to estimate those states which are observable, meaning that one cannot hope to estimate many wave amplitudes if the measurement equation does not allow it. In order enable convergence of the filter, the measurement vector is built not only from the present measurements but also from several lagged ones (Pascoal and Guedes Soares, 2009) and n_r is incremented accordingly as many times as there are lags.

One of the characteristics of the Kalman filter in its basic form is that the estimates converge to the probabilistic expected value while the error covariance matrix converges to a constant value typically corresponding to the lowest filter gain. This characteristic is not desired for estimation under changing vessel speed, heading or sea-state and therefore an adaptive term was added. The measurement noise covariance was updated as:

$$\hat{\Theta}_k = diag^2\left(E\left[r_k - C_k\hat{X}_k^-, \ \left(r_k - C_k\hat{X}_k^-\right)' \right] \right) + C_k P_k^- C_k', \tag{14}$$

where $diag$ is the operator taking a matrix diagonal into a vector and vice-versa, applied the number of times represented in the superscript. P_k^- is the state noise covariance estimate in the time update phase of the filter. Furthermore, because the time constants associated with the filter were very small, the state estimates were very erratic. This is ideally counteracted by saying that the transition matrix corresponds to that of a low pass filter with time constants to be tuned. Again, a simpler, numerically faster, alternative was chosen which corresponds to a moving average:

$$\hat{X}_{k+1}^- = 1/3 \cdot I \cdot \left(\hat{X}_k + \hat{X}_{k-1} + \hat{X}_{k-2} \right) \tag{15}$$

The initial state error, the state noise and the measurement noise covariance matrices, respectively P_1, Q_1 and Θ_1, have been kept constant throughout the analysis in this document and are as follows:

$$Q_1 = P_1 = \begin{bmatrix} I_{m \times m} & O_{m \times m} \\ O_{m \times m} & 0.5 \times I_{m \times m} \end{bmatrix} \tag{16}$$

$$\Theta_1 = diag\left(conc\left(\begin{bmatrix} 4 \times 10^{-2} & 10^{-4} & 10^{-4} & 10^{-2} \end{bmatrix}, \frac{1}{5} n_r \right) \right) \tag{17}$$

where $conc(a, u)$ operator concatenates vector a by a number of times represented by u. The value of m is selected as half the length of X. The arguments behind the selection of these matrices follow. Matrices have been selected as diagonal because it is a simple and conservative way to proceed in the absence of information about other terms, the terms for higher frequencies have been given lower values of covariance in order to lower the initial gain associated with those frequencies, and the values for the measurement noise covariance have been selected as those provided or estimated from the sensor datasheet.

2.2 *Parametric Formulation*

The parametric formulation is devised in much the same way as non-parametric, with the same cost function being valid, but the unknowns are shifted to the integrated wave parameters and one does not need to impose additional smoothness constraints on the spectral ordinates.

In the proposed procedures, the most commonly adopted parametric form has been to use the summation of JONSWAP spectra, each of which directionally spread by a cosine spreading function. In this way it is possible, e.g., to deal sea states that have two components, appearing as a double peaked spectrum (Guedes Soares 1984).

Because the parametric formulation more easily falls into local minima such as those induced by situation depicted in Figure 1, the use of a global search technique is thus advised or, as an alternative, tests can be performed by post-optimization step testing for the other directions.

3 EXPERIMENTAL RESULTS

The experimental results presented here relate to data which have been acquired in 2009, onboard the Portuguese Navy Oceanographic vessel "NRP Almirante Gago Coutinho" where an on-board digital data acquisition system was installed for the purpose. This ship travels at relatively low speeds, roughly up to 10 kn, and has a length over-all of approximately 70 m, an approximate breadth of 13 m, an operational draught of 4.6 m

and a 2335 ton displacement. The vessel travelled several times from Portuguese mainland to the Azorean archipelago and the vessel has performed some manoeuvres specifically requested to enable the research reported herein.

The research team had no possibility of being onboard and thus estimation was performed as a post-processing step. One of the most important lessons from these trials was that there are several sensor glitches, maybe due to poor electrical contacts, that need to be filtered, or voted by redundant sensing before being used, and another was that the system needs to be completely self-recovering because of eventual power failures.

The oceanographic vessel was instrumented with a six degree of freedom fiber optic gyro (Figure 2), complemented with a rate gyro, several accelerometers, GPS receiver and a bow mounted down-looking wave radar (Figure 3). Data acquisition was performed using a real-time CompactRIO® controller connected via Ethernet to a laptop used for bulk data logging and human supervision, as shown in Figure 4. The spectral estimates presented herein use only ship sway, heave, pitch and yaw. The transfer functions for the required motions have been estimated using a 3D panel method.

As mentioned earlier, data had to be tested for quality and filtered to remove sensor glitches. The filtering procedures to be applied in such systems need to be fast, stable and should introduce a practically constant, minimal, time lag in the region of interesting frequencies. A simple five point moving average filter was tested but the results were not very satisfactory and thus it was complemented with a threshold based on standard deviation, to identify outlier clusters. Within cluster borders, data sets were linearly interpolated. Sample result of this procedure is shown in Figure 5, with the original signal, the 5 point moving average (MovAvg) and the additional standard deviation based filtering (Filtered) of a heave signal. All data was acquired at a rate of 10 Hz, however, because data made available by the several sensors are not synchronous, a timestamp based resampling is applied to achieve an effective 10 Hz rate of synchronized data.

In order to cross-check at least the scalar spectra, the bow radar (Figure 3) was used. The down-looking device allows one to directly estimate the wave spectrum on the moving reference frame. Please note that the frequencies represented herein are all frequencies of encounter (intrinsic) and the indications of N, E, S, W actually correspond to waves coming from starboard, stern, portside and bow, respectively. The transfer func-

tions obtained from the previously mentioned panel method, as an approximation, have been used directly with the exception that frequency used as parameter was the intrinsic value. The average ship speed was 8 kn during trials.

Only the non-parametric formulations previously proposed by the authors will be used herein. In the past they have been applied only to synthesized data and therefore the real data sets allow simultaneous validation of the simulation procedure and of the algorithms. The presented and analysed results are of quite general nature, including changes of sea state and ship heading. The first analysed set is with respect to data collected on the 28th of June 2009. Two 20 minute segments were chosen, segment 5 and segment 20.

In segment 5, as determined from the radar data, the peak encounter period, Tp, was 9.6 s and the significant wave height, Hs, was 1.46 m (Figure 6). On the first row of Figures 7 and 8, from left to right, are the raw directional and scalar spectra, and, on the second row, are the parametrized directional and scalar spectra. The non-parametric non-linear optimization recovers values of 9.9 s and 1.3 m, respectively for Tp and Hs (Figure 7), while the Kalman filter recovers two very close peaks at 9.2 s and 11 s with the same energy and totalling 1.33 m (Figure 8). These results are very good with relative error in Hs less than 11 % and 5 % in the peak period for any of the algorithms.

The directional raw spectra have been subject to a fast parametrization step described in Pascoal and Guedes Soares (2008), allowing for two components of JONSWAP with cos-2s spreading (10 parameters). This allows for both a common ground of comparison and for parameters which are less sensitive to local characteristics of the raw spectra. There are differences to note between the parameters estimated from the raw spectra made available by the nonlinear optimization and the Kalman filter . The nonlinear optimization estimates the incoming wave field is head onto the ship (180º) and for the Kalman filter that there are two wave fields, one from 150º and the other from 211º, which on average is, not surprisingly, 180.5º and thus combined to give practically head waves. The results of the Kalman filter are seen to be much more irregular and that is easily justified by the fact that there is absolutely no smoothness constraint applied to the estimates.

After segment 5 it is interesting to look at segment 20 because the ship has undergone a change of heading. This statement is justified by looking at Figures 9 and 10 and in fact one can easily say that the change was roughly 93 º. The important point was to determine if the estimators would have behaved accordingly.

First, the new reference spectrum, estimated from the radar data, is plotted in Fig 11 and as one can observe there is now a low frequency swell, the total Hs is 1.59 m and the main peak remains at 9.6 s. The non-linear optimization estimates a single peaked spectrum with total Hs of 1.7 m and a Tp of 9 s (Fig 12), whilst the Kalman filter estimates a two peaked spectrum with a total Hs of 1.36 m and periods of 11 and 8 s (Fig 13). The relative errors are now less than 15 % for Hs or Tp (for Tp using only the most energetic component). The directions are now estimated at 80.3 ° by the optimization and again two components, one at 96.3° together with another at 182°, are estimated by the Kalman filter.

Both algorithms, for reasons yet to be determined, failed to estimate the existence of the low frequency component (which could also be due to diffraction effects and not the incoming waves) but it is interesting to find that the optimization algorithm correctly rotated the spectrum but by roughly 100° and the Kalman filter correctly finds that there is a strong peak at around 90° but also finds one at 180°.

The capability of the estimators to determine the wave direction and peak period is in fact the most important one, because the significant wave height, as with many other procedures, is the most easily calibrated parameter. Thus, having analysed a situation which proves the fundamental capability, it remains to be assessed if the good performance is kept for larger significant wave heights.

The chosen segment corresponds to data collected starting at 12:23:03 of the 9th of June 2009. This segment has a significant wave height of 2.33 m and a peak encounter period of 11.4 s, estimated from the wave radar as seen on Figure 14. There was a wave rider buoy in the vicinity and its data on the same date, and at the closest time, was collected at 11:40. The buoy estimates Hs to be 2.32 m and the mean period 8.6 s (peak period approximately 12 s), with an incoming direction of NW in the earth reference frame.

During the trial in analysis, the ship heading was as presented in Figure 15. Heading is not stationary, but this should not be a problem because both estimators are capable of handling these variations. Results presented in Figure 16 and Figure 17 are respective to the estimate at the end of the 6th minute and, at that time, the heading is 180 °, meaning that the vessel is travelling south and with the section abaft the starboard beam exposed to the incoming waves. As mentioned earlier, waves coming from stern appear in the figures as E and from starboard as S. Thus, both procedures estimated directionality consistent with the existing wave field. After parameterization, the non-linear optimization estimates Hs was 2.27 m and the Kalman filter that it was

1.96 m with one of the smaller peaks, Hs of 0.22 m, having been ignored by the parameterization procedure. Therefore, all peak periods are consistent.

The results of this section are summarized in Table 1. The first column identifies the data set, the six minute segment selected within that set and the ship heading. The average ship speed for all trials is 8 kn. The second column identifies the parameter to be presented on subsequent columns, available from each of the three available sources. The sub-indices 1 and 2 associated with the parameters pertain to the post-processing parametrization, which allows for up to two components, and relate only to the spectra estimated by the non-linear optimization and the Kalman filter. The bow radar is sensor from which the raw reference spectra are estimated, along with significant wave height and peak period. As previously discussed, both algorithms present results which are consistent with respect to energy content average peak period when compared to the reference. The Kalman filter algorithm, in the absence of smoothing constraints tends to present estimates which are less peaked and more spread, as becomes evident from the small values of peak intensification factor, γ, and the large values of spreading coefficient, s, respectively, associated with the most energetic spectral components.

	Parameter	Bow radar (raw)	Non-parametric nonlinear	Kalman filter
Set 28062009 Segment 5 Heading 258	Hs_1, Hs_2 [m]	1.46, -	1.3, -	0.94, 0.94
	Tp_1, Tp_2 [s]	9.6, -	9.9, -	9.2, 11
	θ_1, θ_2	NA	180, -	150, 211
	γ_1, γ_2	NA	3.1, -	0.8, 2.4
	s_1, s_2	NA	1.3, -	1.0, 1.0
Set 28062009 Segment 20 Heading 351	Hs_1, Hs_2 [m]	1.59, -	1.7, -	0.65, 1.2
	Tp_1, Tp_2 [s]	9.6, -	9.0, -	8.0, 11.0
	θ_1, θ_2	NA	80, -	182, 96.3
	γ_1, γ_2	NA	4, -	4, 0.8

14

	s_1, s_2	NA	1, -	5, 2.3
Set 09062009 Segment 5 Heading non- stationary	Hs_1, Hs_2 [m]	2.33, -	1.7, 1.5	0.97, 1.7
	Tp_1, Tp_2 [s]	11.4, -	11, 10	12, 9
	θ_1, θ_2	NA	283, 355	236, 282
	γ_1, γ_2	NA	4, 4	4, 3.4
	s_1, s_2	NA	1, 3.2	3.9, 3.9

Table 1 Comparison of results for documented trials.

4 CONCLUSIONS

This paper presents an experimental validation of the algorithms real-time estimation of the sea surface spectra around a ship proposed by Pascoal and Guedes Soares (2008, 2009). The procedures consist of nonlinear optimization and Kalman filter based spectral estimation which have been applied to experimental data collected onboard the vessel NRP Alm. Gago Coutinho, which is a low speed oceanographic vessel with length overall around 70 m.

The results presented show that in general the estimators have performed well and gave good comparisons with the bow down looking radar and with a waverider buoy in the vicinity. They also performed well with respect to changes in ship heading and sea state.

The procedures are known to not being able to determine high wave frequencies to which the ship does not respond, as has been determined in numerical simulations. The limitations with respect to ship length and observable wave frequencies were not experienced with the available data sets, mainly because the ship is relatively small and most wind waves were within the sensitive range.

For larger ships this can be handled by using external sensors or other responses of the ship sensitive to higher frequencies. This fact needs to be further researched and a solution will probably be possible only in the Kalman filter setting.

The greatest strengths of the Kalman filter are the faster than real-time estimation, easy inclusion of vessel speed of advance, the possibility of using multiple sensors in a sensor fusion setting accounting for the measurement errors and inclusion of model errors which can partly compensate for not having perfect transfer

function estimates and these were the reasons why it was implemented in a decision support system (Perera et al 2012). The main weakness of the presented procedure is the complete absence of smoothing, resulting in a tendency to underestimate the significant wave height and overestimate the directional spread.

With respect to the procedure based on nonlinear optimization, it has the positive aspect that smoothness constraints are easily implemented and thus the spectral estimates are close to what a parametric form achieves. The stability of the estimates is superior due to the use of several minutes of data. Speed of advance is not easily implemented without optimizing simultaneously in direction and frequency, but a step forward has already been made by Hinostroza and Guedes Soares (2016).

5 ACKNOWLEDGEMENTS

6 REFERENCES

Darbyshire, M., 1961, A Method for Calibration of Ship-borne Wave Recorders, J. Ocean Dynamics, 14(2), pp. 56-63.

Drennan, W. M., M. A. Donelan, N. Madsen, K. B. Katsaros, E. A. Terray, C. N. Flagg, 1994, Directional Wave Spectra from a Swath Ship at Sea. J. Atmos. Oceanic Technol., 11, 1109-1116.

Fonseca, N. and Guedes Soares, C. 1998. Time-Domain Analysis of Large-Amplitude Vertical Ship Motions and Wave Loads. Journal of Ship Research. 42(2):139-153.

Guedes Soares, C. 1984, Representation of Double-Peaked Sea Wave Spectra. Ocean Engineering. 11(2):185-207.

Harris, F.J., 1978, "On the use of Windows for Harmonic Analysis with the Discrete Fourier Transform", actas de IEEE, 66(1), pp. 51-83.

Hinostroza, M. A. and Guedes Soares, C., 2016. Parametric estimation of the directional wave spectrum from ship motions. International Journal of Maritime Engineering (accepted for publication).

Iseki, T. and Ohtsu, K., 2000, "Bayesian Estimation of Wave Spectra Based on Ship Motions", Control Eng. Practice, 8, pp. 215-219.

Iseki, T., Terada, D., 2001, "Bayesian Estimation of Directional Wave Spectra for Ship Guidance System", Proc. of the 11th Int. Off. and Polar Eng. Conf., June 11-22, Stavanger, Norway.

Iseki, T. and Daisuke, T., 2002, "Bayesian Estimation of Directional Wave Spectra for Ship Guidance System", International JISOPE, 12(1), pp. 25-30.

Iseki, T., 2004, "Extended Bayesian Estimation of Directional Wave Spectra", Proc 23rd Int Conf OMAE, ASME, paperOMAE2004-51609.

Linfoot, B.T. and Wright, V.J.C., 1995, "Wave Feedforward Control of Floating Production Systems", Control Eng. Practice, 3(5), pp. 687-694.

Maeda, K., Akashi, T., Saito, K., 2001 "An estimation of ocean wave characteristics based on measured ship motions (4th report): Directional wave spectrum estimated from full-scale measurements", J. of the Society of Naval Architects of Japan, 190, pp 241-246.

Masuda, K.., Takaishi, Y., Kawata, S., 2001, "Development of an Onboard System for Wave Data Analysis and Application to Ship Operation", Proc. 20th Int. Conf. Off. Mech. Arctic Eng., ASME, OMAE01/OFT-5108.

Nielsen, U.D., 2005, "Estimations of on-site directional wave spectra from measured ship responses", Mar. Struct., 19(1), pp 33-69.

Nielsen, U.D., 2007, "Response-based estimation of sea state parameters-influence of filtering", Ocean Eng., 34(13), pp 1797-1810.

Nielsen, U.D., 2008, "Introducing two hyperparameters in Bayesian estimation of wave spectra", Probabilistic Eng. Mech., 23(1), pp. 84-94.

Nielsen, U.D., Stredulinsky, D.C. 2012, Sea state estimation from an advancing ship – A comparative study using sea trial data, Applied Ocean Research, 34, pp. 33-44

Perera, L. P.; Rodrigues, J. M.; Pascoal, R., and Guedes Soares, C. 2012, Development of an onboard decision support system for ship navigation under rough weather conditions. Rizzuto, E. & Guedes Soares C., (Eds) . Sustainable Maritime Transportation and Exploitation of Sea Resources. Taylor and Francis Group, London,UK. pp. 837-844.

Pascoal, R., Guedes Soares, C., Sørensen, A.J., 2007, "Ocean Wave Spectral Estimation Using Vessel Wave Frequency Motions", Journal of Offshore Mechanics and Arctic Engineering, 129(2), pp. 90-96.

Pascoal, R., Guedes Soares, C., 2008, "Non-parametric wave spectral estimation using vessel motions", Appl. Ocean Res, 30(1), pp. 46-53.

Pascoal, R., Guedes Soares, C., 2009, "Kalman Filtering of Vessel Motions for Ocean Wave Directional Spectrum Estimation ", Ocean Engineering, 36(6-7), 477-488.

Pinkster, J.A., 1978, Wave-feed-forward as a means to improve dynamic positioning, OTC3057, Houston.

Saito, K., Maeda, K., Matsuda, A., Suzuki, 2000, "An Estimation of Wave Characteristics Based on Measured Ship Motions (3rd Report)", J. of the Society of Naval Architects of Japan, 187, pp. 77-83.

Simos, A.N., Tannuri, E.A., Sparano, J.V., Matos, V.L.F., 2010. Estimating wave spectra from the motions of moored vessels: Experimental validation, Applied Ocean Research, 32, 2, 191-208.

Tannuri, E.A., Simos, A.N., Sparano, J.V., da Cruz, J.J., 2001, "Directional Wave Spectrum Based on Moored FPSO Motions", Proc. 20th Int. Conf. Off. Mech. Arctic Eng., ASME, OMAE01/OFT-1094, Rio de Janeiro, Brazil.

Tannuri, E.A., Sparano, J.V., Simos, A.N., Da Cruz, J.J., 2003, "Estimating Directional Wave Spectrum Based on Stationary Ship Motion Measurements", Appl. Ocean Res., 25, pp. 243-261.

Takekuma, K., Takahashi, T., 1973, "On the Evaluation of Sea Spectra based on the Measured Ship Motions", Transactions of the West-Japan Society of Naval Architects, 45, pp. 51-57.

Tucker, M.J., Pitt, E.G., 2001, Waves in Ocean Engineering, Elsevier

Waals, O.J., Aalbers, A.B., Pinkster, J.A., 2002, "Maximum Likelihood Method as a means to Estimate the Directional Wave Spectrum and Mean Drift Force on a Dynamically Positioned Vessel", Proc. 21st Int. Conf. Off. Mech. Arctic Eng., ASME, OMAE2002-28560, June 23-28, Oslo, Norway.

Welch, P., 1967, "The use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time averaging Over Short, Modified Periodograms", IEEE Transactions on Audio and Electroacoustics, AU-15(2), pp. 70-73.

FIGURES
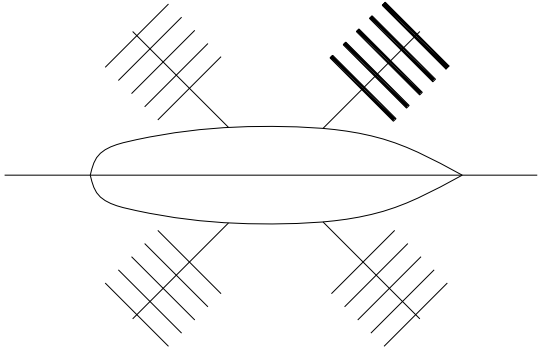
Figure 1 Waves that induce practically the same amplitude of the response but different phases.

Figure 2 Fiber optic gyro with rate gyro and heave accelerometer.

Figure 3 Bow mounted down-looking wave radar with vertical accelerometer for motion compensation.
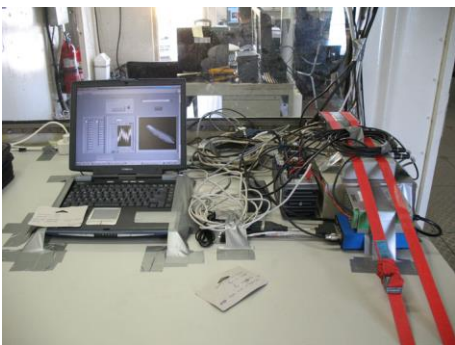
Figure 4 Data acquisition equipment, wave radar processor and GPS.
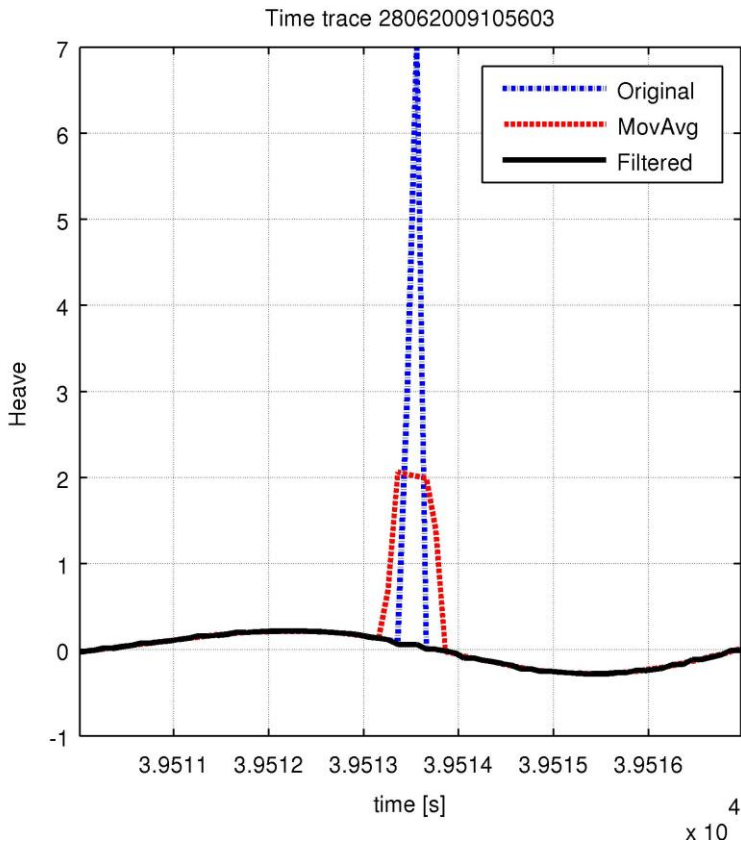
Figure 5 Comparison between moving average and the filtering procedure based on local and simple global statistical properties of the signal.
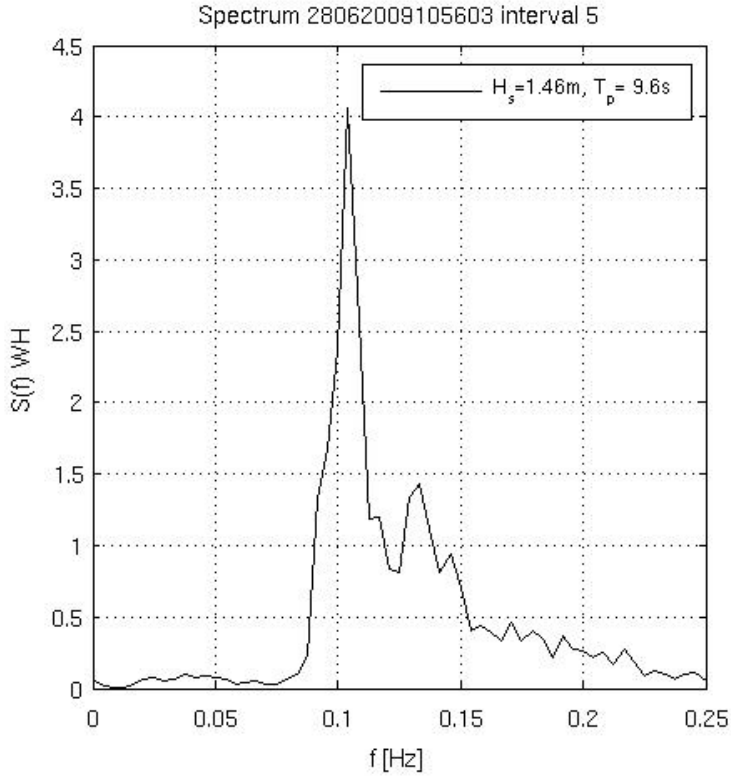
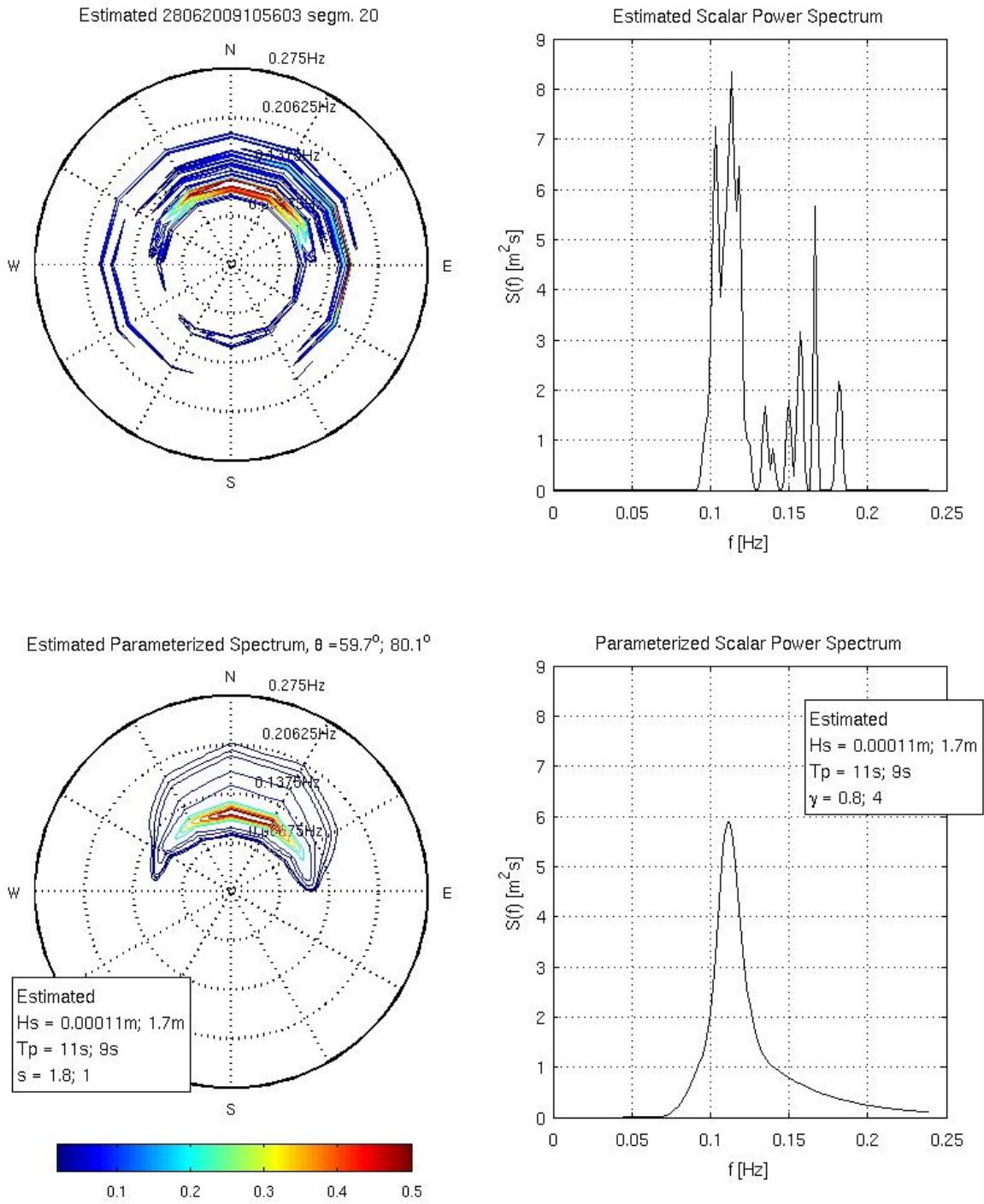Figure 6 Wave encounter spectrum estimated from the bow radar at segment 5.
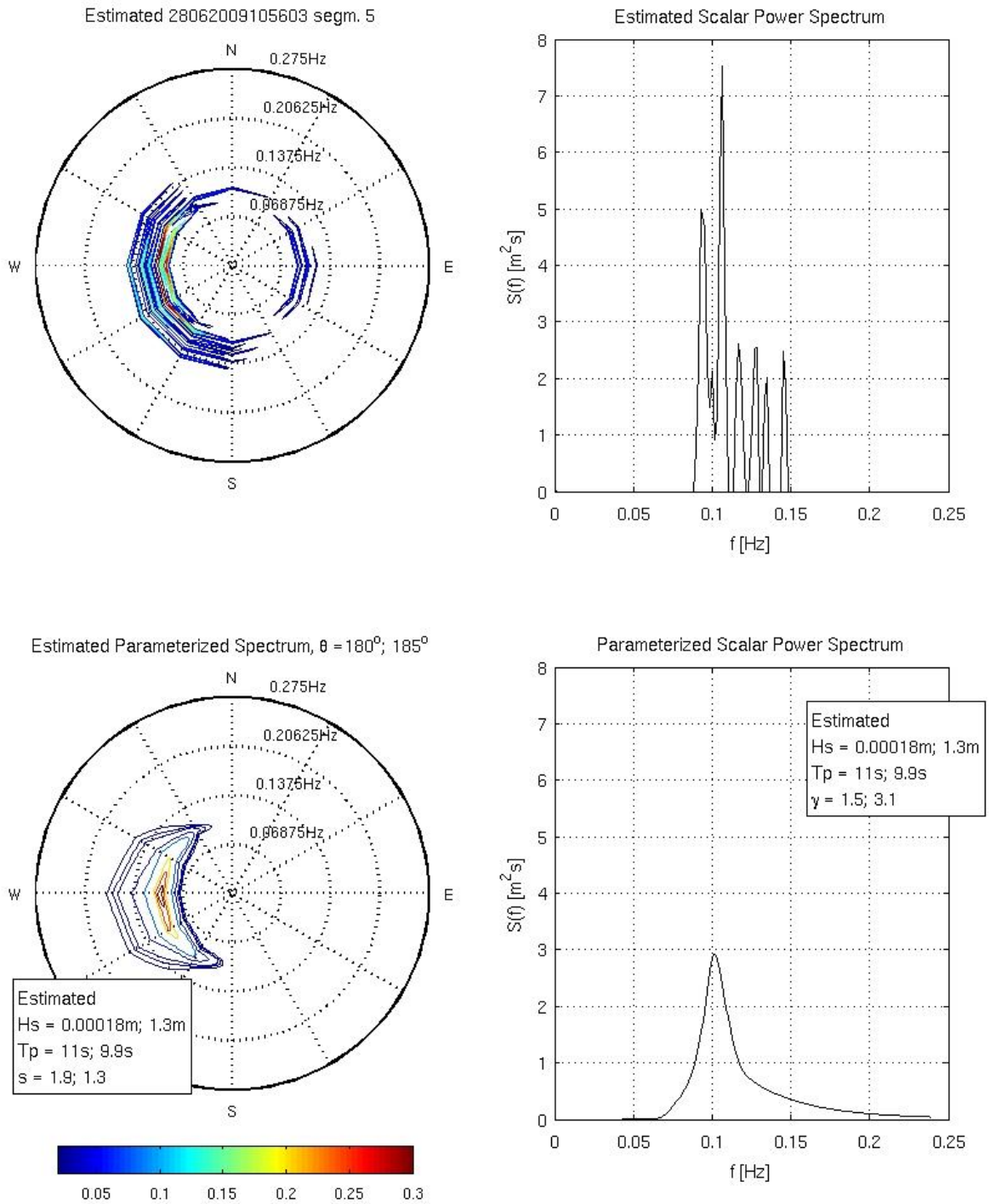
Figure 7 Non-linear optimization applied to segment 5.
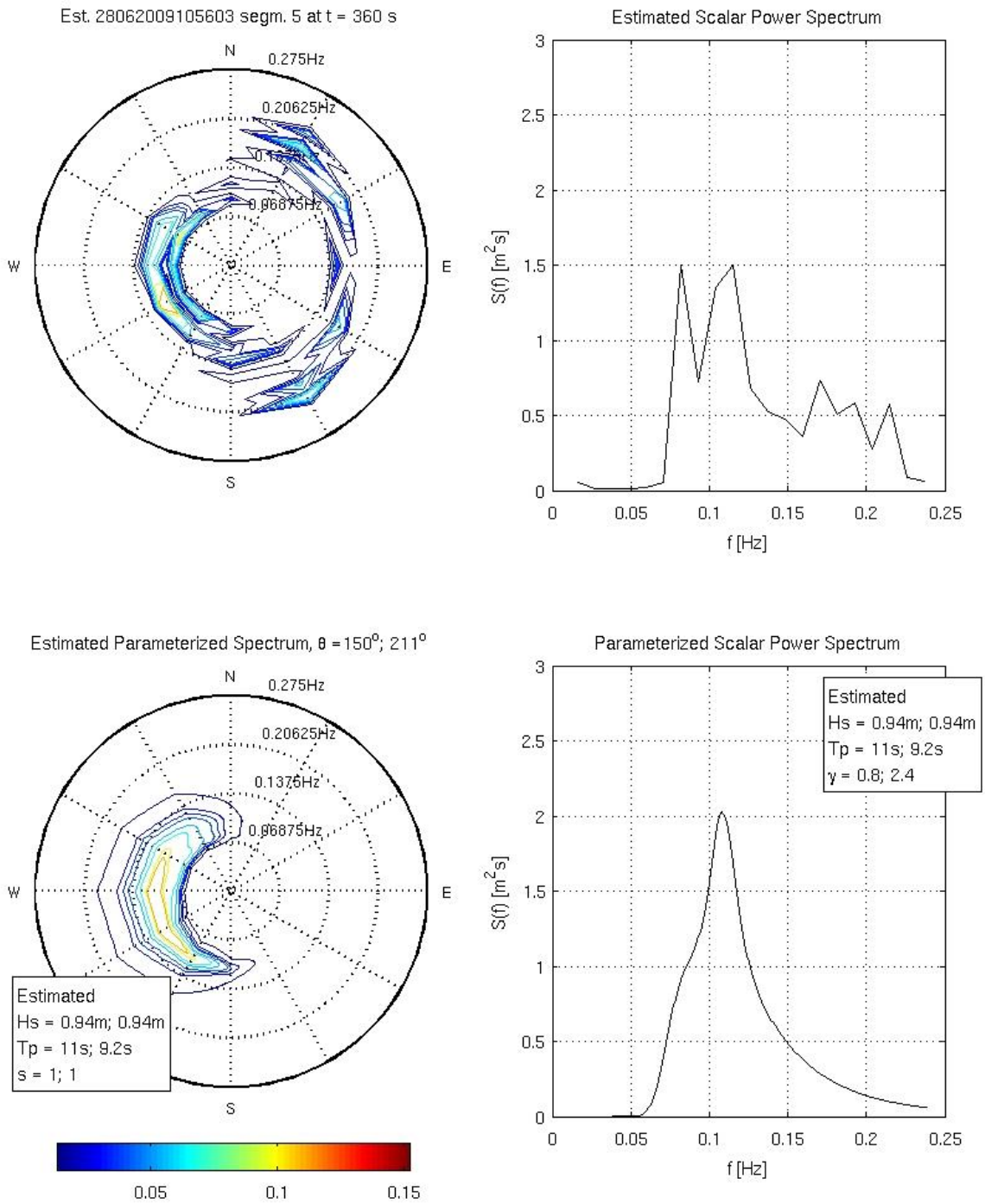
Figure 8 Kalman filter applied on segment 5 and its estimates at t = 360 s.
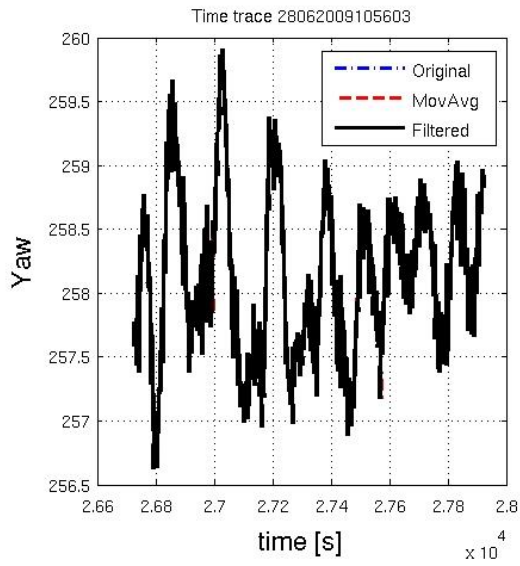
Figure 9 Heading during segment 5.
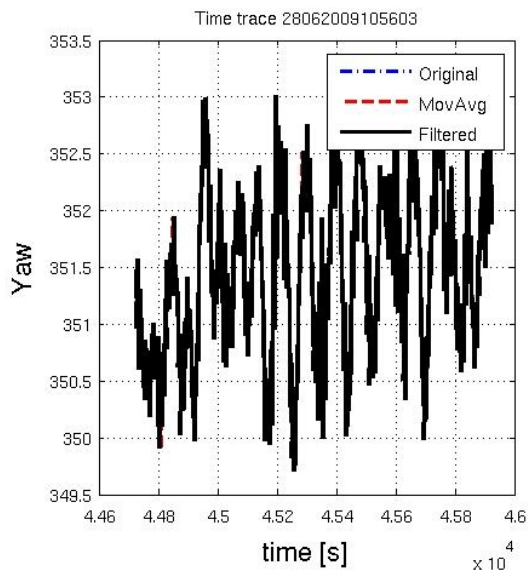
Figure 10 Heading during segment 20.
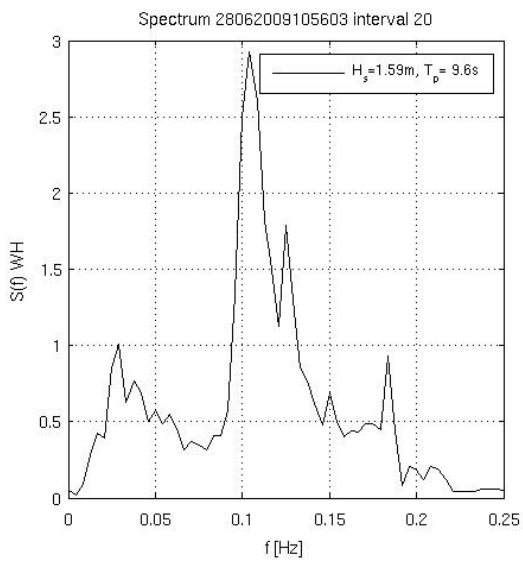
Figure 11 Wave encounter spectrum estimated from bow radar at segment 20.

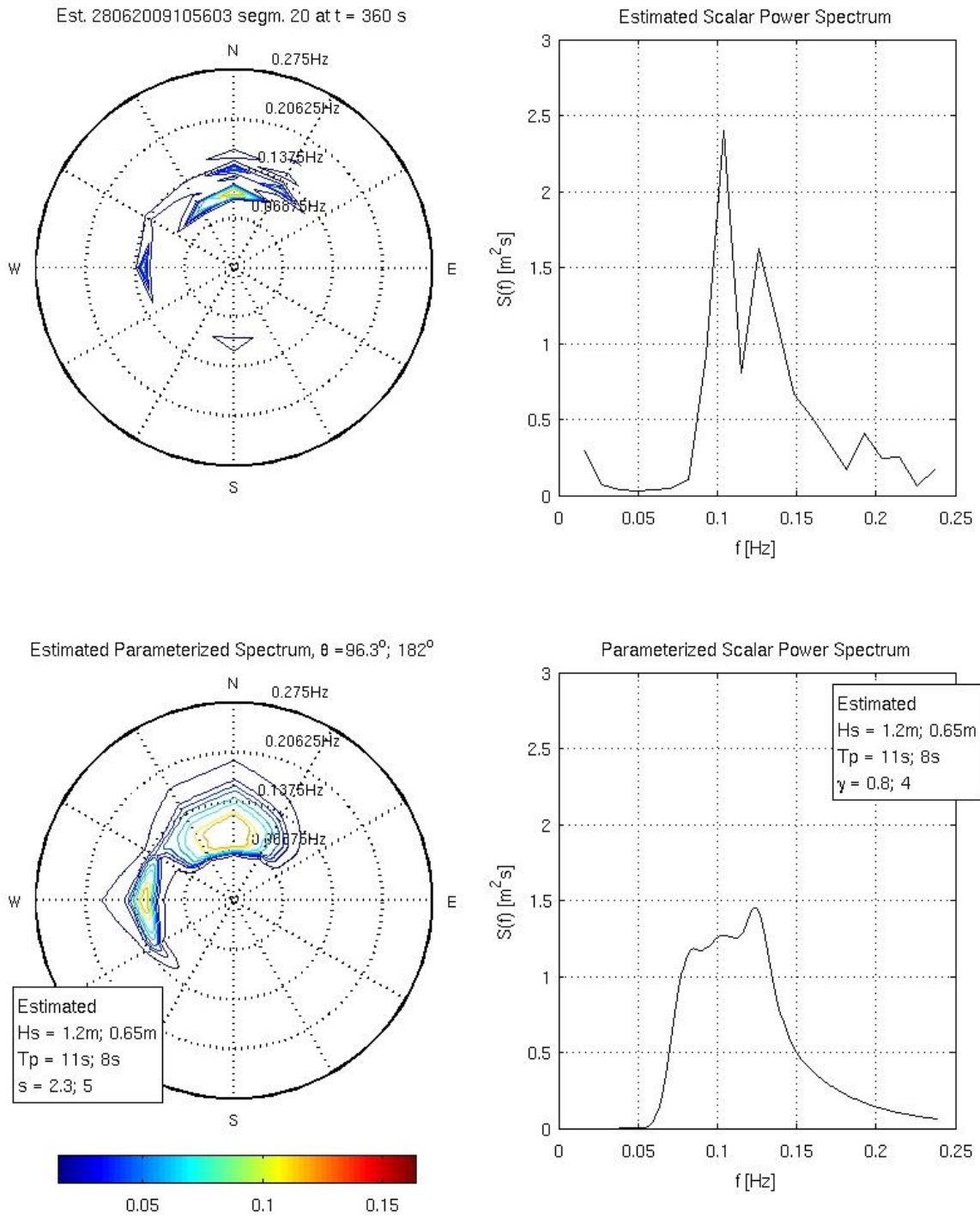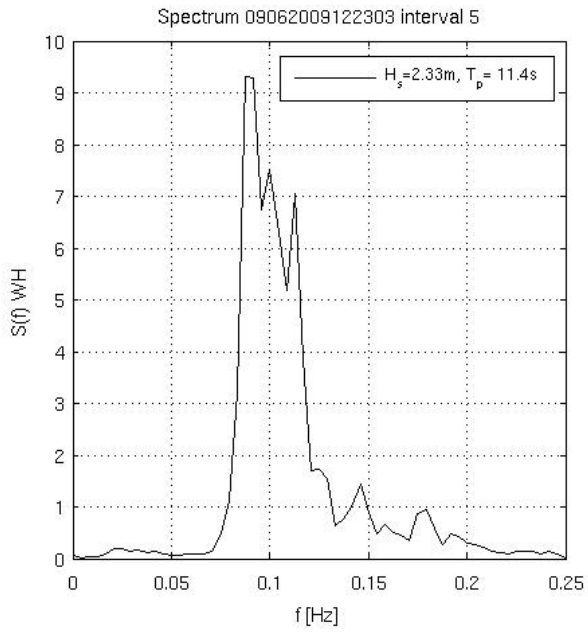Figure 12 Non-linear optimization applied to segment 20.

Est. 28062009105603 segm. 20 at t = 360 s

Estimated Scalar Power Spectrum

Estimated Parameterized Spectrum, θ = 96.3°; 182°

Estimated
Hs = 1.2m; 0.65m
Tp = 11s; 8s
s = 2.3; 5

Parameterized Scalar Power Spectrum

Estimated
Hs = 1.2m; 0.65m
Tp = 11s; 8s
γ = 0.8; 4

Figure 13 Kalman filter applied on segment 20 and its estimates at t = 360 s.
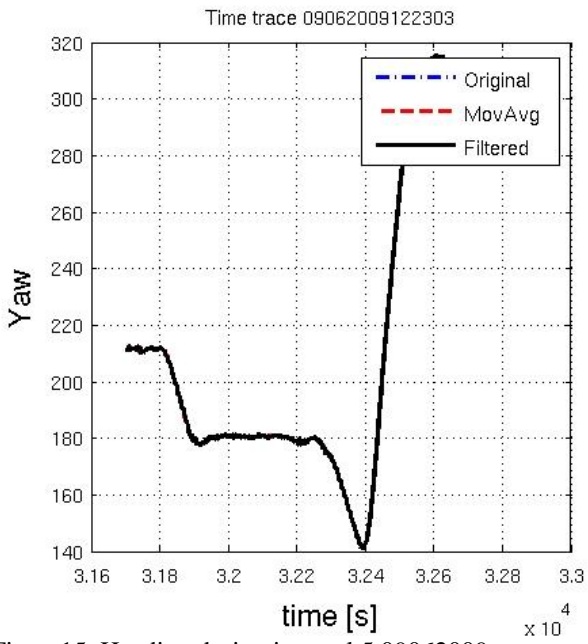
Figure 14 Wave encounter spectrum estimated from bow radar.

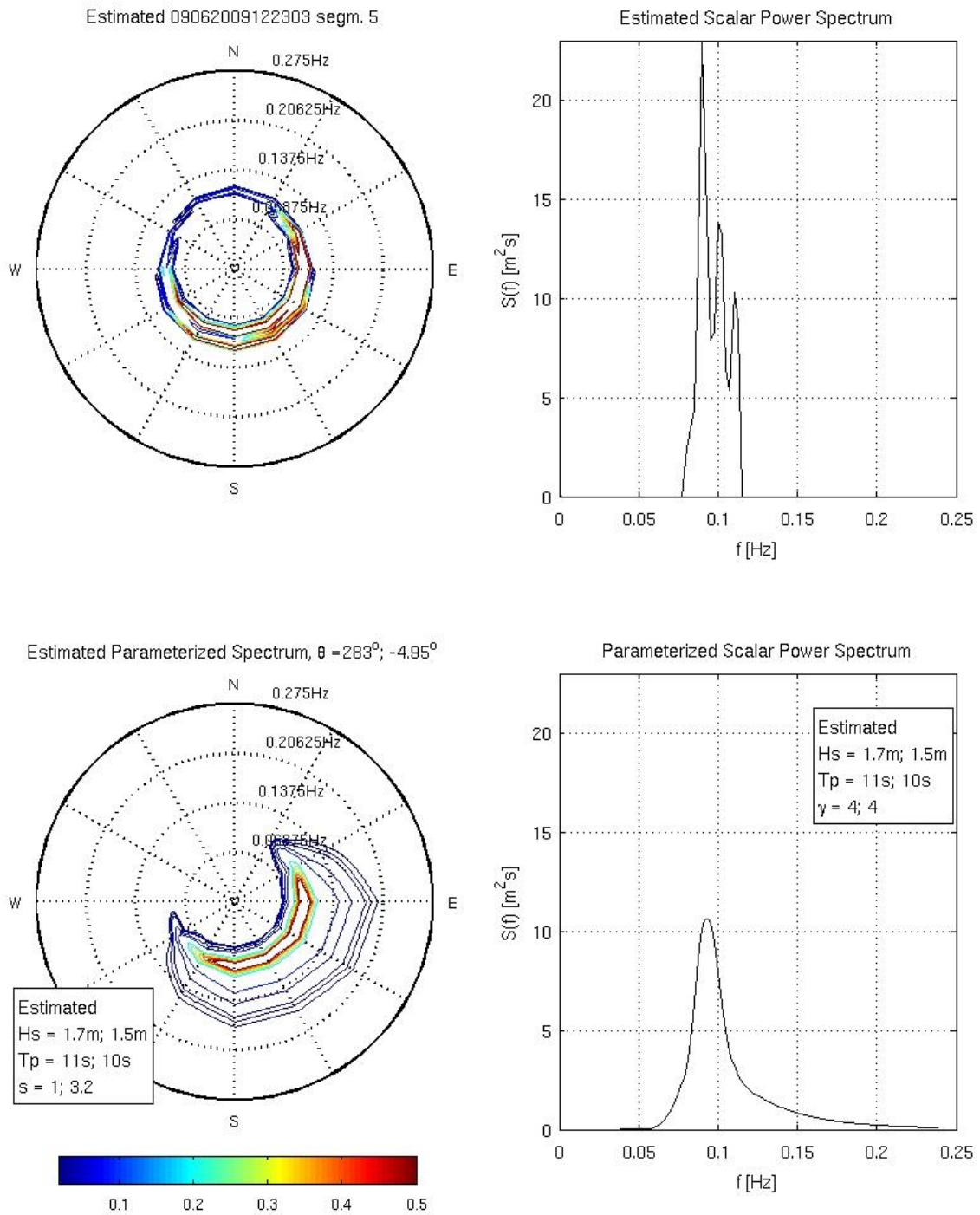Figure15 Heading during interval 5 09062009

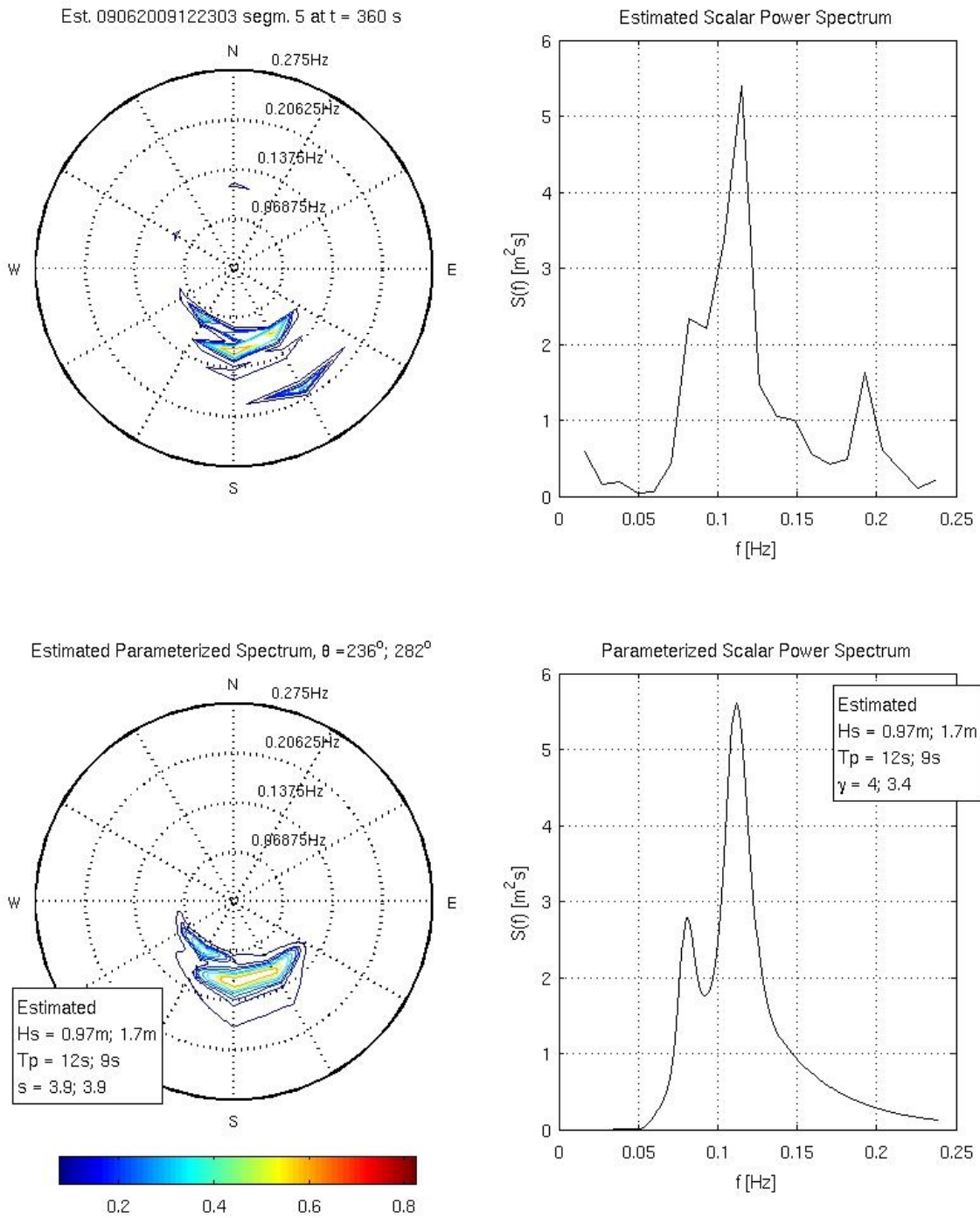Figure 16 Non-linear optimization applied to interval 5 09062009

Figure 17 Kalman filter applied on interval 5 09062009 and its estimates at t = 360 s.