VIRTUAL BUOY: A NOVEL APPROACH FOR MEASURING NEAR-SHORE WAVE PEAK PERIOD

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Abstract:

The wave peak period or peak frequency (T_p or f_p) is a statistical parameter commonly used to describe the energy spectrum of waves. It is important for the assessment of coastal structures, and wave modeling and prediction. In this paper, an image-based method for estimating the peak period of swell waves in near-shore environments is developed and validated. The method uses visual features of ocean waves presented in timestack images captured by video monitoring systems. The results of the algorithm are compared to measured data from 4 beaches (Bunkerhill Beach, Sylt Island, Germany; Cala Millor and Playa de Palma beaches, island of Mallorca, Spain; and Bocagrande beach, Cartagena, Colombia) with different hydrodynamic and morphodynamic characteristics. The method shows accurate results for 75% of the analyzed images despite the variable light conditions and noisy signals. Errors for Cala Millor and Bocagrande beach are around ~ 1 s (mean error) and ~ 1 s (standard deviation), which gives an error of less than 2 s for most of the results.

Keywords: Peak period; Peak frequency; Video imagery; Near-shore; Wave spectrum.

1 INTRODUCTION

The wave peak period or peak frequency (T_p or f_p) is a statistical parameter often used to describe the energy spectrum of waves (Hasselmann, 1974; Huang et al., 1981; Mitsuyasu et al., 1975; Ochi and Hubble, 1977; Soares, 1984), which is important for modeling the transformation of waves in coastal areas (Grasmeijer and Ruessink, 2003; The SWAMP Group, 1985; The Wamdi Group, 1988). Wave period data is important for evaluating the interaction of waves with human-built structures

such as drilling platforms and harbors, among others. If the natural vibrational modes of these structures coincide with the peak frequency of waves, resonance phenomena will lead to inoperability or even failure (Bellotti, 2007). Overtopping of waves in seawalls and dikes depends on structure parameters, such as the crest geometry and seaward slope, and on wave parameters, such as wave height and peak period (dos Reis, 1998).

Peak period is commonly measured by installing in situ instruments and developing an extensive field survey (for instance, the experimental setup described by Anctil & Donelan, 1996; Hasselmann et al., 1973; Larson & Kraus, 1994; Ruggiero et al., 1999). In recent decades, technical developments have allowed for the use of remote sensing based methods with lower costs compared to traditional methods (Mumby et al., 1999). Some of these methods include those described in Mattie, Hsiao and Evans (1981) where aerial photography and radar systems (SAR and coastal imaging radar) were used to measure wave direction, showing agreement with installed pressure sensors. Recently, Zhang and Zhang (2008) used sea surface video imagery to determine wave direction.

Many research projects have tried to solve the problem of lack of data in coastal areas by using low cost, autonomous remote sensors, mainly near shore video-camera systems (Brignone et al., 2012; Holman and Stanley, 2007; Nieto et al., 2010; Pérez Muñoz et al., 2013; Taborda and Silva, 2012). These have been used either for management purposes (Jiménez et al., 2007; Kroon et al., 2007) or to provide direct and indirect morphodynamical data (Alexander and Holman, 2004; Catálan and Haller, 2008; Hamylton, 2011; Múnera et al., 2014; Nieto et al., 2010; Osorio et al., 2012; Plant and Holman, 1997; Smit et al., 2007). Today, video imagery is a mature technique widely used worldwide to infer bathymetry in coastal areas, help in morphodynamical beach analyses to measure wave height and celerity, or to estimate beach run-up. However, to date, little attention has been devoted to the use of video systems to obtain the wave spectrum and peak period. An initial approach presented by Holthuijsen (1981) applied stereographic techniques to aerial photographs generated in Sylt (Germany). The sea surface elevations obtained were subjected to spectral analysis in the

frequency and space domain. Yim et al. (2006) applied a three dimensional Fourier transform to radar images from Taipei Harbour showing that the square root of the zero-th moment of the power spectrum of the images was correlated with the significant wave height in a linear way. They also showed that the directional wave rose obtained from the radar images displayed similar patterns to those acquired from current meters installed at the study site. Recently, Greenwood et al. (2018) used X-band radar signals to approximate the sea surface. The energy spectrums generated from sea surface approximation were in excellent agreement with those generated from buoy recordings.

Although high spatial resolution and relatively large coverage can be obtained by means of aerial photography and radar systems, these measuring techniques are still expensive, making alternatives such as that presented by Chou et al. (2004) more attractive. In their work, the water surface fluctuations in a wave basin were analyzed using CCD cameras, showing that pixel brightness and wave gauge recordings are strongly correlated for both regular and irregular wave conditions. However, their work was limited to laboratory environments in which the brightness conditions were carefully controlled to minimize the noise produced by brightness fluctuations.

Later, Yoo et al. (2005) used video image analysis techniques to estimate wave parameters at Myrtle Beach, South Carolina (USA). Video estimations of wave period for one day of data gives the most common result (10 s) while spectral analysis of measured wave data shows T_p to be 10.4 s. However, no accuracy analysis was presented by Yoo et al. Zikra et al. (2011) obtained directional wave spectra from pixel intensity series extracted from video image sequences. These were collected by a single digital video camera installed on Hasaki beach (Japan). Normalized frequency spectra, as well as directional spectra obtained from the images, show satisfactory agreement with wave gauge measurements and SWAN numerical models. The images used by Zikra were subjected to visual inspection before the analysis was carried out.

Recently, Abessolo Ondo et al. (2016) used video image analysis techniques previously reported by Lippmann and Holman (1991) and Stockdon & Holman (2000) to estimate T_p at Grand Popo beach,

Benin. The method used for calculating peak frequencies was based on spectral analysis of pixel intensity time series and filtering procedures in order to avoid noisy signals. Although in the work of Abessolo Ondo et al. the video image estimations of T_p were close to the measurements (root mean square error, RMSE= 1.31 s), the accuracy could be improved by applying further pre-processing steps before spectral analysis. At James Town Beach in Ghana, a similar approach for estimating T_p was adopted by Angnuureng et al. (2016). The results were in good agreement with hindcast modeled data ($R^2= 0.9$ and RMSE= 0.7), but a comparison with field data is missing from their study.

The works of Yoo et al. (2005), Zikra et al. (2011), Angnuureng et al. (2016), and Abessolo Ondo et al. (2016) suggest that video camera systems can be used to estimate wave spectra in uncontrolled illumination environments. However, these studies are not conclusive since they used a limited number of sites and uncertainty and accuracy analysis was not carried out. Moreover, it is important to avoid visual inspection of the images in order to achieve automaticity of the method without loss of accuracy. The aim of this paper is to present a method for estimating nearshore wave spectrum parameters, specifically the peak period, based on image analysis techniques and video monitoring systems. Novel contributions presented herein include the validation of the method in four locations with different hydrodynamic and morphodynamic conditions, as well as an improved processing method in which automated treatment of noisy signals produced by environmental illumination fluctuations is implemented. The paper is structured as follows: first the main features of the study sites are introduced; second, sources of data series used to validate the method are presented and detailed; third, image acquisition systems are described for each site; fourth the algorithm is developed in detail and the results are shown; and finally, the summary and conclusions are presented.

FIG 1. Study sites: (a) Bunkerhill beach; (b) Playa de Palma and Cala Millor beaches; and (c) Bocagrande beach.

2 STUDY SITES

Bunkerhill beach.

This study area is situated on Bunkerhill Beach on the west coast of Sylt. The island of Sylt is part of the North-Frisian Islands, a chain of barrier islands located in the German Bight [see figure 1(a)]. Bunkerhill Beach is a high-energy beach with mean significant wave heights H_s between 1 m to 1.2 m and mean wave periods between 3 s to 5 s (Blossier et al., 2017). The tidal range is about 2 m. The beach can be categorized as an intermediate type beach with high seasonal variations (Menn, 2002).

Cala Millor and Playa de Palma beaches.

These two beaches are micro-tidal sandy beaches located on the island of Mallorca in the Mediterranean Sea [see figure 1(b)]. Cala Millor is exposed to offshore waves from the NE to ESE while Playa de Palma beach is exposed to offshore waves from the SE and SW. According to Enríquez et al. (2017), on Playa de Palma beach significant wave height (H_s) in deep water has values of between 0.3 m and 1.6 m, with peak periods (T_p) varying between 3 s and 7 s. On the other hand, for Cala Millor beach, H_s varies between 0.4 m and 2.5 m, and T_p varies between 3.7 s and 9.3 s. Moreover, both beaches display low-energy wave conditions, with Cala Millor being more energetic than Playa de Palma.

Bocagrande beach.

Bocagrande beach is a micro-tidal sandy beach located in the city of Cartagena on the Caribbean coast of Colombia [see figure 1(c)]. Tides in the study zone are mixed diurnal micro-tides with an amplitude of less than 0.50 m. Surge has a strong effect on the mean sea level, often making it rise by 0.15–0.20 m. Wind waves come from the N and NE directions with an average height of 0.25 m. There are also waves that come from the E direction with an average height of 0.5 m to 1 m (Conde-Frias et al., 2017). Peak periods in the range of 3 to 14 seconds can appear on this beach, the most common being between 6 s and 8 s.

3 DATA AND METHODS

3.1 VALIDATION DATA

Available data for the study sites is presented in terms of significant wave height (H_s) and peak period/frequency (T_p or f_p). The wave spectrum is generally unavailable. The estimation of significant wave height from video imagery requires the application of stereographic techniques and at least two cameras focusing on the same region (de Vries et al., 2011). Because such a configuration was not considered in the video monitoring systems available, it was not possible to measure H_s from video imagery. Therefore, validation of the algorithm was limited to comparison against the measured T_p . For the Bunkerhill site, the data was obtained from records of the HZG COSYNA wave buoy *Bunkerhill1* located approximately 1 km seaward from the shore at the study site [red dot in Figure 1(a)]. The data covers the period from 30th-May-2014 to 1st-October-2014. For Cala Millor and Playa de Palma beaches, T_p was recorded using two directional acoustic waves and Currents (AWAC), covering the period from 9th-January-2014 to 31st-December-2014. The measurements were carried out as part of the beach-monitoring program of the Balearic Islands Coastal Observing and Forecasting System (SOCIB) and the Mediterranean Institute for Advanced Studies (IMEDEA). For Bocagrande, the T_p series was also obtained using an AWAC (see red dot in Figure 1(c) for its location). Hourly data were collected from February 11th to 13th 2011.

3.2 CAMERA SYSTEMS/ IMAGE DATA

Time-stack images for Sylt were obtained from a camera system implemented by the Coastal Dynamics Group (MARUM). Time-stacks were recorded at 4 frames per second for approximately 19 minutes (Blossier et al., 2017). The images correspond to 25 days between July and October 2014. They were recorded at different times, but most commonly at 10:00 UTC.

Time-stack images for Cala Millor and Playa de Palma beaches were obtained from the video-based coastal zone monitoring system SIRENA developed by SOCIB and IMEDEA (Nieto et al., 2010). Time-stacks used in this work correspond to 10 different days between January and July 2014, at 09:00, 12:00 and 15:00 UTC. The time-stacks recorded by the SIRENA system were taken at 7.5 frames per second for 10 minutes.

Time-stacks for Cartagena were generated from video imagery captured by the video monitoring system HORUS implemented in the study zone by the Oceanography and Coastal Engineering Research Group (OCEANICOS) from the Universidad Nacional de Colombia and Universidad de Cantabria (Múnera et al., 2014; Pérez Muñoz et al., 2013). Videos were recorded for the same period and time as measured data, with a rate of 1.85 frames per second for 17 minutes.

3.3 ALGORITHMS

As demonstrated theoretically by Jähne and Schultz (1992), the pixel intensity registered by a video camera varies with the slope of the observed surface. This phenomenon is also known as specular reflection of downwelling sky radiance (Stockdon and Holman, 2000), and makes the seaward face of the wave be brighter than the landward face (see Figure 2). Therefore, time series of pixel intensity for a particular pixel in the video image will follow an oscillatory signal from lower to higher brightness (produced by passing waves through the specific pixel location). This would give an approximately equal shape to that given by surface elevation series if they were measured, as shown by Chou, Yim and Huang (2004) and Zikra (2012). Since a time series has similar patterns, spectral representation in the frequency domain of both pixel intensity and surface elevation series presents a similar shape and position, hence the peaks of both spectrums are allocated near the same frequency. This particular frequency is defined as the peak frequency. Calculating the peak frequency from the pixel intensity spectrum will coincide with the peak frequency of the wave height spectrum, a feature used in this work to estimate the peak frequency of waves.

The proposed method uses time-stack images rather than video records. Time-stack images can be understood as a concatenation of a particular pixel column extracted from video images at different frames or times [see Figure 3(a)]. In Figure 3(b), the resulting time-stack shows pixel columns in the vertical ordinate that are concatenated horizontally, giving time or frames in the horizontal ordinate. Each row of the timestack image represents a pixel intensity time series of one point in the video. An example of the pixel intensities stored in one row of a timestack composed of 4500 frames is shown in Figure 4.

Prior to the spectral analysis, some filtering has to be performed in order to remove noisy signals and spectral leakage. Noisy signals come from different features in time-stack images, such as illumination changes through the record [Figure 5(a)], roller foam developed by broken and breaking waves [Figure 5(b)], direct sunlight hitting the sea surface [Figures 6(a) and 6(b)] or glittering caused by the sun [Figure 6(c) and 6(d)]. Other factors might be environmental and climatic conditions. Spectral leakage arises from the lack of periodicity of finite signal sampling contrary to the assumed periodicity in Fourier transform. This generates frequencies in the spectrum that are not present in the true signal or produces spilling of those which are present (Harris, 1978). The operations applied to filter the time series are described in the next section.

FIG 2. Visual wave features: dark frontal face and bright back face.

FIG 3. Time-stack image: (a) pixel column concatenation; and (b) resulting time-stack.

FIG 4. Example of one row of pixel intensity time series.

FIG 5. Sources of noise in timestack images: (a) Environmental illumination (clouds) changes viewed in time-stack image; (b) Foam from breaking waves viewed in time-stack image.

FIG 6. Sources of noise in timestack and snapshot images: incidence of direct sunlight in (a) snap-shot image and (b) time-stack image; and sun glittering in (c) snap-shot image and (d) time-stack image.

3.3.1 Treating breaking waves and sunlight saturation

The foam of breaking waves is inherent in the surf zone. Therefore, it is necessary to limit the region of analysis to that in which foam is not present. Foam is easily identified by its white color contrasting with dark tones of seawater. The thresholding method proposed by Otsu (1979) has been adopted here to identify the zone of non-breaking water in the image. This zone is used to obtain the pixel intensity time series. Since sunlight saturated regions of the image (i.e., sun incidence) present higher pixel intensities, thresholding can also identify the saturated regions.

It was observed that when the region remaining after thresholding is too small (let's say 5 rows or less), the analysis produces inaccurate results. A discarding criteria is recommended when the time-stack image presents excessive saturation or a large breaking zone compared with the non-breaking zone. In this work, the criterion applied was the number of remaining rows, and rejection occurred when there were less than 5 rows available for analysis.

3.3.2 Noisy signals treatment.

As already stated, the pixel intensity time series obtained from video imagery is contaminated by noise from multiple sources related to sunlight variations of both the water surface and the environment. This noise can be removed using a band-pass filter that removes periodic signals which are outside a particular *band* of frequencies defined by a *low cut-off* frequency and a *high cut-off* frequency. The filter consists of a convolution of a transfer function and the signals. The function shapes the frequency spectrum in a way that amplitudes inside the range of target frequencies are preserved while others are led to zero (Oppenheim, 2011). In general, it is desired that the shape of the filter approaches a rectangle with a width equal to the frequency band and a gain equal to 1 in

order to preserve the shape of the spectrum inside the bandwidth. Here, the Butterworth filter was selected for its ability to meet these requirements (see Figure 7). However, other filters can be used depending on the specific noise to be eliminated. Three parameters are used to describe the Butterworth filter: low and high cut-off frequencies and the filter order. The latter defines how fast the amplitude of the spectrum changes from 1 inside the band of frequencies to 0 outside the band. The filter order was set to 10 in order to approach a rectangular shape.

FIG 7. Butterworth filter shape for different filter orders (N).

Selecting the cut-off frequencies was a more difficult task. As a first approximation, it was defined that they should contain the typical range of frequencies presented in sea wind waves (Munk, 1951), going from 0.03 Hz (period of 30 seconds) to 0.5 Hz (period of 2 seconds). However, it was found that noisy signals caused by environmental light variation were contained within this range (e.g. 0.07 Hz for many images). Thus, a low cut-off frequency identification method was applied before the signals were processed. The method approaches the cut-off frequency by estimating the main frequency of the noisy signal. The only input needed for this purpose is a series from the noisy signal. As seen in Figure 8(a), environmental changes in light are present on both the sea surface and the nearshore landscape. The water surface contains mixed signals of both surface variation and environmental brightness fluctuation, with the latter being difficult to isolate. On the other hand, the land region contains environmental sunlight signals only, meaning that it is adequate to obtain noise signals whose periodicity ranges between 0.03 Hz and 0.5 Hz. Fast Fourier Transform (FFT) was applied to the land pixel intensity series [see Figure 8(b)] and the frequency of the spectrum peak was selected as the low cut-off frequency [Figure 8(c)]. Because some spectra display multiple peaks in a narrow neighborhood of frequencies [as shown in Figure 8(c)], the spectra were smoothed and the peak frequency was incremented by a factor of 0.3 in order to take into account its width. However, the cut-off frequency must not be less than 0.03 Hz due to the physical reasons explained above. In

Figure 8(c), the peak spectrum is located at a frequency of 0.044 Hz, and an increment of 30% gives 0.0572 (equivalent to a period of 17.5 s) for the low cut-off frequency.

FIG 8. Environmental sunlight noise: (a) time-stack image feature; (b) average pixel intensity series in a land region; (c) corresponding spectral representation.

3.3.3 Spectral leakage treatment.

Spectral leakage can be minimized by softening the time series near the ends such that the finite sample achieves periodicity when extended successively in the time domain (see Figure 9). For this purpose, the time series are modulated by a window function whose shape goes from 1 near the middle of the sample to 0 at the ends. There are multiple window functions which can be used.

FIG 9. Non-periodic extension for a sample of periodic series.

As shown by Harris (1978), windowing affects the frequency spectrum similar to the impact produced by the filtering process. Therefore, the window function must be carefully chosen in order to avoid spectral distortion of the series. In this work, well known features of the shape of swell wave spectra were the basis in determining an adequate window function. These features were:

- (i) no presence of harmonics at 0 Hz frequency (i.e. series mean set to 0)
- (ii) fast decay of the spectrum at saturation frequencies, and
- (iii) clear definition of multiple peaks if they were present.

Following the work of Harris (1978), adequate windowing functions for these purposes are Tuckey, Blackman, and Chebyshev windows. A sensitivity analysis was done in order to detect the sensitivity of windowing to filtering (i.e. frequency filtering). It was found that the Blackman window was the least sensitive to the filtering process so it was selected as the window function. The results of the sensitivity analysis for windowing are presented in the following sections.

3.3.4 Spectral analysis: Fast Fourier Transform.

After the filtering process, time series are displayed in the frequency domain by means of a Fast Fourier Transform (FFT). The spectrum obtained is virtually free of noise signals and leakage, and the estimated peak frequency is more reliable. The peak period is estimated as the multiplicative inverse of the peak frequency.

Because each row in the time-stack represents a pixel intensity series, there are multiple peak frequencies (one per row). Therefore, the mean spectra shape should be used before identifying the peak frequency. It should be noted that the results are practically insensitive to either taking the average of the peak frequencies and then estimating the peak period from this value or calculating the peak period as the mean value of peak period of each row.

The algorithm is summarized in the flowchart presented in Figure 10. In order to attain a better understanding of each step, the effects of each step in the time series and their influence on the accuracy of the algorithm are illustrated in the following sections.

4 RESULTS

This section presents the output results, step by step in order to give a better understanding of the algorithm, the effect of each step and how they improve the peak period estimation. The accuracy of the method for each site is also presented and discussed.

4.1 Step 1: Binarization

A time-stack image using Otsu thresholding is shown in [Figure 11(a)] and then binarized [Figure 11(b)]. In the binarized image, breaking waves are identified by white regions while foam-free surface is identified by black regions. Selecting only the black regions results in an image of free breaking waves [see Figure 11(c) and the dashed-line marked region in Figure 11(a)].

4.2 Step 2: Filtering

As mentioned above, the raw pixel intensity series presents noisy signals shown in Figure 12 (a) corresponding to the time-stack presented in Figure 8 (a). The resulting spectrum of this series [Figure 12 (b)] is still different from typical wind wave spectra, presenting a large peak near the 0 frequencies and a negligible and nearly constant amplitude at the remaining frequencies. When the low cut-off frequency is identified and the filtering process is applied, the resulting mean of the series is set to 0 [see Figure 12(c)] while the corresponding spectrum looks like a typical ocean wave spectrum [see Figure 12(d)].

4.3 Step 3: Windowing

As mentioned in section 3.3.3, the windowing procedure modifies the shape of the signal spectra. It was found that, for different window functions, the peak of the spectra varies its position to a higher or lesser degree (i.e., affecting the accuracy of the T_p estimation) depending on the selected cut-off frequencies. Since the cut-off frequency could vary among the images, the windowing function used in the analysis must be as insensitive to the cut-off frequency as possible. In order to select the window with this characteristic, a sensitivity analysis was carried on a sample of time-stack images from Bunkerhill beach. In the analysis, the low cut-off frequency was varied and the Tuckey, Chebyshev and Blackman windows were applied. The estimations of T_p for each combination of window function and cut-off frequency are plotted against measured values of T_p in Figure 13. The results obtained with the Chebyshev window are not presented here since it produced the same results as the Blackman window. The mean and standard deviation of error are summarized in Table 1, showing that Blackman (or Chebyshev) windows are the most suitable due to the low mean error variations in comparison with the Tuckey window when the cut-off frequency is changed. Since the Chebyshev and Blackman windows produced the same results, the selection of one or the other would seem to be arbitrary.

4.4 Step 4: Spectral analysis

A spectra can be obtained for each row in the time-stack image. Therefore, multiple peak frequency values (i.e., T_p values) can be generated from a single time-stack image. In order to obtain a single value for each time-stack, the data generated from each row must be averaged. However, this could be done in different ways. The first approach consists of determining the peak frequency from the averaged spectra ($\langle S \rangle$) of all the rows in the time-stack. The average spectra $\langle S \rangle$ are computed according to Eq. (1), where S_i is the spectra for row i and n the number of rows analyzed after thresholding. Another way is to obtain a peak frequency from each row and then average the data according to Eq. (2), where i and n have the same meaning as in Eq. (1). The corresponding peak period value can be obtained as $(\langle f_p \rangle)^{-1}$. On the other hand, T_p values can be computed for each row as f_p^{-1} and then the average value $\langle T_p \rangle$ could be taken as the corresponding peak period of the time-stack following Eq. (3) which is mathematically different to Eq. (2).

$$\langle S \rangle = \frac{\sum_{i=1}^n S_i}{n} \quad (1)$$

$$\langle f_p \rangle = \frac{\sum_{i=1}^n f_{pi}}{n} \quad (2)$$

$$\langle T_p \rangle = \frac{\sum_{i=1}^n 1/f_{pi}}{n} \quad (3)$$

FIG 10. Algorithms flow-chart.

FIG 11. Otsu thresholding procedure: (a) Timestack image; (b) Binarized image; and (c) Selected rows.

Table 1. Peak Period Error Analysis of Windows: BM denotes the Blackman window; TK denotes the Tuckey window.

FIG 12. Pixel intensity time series processing: Unfiltered time series - (a) Pixel intensity series and (b) Frequency spectrum; Filtered time series - (c) Pixel intensity series and (d) Frequency spectrum; and Windowed time series - (e) Pixel intensity series and (f) Frequency spectrum.

FIG 13. Window comparison for Bunkerhill data: BM denotes the Blackman window; TK

denotes the Tuckey window; L denotes low cut-off frequency in Hz; and H denotes high cut-off frequency in Hz.

In order to select the procedure that achieved the maximum accuracy, these three approaches were tested and compared using the mean error. Comparison of the approaches was made using the mean error (M.E.) of the estimation. The error was computed according to equation (4), where P represents the estimated (i.e., Predicted) T_p and O represents the measured (i.e., Observed) T_p . The values of T_p from each approach were plotted against the measured T_p and are presented in Figure 14.

$$\text{Error} = |P - O| \quad (4)$$

As mentioned earlier, the approach adopted to calculate the peak period has no significant effect on the accuracy of the estimation.

4.5 Overall accuracy

The complete algorithm was applied for 105 arbitrarily selected images and when the resulting peak period was compared with the measured data it showed a strong agreement (Figure 15). In order to assess the accuracy and capabilities of the proposed method, the mean and standard deviation of the error were computed. The correlation coefficient (r) and index of agreement (d) (Willmott, 1981) were also computed. Error was calculated according to equation (4), while r and d were calculated following equations (5) and (6), respectively. In equation (5), σ_{OP} is the covariance between the estimated and measured values of T_p . σ_O and σ_P are the standard deviation of the measured and estimated T_p , respectively. In equation (6), P and O has the same meaning as in equation (4), while μ_O represents the mean value of the measured data and n the length of the data.

$$r = \frac{\sigma_{OP}}{\sigma_O \sigma_P} \quad (5)$$

$$d = 1 - \frac{\sum_i^k (O_i - P_i)^2}{\sum_i^k (|P_i - \mu_O| + |O_i - \mu_O|)^2} \quad (6)$$

The mean error is $\mu = 1.38$ s and the standard deviation is $\sigma = 2$ s for the whole data. The correlation coefficient is $r = 0.6$ and the index of agreement is $d = 0.78$. However, some images (13 in total) present errors larger than $\mu + \sigma = 3.38$ s. For 8 of these images, the low cut-off frequency was not identified accurately by the proposed approach, forcing the peak of the spectrum to be located at low frequencies. For the remaining 5 images, the peak frequency coincides with the cut-off frequency. The correct peak of the spectrum was then eliminated and the next peak in the spectrum was identified by the algorithm. Therefore, the estimated frequencies were higher than the measured frequencies (i.e. the estimated peak periods are lower than the measured ones). Excluding these data from the analysis, the error sets a mean value of $\mu = 0.71$ s, with a standard deviation of $\sigma = 0.67$ s, and 0.93 and 0.96 for r and d , respectively.

FIG 14. Comparison of peak period approaches.

FIG 15. Estimated vs. measured T_p for the whole data set.

4.6 Accuracy of the method according to site conditions

Scatter plots of measured vs. estimated values of peak period, discriminated according to site, are provided in Figure 16(a)-(d) for Cala Millor, Playa de Palma, Bunkerhill and Bocagrande beaches, respectively. Dashed lines indicate the upper and lower bounds errors. Table 2 summarizes the mean absolute error, the standard deviation, and the agreement parameters r and d for each site.

Table 2. Error and agreement parameters for the study sites.

The mean and standard deviation for the error are larger for the Bunkerhill and Playa de Palma beaches. In the case of Playa de Palma beach, the loss of accuracy is caused by some misleading estimations of the error around 6 s (see dots outside dashed line in Figure 16 (b)). As already stated,

these discrepancies are caused because the low cut-off frequency identification procedure gives a cut-off frequency of 2 to 4 seconds, which coincides with the current peak period of the waves. Therefore, the estimated peak period is shifted to the next peak in the image spectrum, located at a period of approximately 9 seconds. The same situation occurs for periods between 4 and 6 s on Bunkerhill beach. Also, under higher energy conditions (i.e., T_p over 10 s) the peak periods are underestimated for Bunkerhill beach. By inspecting the timestack images corresponding to these data, permanent foam can be observed. The noisy signal that was produced was not correctly eliminated by the thresholding procedure, thereby affecting the results. However, despite the large errors introduced by erroneous results, the index of agreement remains at over 0.7 for both sites, indicating that the estimated peak periods are in satisfactory agreement with the measured data.

FIG 16. Estimated vs. measured T_p for: (a) Cala Millor beach; (b) Playa de Palma beach; (c) Bunkerhill beach; and (d) Bocagrande beach.

The errors for Cala Millor and Bocagrande beach are less than 2 s for most of the results. For Cala Millor, the accuracy is supported by the agreement parameters, which have values of over 0.8. For Bocagrande beach, the agreement parameters are lower despite the small error caused by the limited range of measurements.

It is assumed that values of error of less than 2 s represent a satisfactory estimation of the peak period because beyond this value energy conditions associated to the estimated T_p will differ from the real conditions by an appreciable amount. From the set of estimated T_p , 19 present an absolute error greater than 2 s. This represents 18% of the analyzed images. Generally, energy conditions associated to the larger errors in the estimated T_p , where there are conditions of high energy for Bunkerhill beach and low energy for Playa de Palma, suggest that accurate estimations are achieved principally for medium energy conditions. Although this could be a limitation of the proposed method, medium energy conditions are presented in most cases. In fact, 82% of the analyzed images present a satisfactory estimation of the peak period.

5 DISCUSION AND CONCLUSIONS

In the work of Zikra et al. (2011), the root-mean-square error (RMSE) of f_p derived from video images was 0.02 Hz, while a value of 0.07 Hz was obtained for the whole data set. The large error obtained in comparison with the work of Zikra et al. is attributed to the inaccurate results taken from images captured during high and low energy conditions. In the current study, the measured value of f_p varies between 0.06 and 0.5 Hz (or T_p between 2 and 16 s), while the peak frequencies measured by Zikra et al. vary between 0.09 and 0.13 Hz (T_p between 7.7 and 11.1 s) which represent medium energy sea states. When analyzing the Bocagrande beach data (where medium energy conditions were measured), the RMSE was found to be 0.02 Hz, showing that a similar accuracy can be obtained.

Recently, Abessolo Ondo et al. (2016) obtained a T_{p_RMSE} of 1.31 s, while a value of 0.7 s was obtained for the whole data set. The method proposed by Stockdon & Holman (2000) for calculating peak frequencies is also based on the spectral analysis of pixel intensity time series, but differs with the present method in the filtering procedure. According to Stockdon & Holman, bandpass filtering uses 0.05 and 0.5 Hz as low and high cut-off frequencies for every image, in contrast with the present method in which a suitable low cut-off frequency is estimated for each image.

From the discussion above, it is suggested that carrying out the proposed processing steps previous to the spectral analysis improves the overall accuracy of the method. It is worth noting that no visual examination of the images was performed before analysis, thereby achieving automaticity of the method. However, during high and low energy sea states, the algorithm can lead to inaccurate results.

As a final conclusion, and to summarize the contribution of this work, a novel approach for estimating spectral parameters of swell waves in near-shore environments, specifically the peak period, has been presented and validated. The present method is based on video image analysis and signal processing techniques. It has been demonstrated that applying signal processing techniques improves the results of the algorithm. The parameters of the signal processing elements were selected based on the physical phenomena. The method exposes the powerful capabilities of near-shore video monitoring

systems to automatically detect the peak period of near-shore waves with reasonable accuracy. This is achieved without taking into account the camera configuration and requires only that a representative amount of land pixels appear in the images in order to adequately eliminate noisy signals produced by environmental light fluctuations. From the whole set of analyzed data, only 18 images present an error greater than 2 s, while another 10 images not included in the plot were not suitable for analysis (less than 5 rows remain after the binarization process). Nearly 75% of the database (87 images out of a total of 115 were shown to be suitable for the analysis) produced accurate results, therefore suggesting that the technique has a promising future. Some limitations were found in the application of the automatized method for images showing extremely low-energy conditions, i.e., $T_p < 4$ s for Playa de Palma and Cala Millor beaches, and T_p between 4 and 6 seconds for Bunkerhill beach. The same was found for high-energy conditions, i.e., $T_p > 10$ s for Bunkerhill beach. Future lines of research should include the estimation of other spectral parameters, such as the height of the peak in the spectrum (i.e., H_s) and the directional distribution of wave energy.

6 ACKNOWLEDGEMENTS

The work described in this paper is part of a research project entitled “Analysis of the hydrodynamic and morphodynamic characteristics of a sandy beach by means of numerical modeling and image processing”. It is being carried out in the Department of Geoscience and the Environment, which is part of the Faculty of Mines at the Universidad Nacional de Colombia. The project is funded by research grants made available by the Universidad Nacional through the “National call for projects to strengthen research, creation and innovation at Universidad Nacional de Colombia” (Convocatoria Nacional de proyectos para el fortalecimiento de la investigación, creación e innovación de la Universidad Nacional de Colombia). These resources are gratefully acknowledged. The authors also wish to express thanks to the OCEANICOS and MARUM research groups, and the SOCIB and IMEDEA monitoring programs for the data they provided. Data from the HZG COSYNA

“Bunkerhill” wave buoy was obtained from an open website. Finally, the helpful comments made by the reviewers are appreciated.

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TABLES

Table 1. Peak Period Error Analysis of Windows: BM denotes the Blackman window; TK denotes the Tuckey window.

Window	Error (s)	
	Mean	Std. Dev
BM 0.03-0.5 Hz	4.80	6.23
TK 0.03 - 0.5 Hz	22.69	4.62
BM 0.05-0.5 Hz	3.04	3.82
TK 0.05 - 0.5 Hz	7.99	6.62
BM 0.07-0.5 Hz	1.99	2.53
TK 0.07 - 0.5 Hz	2.01	2.48

Table 2. Error and agreement parameters for the study sites.

Site	Error (s)		<i>r</i>	<i>d</i>
	Mean	Std. Dev.		
Cala Millor	0.82	1.15	0.84	0.91
Playa de Palma	1.79	2.69	0.02	0.72
Bunkerhill	2.02	2.46	0.63	0.79
Bocagrande	0.82	0.67	-0.09	0.38

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638 **FIG 1.** Study sites: (a) Bunkerhill beach; (b) Playa de Palma and Cala Millor beaches; and (c)
639 Bocagrande beach.

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FIG 2. Visual wave features: dark frontal face and bright back face.

FIG 3. Time-stack image: (a) pixel column concatenation; and (b) resulting time-stack.

FIG 4. Example of one row of pixel intensity time series.

(a)

(b)

FIG 5. Sources of noise in timestack images: (a) Environmental illumination (clouds) changes viewed in time-stack image; (b) Foam from breaking waves viewed in time-stack image.

FIG 6. Sources of noise in timestack and snapshot images: incidence of direct sunlight in (a) snap-shot image and (b) time-stack image; and sun glittering in (c) snap-shot image and (d) time-stack image.

FIG 7. Butterworth filter shape for different filter orders (N)

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663 **FIG 8.** Environmental sunlight noise: (a) time-stack image feature; (b) average pixel intensity

664 series in a land region; (c) corresponding spectral representation.

Periodic
time-series

Non-periodic
extension

665

666

FIG 9. Non-periodic extension for a sample of periodic series.

667

668 **FIG 10.** Algorithm flow-chart.

(a)

(b)

(c)

669

670 **FIG 11.** Otsu thresholding procedure: (a) Timestack image; (b) Binarized image; and (c) Selected

671 rows.

(a)

(b)

(c)

(d)

(e)

(f)

FIG 12. Pixel intensity time series processing: Unfiltered time series - (a) Pixel intensity series and (b) Frequency spectrum; Filtered time series - (c) Pixel intensity series and (d) Frequency spectrum; and Windowed time series - (e) Pixel intensity series and (f) Frequency spectrum.

FIG 13. Window comparison for Bunkerhill data: BM denotes the Blackman window; TK denotes the Tuckey window; L denotes low cut-off frequency in Hz; and H denotes high cut-off frequency in Hz.

FIG 15. Estimated vs. measured T_p for the whole data set.

(a)

(b)

(c)

(d)

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685 **FIG 16.** Estimated vs. Measured T_p for: (a) Cala Millor beach; (b) Playa de Palma beach; (c)

686 Bunkerhill beach; and (d) Bocagrande beach.