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Video-based depth inversion techniques, a method comparison with synthetic cases

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ABSTRACT

Applications of (video-based) depth inversion in the near-shore coastal environment are growing in numbers. Video-based capabilities in nearshore monitoring are improving and coastal monitoring programs are expanding due to greater availability and reduced costs. Video-derived beach (state) indicators such as beach width, bar position and wave and current parameters are supplemented by accurate depth estimations through inversion. Video-based depth inversion knows two main approaches, a spectral and temporal method of celerity estimation. The two methods have so far never been compared as video-systems are often tailored for the chosen celerity estimation method. Here, a spectral and temporal method are compared using controlled synthetic datasets obtained using the SERRE1D Boussinesq model to estimate celerity and invert depth. The assessment is carried out on a set of wave boundary conditions with over linear and barred bottom profile. Both methods invert depth with a similar accuracy for the most realistic JONSWAP cases. An evident correlation is found between wave skewness, non-linearity and depth estimation error linked to the limits of the linear dispersion relation. A residual 'sensing' error is linked to method-based parameters and a changing wave shape as incident waves propagate inshore. The inversion-error can be reduced significantly including a wave height dependent non-linear correction. Importantly, a method-based error is introduced for the temporal method to increase the suitability for data assimilation. Likewise, the spectral method has its own existing depth-error estimation to feed into the Kalman Filter. However, these method-based error estimates show very weakly or no relation to the observed error between estimated cross-shore profile and bottom profile used for the model input.

1. Introduction

Increase in the worlds coastal population, a related greater number of valuable assets at coastal regions and human-shaped coastlines (Lazarus et al., 2016; Werner et al), in combination with a dynamic and more extreme environmental setting requires understanding and predictive skills of coastal morphodynamics. Forecasting models, such as (Flood) early warning systems, rely on accurate boundary conditions for their predictive skill e.g. wave conditions and accurate bathymetric information from hours to years in temporal and local to regional on spatial scale (Werner et al; Baart et al., 2016; Bogaard et al). Traditionally, bathymetric data is obtained using ship-mounted echo sounding technology. Depths are measured by the time of flight of a bed-reflected acoustic signal. More recently, remote sensing techniques, such as radar, satellites and video, successfully obtained bathymetries through depth inversion (Bell, 1999; Holman and Stanley, 2007). Depth inversion through remote sensing often uses a mathematical relation between wavelength, wave celerity and wave depth, with similar accuracy as traditional methods (Seiwell, 1946). Depth inversion through remote sensing allows for a large spatial domain with O(10 m) spatial resolution on a higher temporal resolution – hourly but potentially near continuous. Compared to a single echo-sounding survey, remote sensing techniques are, in case of video systems, a fraction of the costs. The resolution and the low cost in combination with a need for accurate, up-to-date, bathymetric information for numerical predictive models explains the recent efforts made and migration to remote sensing (Almar et al., Roelvink; Bell, 1999; Stockdon and Holman, 2000; Misra et al., 2003; van Dongeren et al., 2008; Holman et al., 2013).

In the sub-tidal zone, remote sensing efforts have opened up the possibility to estimate depths accurately, primarily using video imagery or X-band radar. The most common approaches are depth-inversion methods, using the linear dispersion relation (Almar et al., Roelvink; Bell, 1999; Stockdon and Holman, 2000), non-linear depth inversion (Holland, 2001; Catálan and Haller, 2008) and extended Boussinesq

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equations (Kennedy et al., 2000; Misra et al., 2003). Another approach is the coupling video-based wave energy dissipation patterns and rates to modelled wave energy dissipation patterns and rates with a numerical model (Aarninkhof et al., 2005). van Dongeren et al. (2008) used the principle of Aarninkhof et al. (2005) and merged multiple depth estimations (depth through dissipation rates and celerity estimation) together in a data assimilation technique. Wilson et al. (2010) shows that through further data assimilation (the addition of wave and current measurements) using an ensemble Kalman filter, the accuracy of an updated, modelled, bathymetry can be enhanced. Remotely sensed (e.g. optical and radar) shorelines (Aarninkhof et al., 2005), wave celerity (Holman et al., 2013) and current fields (Chickadel, 2003) together can estimate morphology accurately through data assimilation without in-situ measurements (Birrien et al., 2013; Wilson et al., 2014; Almar et al., Roelvink). In case of video camera systems and depth inversion using the linear dispersion relation, two main approaches exist; a temporal and spectral method. A temporal method that correlates temporal wave-like pixel intensity signals at different positions (Almar et al., Roelvink; Catálan and Haller, 2008; Bos, 2006) and a spectral method that correlates wave like pixel intensity phases at different positions (Stockdon and Holman, 2000; Plant et al., 2008; Holman et al., 2013). Holman et al. (2013) combined the earlier techniques used in Stockdon and Holman (2000) and Plant et al. (2008) and added a Kalman like assimilation for robustness and error reduction. Bergsma et al. (2016); Smith et al applied this depth inversion technique successfully in a challenging highly energetic macro-tidal environment after accounting for the low ratio between camera height and tidal range. In addition, a solution was presented for camera seam problems (observed by (Smith et al; Rutten et al., 2017)) and showed the importance of tidal elevation based floating (non-fixed) pixel position.

The difference between the temporal and spectral methods is particularly the estimation of wave celerity in respectively the time and spectral domain. The temporal method (Almar et al., Roelvink) correlates time-varying wave signals in space to find the best correlation that is related to the celerity. The spectral method (Plant et al., 2008; Holman et al., 2013) attempts to find the celerity by deploying a cross-spectral correlation to determine the most coherent frequencies which are associated to a cross-shore spectral phase ramp, hence wavenumber k leading to celerity c. Video camera systems are often tailored to the specific method. The temporal method (Almar et al., Roelvink) uses the full set of available pixels while the Argus systems (Holman and Stanley, 2007) greatly reduce the data by collecting pixel intensities on a pre-defined grid, neglecting pixels situated in-between grid points. The tailored video settings might play a significant role in the depth accuracy obtained with inversion in the field. Furthermore, few efforts have been made to compare the performance of inversion models in a more controlled setting using realistic derived free surface elevations from a numerical model (Misra et al., 2003). Considering this and to rule out the tailored video settings, the spectral and temporal methods are compared against each other through the use of a Boussinesq model (Cienfuegos et al., 2010). In addition, non-linear inversion is assessed here considering that the numerical model supplies the wave amplitude information. In reality, in-situ wave height measurements are required for a non-linear depth inversion. Catálan and Haller (2008), Almar et al. (2012), Flores et al. (2016) presented a wave height estimation technique from video, providing the opportunity for non-linear depth inversion without additional instruments and potentially solves the issue of additional in-situ measurements.

This work focuses on the comparison between the temporal inversion method (Almar et al., Roelvink) and spectral method (Holman et al., 2013). The depth inversion results are compared to wave characteristics such as non-linearity, asymmetry and skewness. The method and assessment parameters are further introduced in Section II. Section III introduces the synthetic cases whereas Section IV is used to interpret the depth inversion results. Section V is devoted to the discussion of the performance of the two inversion methods and further extension of the non-linear capabilities. The analysis is summarised and conclusion are presented in Section VI.

2. Methods

The temporal and spectral video-based depth inversion techniques both use of the linear dispersion relation for free surface waves to invert depths from pixel intensity time-stacks, presented in (1).

$$c^2 = \frac{\Delta x^2}{\Delta t^2} = \frac{\sigma^2}{k^2} = \frac{g}{k}\tanh(kh) + \vec{U}^2 k^2 \tag{1}$$

wherein c is wave celerity, t is time, x represents absolute distance, σ is angular wave frequency, k represents the wave number, g is the gravitational acceleration, h is depth and $\vec{U}$ represents the mean current. $\vec{U}$ in the right-most term of the right-hand side of (1) is considered small compared to the phase speed of the wave in the direction of wave propagation. Field measurements carried out by (Merrifield and Guza, 1990) and (Holland, 2001; Holman and Stanley) confirm a minor influence relative to the phase speed. $\vec{U}$ is therefore neglected. Note that this is only valid for open beaches and not the universal truth, e.g. in case of more complex beaches with for example rip channels this assumption inherently leads to a depth estimation error (Holman and Stanley; Bergsma, 2017).

After rearranging the linear dispersion relation for free surface waves (1), depth can be found as a function of the wave celerity (c) as presented in (2).

$$c^2 = \frac{g}{k}\tanh(kh) \Leftrightarrow h = \frac{\tanh^{-1}\left(\frac{c^2 k}{g}\right)}{k} \tag{2}$$

Following (2), depth inversion requires knowledge of the wave celerity, either as $\frac{\sigma}{k}$, as shown in (1), in frequency space (used in the spectral method) or $\frac{\Delta x}{\Delta t}$ in temporal space (used in the temporal method).

2.1. Spectral method

The spectral depth inversion method *cBathy* (Holman et al., 2013) and (Bergsma et al., 2016) is applied in this work. In order to invert depths using the right-hand side of (2), the spectral approach seeks to find a wave number (k) and associated frequency (σ). The total *cBathy* package consists of three phases. Phase I contains the estimation of N number of k, σ pairs, where N is user-defined. The second phase of cBathy combines the N number of $k, \sigma -$ pairs into an optimal single estimate for k and σ through a best weighted-fit with the linear dispersion relation. Phase III comprises data-assimilation through the deployment of a Kalman-like filter for error reduction and temporal smoothing. The third phase is not applied here given that the synthetic cases represent a single point in time.

Phase I: After a Fast Fourier transformation of a normalised input pixel time-stack, the spectral matrix is sub-sampled around a point of interest. In Holman et al. (2013) the sub-sampling domain varies depending on the distance from the camera, here the sub-sampling domain fixed. This subset is subsequently used to estimate the depth around the selected point of interest. For the subset, frequencies are selected based on their spatial coherence squared, so that only the N most coherent frequencies are analysed and corresponding k-values are sought. Over the subset the cross-spectral matrix is found and subsequently filtered by a spatial EOF analysis. The first EOF-mode (υ_1) of the cross-spectral matrix is employed for further analysis as it is believed to represent a wave train. The corresponding EOF filtered phase υ'_1, following the left-hand part of (3), represents the spatial phase ramp of a wave. The best-fit theoretical phase (the right-hand part in (3)) is found through a non-linear least squares fitting procedure with Hanning-filter so that wave number k, wave direction α and phase shift Φ are obtained.