Detection of Breaking Waves in Single Wave Gauge Records of Surface Elevation Fluctuations

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ABSTRACT

We report the development of a new method for accurate detection of breaking water waves that addresses the need for an accurate and cost-effective method that is independent of human decisions. The new detection method, which enables the detection of breakers using only surface elevation fluctuation measurements from a single wave gauge, supports the development of a new method for research relating to water waves and wind-wave interactions. According to the proposed method, detection is based on the use of the phase-time method to identify breaking-associated patterns in the instantaneous frequency variations of surface elevation fluctuations. A wavelet-based pattern recognition algorithm is devised to detect such patterns and provide accurate detection of breakers in the examined records. Validation and performance tests, conducted using both laboratory and open-sea data, including mechanically generated and wind-forced waves, are reported as well. These tests allow us to derive a set of parameters that assure high detection accuracy rates. The method is shown to be capable to achieve a positive detection rate exceeding 90%.

1. Introduction

Physical processes associated with the breaking of water waves play an important role in phenomena such as wave generation and evolution under wind forcing, propagation of waves energy, and sea-atmosphere gas and heat exchange. This renders the research of breaking waves essential for the fields of physical oceanography and climatology. From an engineering point of view, the breaking-wave phenomenon impacts the design of wave energy converters (Brown 2004), wave forecasting, and the design of shoreline protection against flooding and other extreme weather-related hazards. Despite its importance and many years of research efforts, the breaking of water waves is not entirely understood to this day (Babanin 2011). One of the main obstacles to such an understanding is the lack of a reliable and cost-effective method for detection of breaking waves. A perfect detection method is one that is capable of detecting breaking waves in all environments and setups, starting from regular waves generated

mechanically in a laboratory to the most complex, irregular wind-forced wave fields formed in the open ocean. For a comprehensive overview of the current state of knowledge, including recent achievements in defining wave breaking criterion, we direct the reader to recent publications by Perlin et al. (2013), Shemer (2013), Kurnia and van Groesen (2014), Shemer and Liberzon (2014), Shemer and Ee (2015), and Barthelemy et al. (2018).

Currently available breaking detection methods have evolved in tandem with the development of probing technologies. A well-structured synopsis of breaking-wave detection techniques describing the historical and technological achievements can be found in chapter 3 of Babanin (2011). The historical precedence of visual detection methods is easy to understand considering human physiology, and early observations of breaking events relied on sea surface photos to find correlations between wind speed and whitecap coverage. Further development of sea surface mapping instrumentation allowed tagging of visually identified breakers in water surface fluctuations records (e.g., Weissman et al. 1984; Holthuijnjen and Herbers 1986) and even synchronous videotaping of entire experiments (Katsaros and Ataktürk 1992). Modern visual detection techniques, regardless of the equipment used, shifted breaking-wave identification from human observers to algorithm

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decisions, enabling automation of the entire process of data processing and detection of individual breakers or groups of breakers (Melville and Matusov 2002; Gemmrich et al. 2008; Mironov and Dulov 2008; Kleiss and Melville 2011; Sutherland and Melville 2013, 2015). However, when computer algorithms are implemented, the recording and processing of experimental data become storage and time consuming, since high-resolution video recordings or the most recently advanced stereo imaging of waves are required. Furthermore, the human factor cannot be discarded, as existing algorithms depend on the selection of appropriate thresholds that are usually based on wave whitecap pixel intensity, which in turn is selected manually by the experimentalist (Melville and Matusov 2002; Gemmrich et al. 2008). A successful breakers detection rate depends, therefore, on the experimentalist's skill and on the environmental conditions of the experiment such as sky brightness, cloud coverage, and other weather conditions. To mitigate dependence on human decisions, several rather similar techniques were developed to enable automated and objective derivation of the detection threshold from recorded images of whitecap coverage, using a several-step preprocessing algorithm (Sugihara et al. 2007; Mironov and Dulov 2008; Callaghan and White 2009; Kleiss and Melville 2011).

Unlike visualization-based techniques, instrumental detection methods rely on direct measurements of variations in specific wave-related parameters. Data on parameters such as surface elevation, velocity, acceleration, surface temperature, and volume of air trapped in the bulk water after breaking are recorded and passed through a detection filter (Tucker and Pitt 2001; Babanin 2011). Such filters, which are usually based on one or more parameter values crossing a specified threshold, provide a distinction between breaking and nonbreaking waves.

Historically, the first breaking-wave detection methods were developed for water surface elevation records collected using wire wave gauges. The simplicity of the surface elevation sampling explains its extensive implementation and abundance of breaker discrimination procedures based on the jump of the surface slope (Thorpe and Humphries 1980; Longuet-Higgins and Smith 1983), kinematic and geometric criteria (Hwang et al. 1989), and spectral energy (Weissman et al. 1984). Since the amount of literature on this topic is overwhelming, we mention only a short list of pioneering works and direct the reader to chapter 3 of Babanin (2011) for further details. Utilization of water void fraction, suggested by Longuet-Higgins and Turner (1974), was experimentally proven viable by Su and Cartmill (1992), Lamarre and Melville (1994), and Gemmrich and Farmer (1999). Manasseh et al. (2006) implemented a passive acoustic

method in which generation of bubbles served as a parameter for the detection of breakings, while several other researchers used sea spikes in radar-sampled sea surface data for that same purpose (e.g., Melville et al. 1988; Jessup et al. 1990; Phillips et al. 2001; Haller and Lyzenga 2003; Catalan et al. 2011). Variance of surface elevation spatial gradients, as obtained by lidar, was the chosen parameter in Martins et al. (2017), while other researchers used infrared sensing techniques to measure temperature unevenness in the sea surface skin layer as a breaking detection parameter (Jessup et al. 1997; Zappa et al. 2001; Jessup and Phadnis 2005; Sutherland and Melville 2013, 2015).

Use of laser Doppler anemometry and planar and volumetric particle imaging velocimetry techniques facilitated the understanding of breaking-induced turbulence (Lin and Rockwell 1994; Chang and Liu 1998; Chiapponi et al. 2017), verified a kinematic breaking criterion (Perlin et al. 1996; Chang and Liu 1998; Qiao and Duncan 2001; Stansell and MacFarlane 2002), quantified turbulent energy spreading (De Serio and Mossa 2006; Clavero et al. 2016), and predicted the Reynolds shear stress distribution (De Serio and Mossa 2006; Longo et al. 2017). While measuring turbulence beneath waves can serve as a breaking process marker, it is nevertheless quite cumbersome as such techniques require complex measurements, setups, and laborious and time-consuming data treatment. Such methods are, therefore, more suitable for realization in controlled laboratory environments and much less so in open-field experiments.

The main advantage of most instrumental detection methods is their relative overall cost-effective data processing and universality of implementation across various wave-field conditions in which specific thresholds are known from prior calibration. Albeit, the main shortcoming of these methods is their inability to derive a universally applicable detection threshold.

Here we discuss the development of a new breaking detection method that addresses the need for a cost-effective method, in terms of required instrumentation, data storage, and data processing, that is independent of human decisions and applicable under the widest possible range of conditions. This new method relies on the phase-time method (PTM) processing of the water surface elevation fluctuation records obtained by a single wave gauge (Huang et al. 1992; Stansell and MacFarlane 2002). The variations in the instantaneous waves frequency, provided by the PTM, are scanned by a wavelet-based pattern recognition algorithm devised to detect patterns associated with the occurrence of breaking waves. The wavelet-based algorithm achieves high rates of positive breakers detection, well above 90%, using both laboratory and open-sea data.

The report is organized as follows: [Section 2](#) provides a short background of the PTM and wavelet analysis followed by an explanation of the implementation principle of the developed method, validated against several laboratory and open-sea experimental datasets. [Section 3](#) details the datasets used in this work, and [section 4](#) elaborates on the method's algorithms, using examples from the available datasets. In [section 5](#) we present method performance tests, and in [section 6](#) we discuss our conclusions.

2. Scientific background

In the simplest terms, the method suggested here allows accurate detection of breaking waves in records of instantaneous water surface elevation fluctuations $\eta(t)$ obtained by a single wave gauge. The records are processed using the PTM to obtain the signal representing the instantaneous frequency variations $F(t)$. Patterns in $F(t)$, being a manifestation of breaking waves, are then accurately detected by a wavelet transform (WT)-based pattern recognition algorithm. Such patterns result from the steepening crest and the formation of irregularities on the leeward side of breaking waves. The first implementation of the earlier version of the method presented here was reported by [Itay and Liberzon \(2017\)](#), who accurately detected a single breaker in shoaling wave trains. The method reported here substantially expands that initial version, making it applicable for implementation in a wide range of experimental conditions, including wind-forced wave fields. This section lays down the scientific basis for all parts of the detection method.

a. Phase-time method

The PTM ([Huang et al. 1992](#)) provides the instantaneous variations of the water surface elevation fluctuation phase by applying the Hilbert transform on $\eta(t)$. The phase function is defined as

$$\Phi(t) = \tan^{-1} \left[\frac{H(t)}{\eta(t)} \right], \quad (1)$$

where $H(t)$ is the Hilbert transform of $\eta(t)$. Following the PTM, the phase is then unwrapped and detrended. Variations in the surface elevation fluctuation frequency $F(t)$ are then obtained by time derivation of the unwrapped phase function ([Stansell and MacFarlane 2002](#)):

$$F(t) = \partial\Phi/\partial t. \quad (2)$$

Or, in a slightly different form,

$$F(t) = \frac{\frac{\partial H}{\partial t}\eta - \frac{\partial \eta}{\partial t}H}{\eta^2 + H^2}. \quad (3)$$

The $F(t)$ provides information about the nonlinear events in the wave train, such as breaking waves. As the wave develops toward the inception of breaking, its crest steepens and crest propagation speed decreases, a behavior manifested by an increase in the instantaneous frequency variations in the vicinity of the crest ([Banner et al. 2014](#); [Shemer and Liberzon 2014](#); [Itay and Liberzon 2017](#)). [Griffin et al. \(1996\)](#) were probably the first to employ the PTM in their study on wave breaking and wave steepness in the absence of wind. They reported that PTM analysis is a “promising alternative” in the study of unsteady wave properties such as local variation of wave frequency and amplitude, the geometric properties of the wave near the inception of breaking, and the energy content around breaking point. Several later works reported on the development of an effective breaking detection technique that monitors the instantaneous frequency increase toward the inception of breaking ([Zimmermann and Seymour 2002](#); [Irschik et al. 2011](#)). Breaking detection was achieved by setting the detection moment to the point in time when the instantaneous frequency value, normalized by the peak frequency of the underlying spectrum, crosses a specified threshold. While such an approach enables accurate detection of breaking events in regular waves and in more complex wave fields under specific experimental conditions, it requires setting a unique threshold value for each experimental condition, and thus cannot be implemented universally or without prior calibration of the threshold parameter. Already in [Zimmermann and Seymour \(2002\)](#) it was noticed that besides increasing, the instantaneous frequency variations at the inception of breaking also exhibit a specific pattern that is the manifestation of the bulge that forms on the leading edge of the wave, close to or at the crest [see section 2.2 in [Perlin et al. \(2013\)](#) for an extended literature review of the topic]. This bulge then propagates along the leading edge and is either transformed into rolling forms (spilling breakers) or projected forward causing eventual overturning (plungers). This highly nonlinear process translates to a very sharp rise in the instantaneous frequency variations followed by an exponential decay. [Figure 1](#) illustrates such a case; the top panel demonstrates a segment of water surface elevation fluctuations, with the corresponding $F(t)$ variations calculated by Eq. (3) presented in the bottom panel. The presence of a bulge (central crest in the top panel) in the $\eta(t)$ signal is indicative of breaking inception and it manifested by the $F(t)$ signal, as described above.

FIG. 1. Breaking inception and the corresponding sharp rise in the instantaneous frequency variations.

Overall, the PTM is a powerful analytic tool for breakers identification that may be employed in an algorithm for the automatic detection of breakers, with no human intervention and with high accuracy. The frequency threshold as proposed by Zimmermann and Seymour (2002) and by Irschik et al. (2011) cannot, however, be implemented universally, as it is highly dependent on the characteristics of the experimental setup for which the threshold was established. Here, following the first implementation reported by Itay and Liberzon (2017), we adopt a different approach aimed at identifying the specific pattern in the $F(t)$ signal that is the manifestation of a breaking crest (Fig. 1). Hence, the problem of breaking detection now becomes a pattern detection problem to be solved by implementing a WT-based algorithm, as discussed next.

b. Wavelet transform

The algorithm selected for pattern recognition is based on the wavelet transform. Implementation of the WT analysis in waves breaking research is not new. It originated in geophysics (Morlet et al. 1982; Morlet 1983), where the wavelet transform was immediately adopted for turbulence analysis (Farge 1992) as a reliable alternative to the Fourier transform when dealing with transient signals. Since turbulent flows are an inseparable part of breaking waves, the new method spread throughout the oceanographic scientific community and proved to be a useful tool in the investigation of the spectral properties of waves (Donelan et al. 1996), the turbulence structure in the immediate prebreaking spilling waves (Longo 2003, 2009) and under them (Huang et al. 2010), and in the study of breaking waves (Liu 1993; Mori and Yasuda 1995; Liu and Babanin 2004). Here the WT is utilized to accurately detect breaking-related patterns in the $F(t)$ signal. We provide only a very brief description of the

WT analysis, as needed for the pattern recognition scheme implemented here.

The wavelet transform of a time series, in our case the $F(t)$, can be defined as (Farge 1992; Liu 2000; Mallat 2009)

$$\text{WT}[F(t)] = \mathfrak{I}(a, b) = \int_{-\infty}^{\infty} F(t) |a|^{-1/2} \psi^* \left(\frac{t-b}{a} \right) dt. \quad (4)$$

Here $a > 0$, $-\infty < b < +\infty$, and $\psi^*(\cdot)$ is the basic complex conjugate of a function family defined as

$$\psi_{ab}(t) = |a|^{-1/2} \psi \left(\frac{t-b}{a} \right). \quad (5)$$

The family of functions defined by Eq. (5) is obtained by dilation with factor a and translation with factor b of a fixed basic function $\psi(t)$ called the mother wavelet. In other words, the wavelet transform of $F(t)$ is the “energy” of $F(t)$ of scale a at time $t = b$. The $a^{-1/2}$ factor satisfies the need for a constant norm for the ψ_{ab} family in the space of square integrable functions:

$$\|\psi_{ab}(t)\| = \int_{-\infty}^{\infty} |\psi_{ab}(t)|^2 dt = 1. \quad (6)$$

For a basic function to be considered a mother wavelet it must comply with the admissibility principle, defined as

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\hat{\psi}(\omega_F)|^2}{|\omega_F|} d\omega_F < \infty, \quad (7)$$

where C_{ψ} is the wavelet coefficients, $\hat{\psi}(\omega_F)$ is the Fourier transform of Eq. (5), and ω_F is the angular frequency of the $F(t)$ signal.

Obtaining the wavelet coefficients provides information about the local behavior of the analyzed signal.

FIG. 2. Mother wavelet shapes.

Locally smooth portions of the signal correspond to small values of the wavelet coefficients, whereas instances in the signal where a singularity or an abrupt change occurs are marked by a drastic increase in wavelet coefficient values. This is a consequence of the dilation covariance property of WT:

$$\text{WT}[F(t)](a_0b) = a_0^{-1} C_\psi(a_0a, a_0b), \quad (8)$$

where a_0 is the dilation constant. If $F(t)$ is continuously differentiable at local point b_0 up to the order m , then

$$C_\psi(a, b_0) \leq a^{m+1} a^{1/2} \quad \text{for } a \rightarrow 0, \quad (9)$$

and $F(t)$ belongs to the Hölder space of functions of exponent. This means that $F(t)$ is continuous and not necessarily differentiable in a_0 but fulfills the equality

$$|F(b + b_0) - F(b)| = \beta |b_0|^\alpha, \quad \alpha < 1, \quad \beta - \text{const} > 0 \quad (10)$$

and

$$C_\psi(a, b_0) \approx \beta e^{\sqrt{-1}\phi} a^\alpha a^{1/2} \quad \text{for } a \rightarrow 0. \quad (11)$$

Here, ϕ denotes the phase of the wavelet coefficients. In other words, the asymptotic behavior of C_ψ when $a \rightarrow 0$ stores information on any possible singularities or abrupt changes present in the signal at position b_0 , their strength β , and their scaling exponent α . An elaborate demonstration of this and other properties of the wavelet transform can be found in Farge (1992), Liu (2000), and Mallat (2009).

Here we utilize Eqs. (7)–(11) and apply the WT on the instantaneous frequency $F(t)$ signal using a mother wavelet that closely resembles the sought-after pattern associated with the occurrence of breaking (Fig. 1). The

result is then additionally processed, looking for the instances at which the WT product demonstrates increased “energy,” hereinafter referred to as the *detection energy* E . Additional statistical processing is then applied to determine at which of these instances the breaking actually occurred, thus constituting detection of wave breaking. Implementation, however, is not straightforward and requires the application of several pre- and postprocessing actions at various stages (elaborated on in section 4). These are carefully chosen on the basis of the physical properties of breaking water waves, the characteristics of the collected surface elevation fluctuations signal, and the desired accuracy of breakers detection. Of special importance is the selection of an appropriate mother wavelet shape. This is performed, following Itay and Liberzon (2017), by examining $F(t)$ shapes at breaking in numerous experimental datasets obtained by the authors and found in the literature. Three mother wavelets, F1, F2, and F3, representing three general patterns of different breakers in $F(t)$ signals, are used in the identification of breaking waves. All three mother wavelets can be described by a single formula in unity space time and frequency coordinates (Fig. 2) as

$$\psi(\tau) = \begin{cases} d\tau; & 0 < \tau < c - \varepsilon \\ m(\tau - c) + n; & c - \varepsilon < \tau < c + \varepsilon. \\ e^{-\gamma(\tau - c)}; & c + \varepsilon < \tau \end{cases} \quad (12)$$

The mother wavelet parametric curve constants are as follows: d is the rate of linear change before point of sharp rise, c is the relative location of sharp rise, m and n define the sharp rise due to the formation of the bulge, and γ is rate of exponential decay.

In the following section, we proceed with a presentation of the experimental datasets used in the development of the algorithm responsible for the detection method

FIG. 3. T-SAIL wind-wave flume and the experimental setup, showing a (a) side view, with 1) blower, 2) silencers, 3) flexible connections, 4) hatches to control flow rate, 5) settling chamber, 6) contraction with honeycomb, 7) mechanical wave makers, 8) test section, 9) shock-absorbing pads, 10) instrument carriage, and 11) wave absorber (beach), and a (b) top view, where the two wave gauges that are used are marked as I and II; the breaking-wave inception locations relative to the wave gauges for the JA/SA and JB/SB experiments are marked by the black wavy curves.

implementation and for its performance validation. This is followed by the detailed, step-by-step method implementation procedure, demonstrated using some of the same datasets for the sake of clarity.

3. Datasets and detection method implementation procedure

The data used in this study originated from two different sources. The lion's share of the experiments and development work was conducted in the wind-wave flume located at Technion Sea-Atmosphere Interactions Research Laboratory (T-SAIL) at the Technion—Israel Institute of Technology. Additional datasets were from the Lake George experiments recorded over the period 31 October–1 November 1997 (Babanin et al. 2001). Data collection at both sites was performed similarly, by an array of wave gauges that recorded the instantaneous water surface fluctuations $\eta(t)$ of various wave fields along with simultaneous filming of the waves using a video camera. The T-SAIL data consisted of numerous wave fields of mechanically generated waves, with and without additional wind forcing. The Lake George data were an open-field dataset of wind waves, corresponding to various wind forcing conditions. Video recordings of the waves, used for the performance tests of the developed detection method as explained later in the text, were filmed by fast cameras in T-SAIL; the video recordings that accompanied the Lake George

datasets were generously provided by the leading author of Babanin et al. (2001), after digitalization of the original analog recordings.

a. Laboratory (T-SAIL) data

The T-SAIL wind-wave flume is a two-level facility that comprises a wind tunnel on the upper level and a 17.5-m-long and 1.2-m-wide wave flume below. Holding water up to 0.8 m deep, the rest of the 1.4-m-high test section is free for airflow (Fig. 3). During the measurements described below, the water depth was kept at 0.7 m. The flume walls and bottom, which are made of transparent glass panels encased within an aluminum frame, allow visual observation of both the airflow and the water waves inside the flume from various directions. A wave energy absorber (beach) located at the end of the flume test section dissipates the waves and prevents reflections. The wind tunnel is equipped with a 10-horsepower (7.457 kW) blower controlled by a variable-frequency drive that drives the airflow inside the test section at prescribed flow rates. A force-feedback controlled mechanical wave maker, consisting of four flap-type paddles, is positioned on the right side of the flume, just below the airflow inlet. The wave maker is controlled by a personal computer program and can generate water waves independent of the wind action. Considering the dimensions of the beach and the wave maker, the net length of the flume used in the measurements is about 13 m. A motorized carriage mounted atop the flume

FIG. 4. Example of a breaking wave for a JONSWAP spectrum wave train in the absence of wind forcing: (top) wave gauge positioned after the breaking inception (JB) and (bottom) wave gauge positioned at the breaking inception (JA). Wave gauges are pairs of thin metal wires; the wider acrylic rods are a supporting structure that ensures wave gauge integrity in breaking waves.

guarantees a high degree of precision in the positioning of measurement devices and auxiliary components at different fetches along the test section. Data acquisition and instrumentation control are performed by National Instruments Corp. (NI) “LabVIEW” software routines, using two analog-to-digital (A/D) cards (NI USB 6211 and NI cDAQ9184–1B560CB), thus achieving a high level of experiment automation.

A total of eight datasets, each 4 min long, were recorded in the T-SAIL flume by a resistance-type wave gauge array. For synchronization purposes and to ensure smooth results of wavelet transform to be applied subsequently, as discussed later in the text, sampling frequency was set to 840–880 Hz, which is a multiplier of the video recording frame rate. For the purpose of this work, only the data from the first wave gauge were used. The waves were generated by the mechanical wave maker, using repeating realizations of JONSWAP spectra and weakly modulated sine trains. Two JONSWAP and two sine wave trains were recorded without wind forcing. Since waves were breaking in these trains at a constant location along the flume, the wave gauge array was positioned at this location. Two datasets were recorded for each train, one with the first wave gauge in the array positioned at the location of breaking inception and the second with the first wave gauge positioned slightly farther along the flume. This way, breaking waves were recorded at different stages of the breaking process (Fig. 4). The same trains were then generated by the wave makers with the addition of wind forcing at two airflow rates. The wind profile was determined using a Pitot tube

and was characterized by the mean wind velocity profile extrapolated to 10 m above the mean water surface U_{10} .

The dataset naming scheme is as follows: The first letter stands for the wave-train name denoted by J or S, for JONSWAP or sine trains, respectively. The second letter denotes the special condition: A is wave breaking at the wave gauge, B is wave breaking before the wave gauge, or W indicates with the addition of wind forcing. In the case of wind forcing, an additional numeral was added to the set name to denote weak (label 1) or strong (label 2) wind forcing. Thus, dataset JA is the dataset of a JONSWAP train with no wind for which the wave gauge is positioned at the inception of breaking, whereas dataset SW1 is, according to our naming scheme, the dataset for a modulated sine train with weak wind forcing. Table 1 presents details of generated wave trains and the corresponding wind forcing conditions.

Simultaneously with the wave gauge recordings, the wave trains were filmed using a high-speed camera (Vieworks Co., Ltd., model VC-4MC), at a 4-megapixel resolution and a frame rate of 60–80 frames per second. An external signal generator was used to produce a camera acquisition signal, which was also recorded by the A/D card, simultaneously with the signal from the wave gauges. This allowed us to synchronize the wave gauges that provided surface elevation fluctuations data with the recorded video timeline. The experimentalist visually inspected the video signal, frame by frame, to identify the breaking waves and their exact time and spatial location. Visual inspection results were stored on a file and were used as the breaking-wave detection reference.

TABLE 1. Details of the datasets.

Dataset name	Type	Dominant wave period (s)	Significant height (m)	Breaking point	Spectral width	Duration (min)
SA	Modulated sine spectrum	1.25	0.12	At the wave gauge	0.2	4
SB	Modulated sine spectrum	1.25	0.11	15 cm before the wave gauge	0.2	4
JA	JONSWAP spectrum	1	0.12	At the wave gauge	0.01	4
JB	JONSWAP spectrum	1	0.12	5 cm before the wave gauge	0.01	4
SW1	Modulated sine spectrum + wind $U_{10} = 9.9 \text{ m s}^{-1}$	1.25	0.12	Not predetermined	0.2	4
SW2	Modulated sine spectrum + wind $U_{10} = 13.8 \text{ m s}^{-1}$	1.25	0.12	Not predetermined	0.2	4
JW1	JONSWAP spectrum + wind $U_{10} = 10 \text{ m s}^{-1}$	1	0.13	Not predetermined		4
JW2	JONSWAP spectrum + wind $U_{10} = 13 \text{ m s}^{-1}$	1	0.13	Not predetermined	0.01	4
LGN	Night Lake George expt	2.53	0.32	Not predetermined	0.1	60
LGD	Daylight Lake George expt	2.63	0.30	Not predetermined	0.12	140
LGH	High wind ($U_{10} = 17 \text{ m s}^{-1}$) Lake George expt	2.68	0.43	Not predetermined	0.15	20

b. Field (Lake George experiments) data

Other datasets were received from the Lake George (New South Wales, Australia) experimental site. For a detailed description of the facility and experimental conditions, we refer the reader to Babanin et al. (2001) and Young et al. (2005). The site, which was located 50 m offshore on the eastern side of Lake George, was equipped with a set of instruments for both waves and wind measurements. An array of eight Teflon-coated capacitance-type wave gauges recorded the fluctuations of the water surface at a 25-Hz sampling frequency and stored the signals on a personal computer. This recording was synchronized with the video recordings of the wave gauge array area. Here too, data from only one wave gauge were used. Wind speed was sampled by several anemometers at six logarithmically spaced heights. Video recordings corresponding to the period between 1500 LT 31 October and 1000 LT 1 November 1997 were digitalized and made available to us for processing by the leading author of Babanin et al. (2001). During this period, the wind forcing exhibited significant variations as did the lighting conditions, which led us to divide the data into three representative sets as explained below.

After examining the wind forcing conditions in terms of U_{10} (Fig. 5) and the quality of the available wave gauge data as well as that of the digitalized video recording, three representative datasets were selected (Table 1). Two datasets corresponded to moderate wind forcing and were named LGD and LGN (Fig. 6), where D and N denoted day and night lighting conditions, respectively. Lighting conditions may affect the accuracy

of detection of breaking waves by an observer in the video records. The third dataset, named LGH (Fig. 6), corresponded to a short period of time during which wind forcing was significantly stronger ($U_{10} > 17 \text{ m s}^{-1}$), resulting in a more energetic wave field. The data available for the rest of the time were judged to be unsuitable for the analysis performed here because of missing or poor-quality video records.

4. Detection algorithm and procedure

This section presents the implementation of the detection method for breaking waves, using the abovementioned datasets as examples. The harbinger of the breaking process (i.e., the bulge formation on the breaking crest) has a typical duration of about one tenth of the dominant wave period. This fast evolution of the bulge demands a high enough sampling frequency of water surface elevation so as to collect sufficient sampling points for the PTM processing. Zimmermann and Seymour (2002) concluded that the PTM method “would be useful” with a sampling rate of 25 times the dominant frequency f_p , but for good accuracy they recommended a sampling rate of at least 50 times the peak frequency. The upper frequency limit of the detectable water surface elevation is, of course, a function of both the diameter of the wave gauge used and the local propagation speed of the measured wave. Use of thicker wave gauges in conjunction with longer and hence faster moving waves in open-field measurements, should set the limit for the smallest detectable disturbance at lower frequencies as compared with measurements conducted in laboratory setups. However, even the suggested $50f_p$ sampling rate may be not satisfactory

FIG. 5. Variation of U_{10} at the Lake George site, from 31 Oct to 1 Nov 1997.

for later application of the WT of $F(t)$, because the WT is applied using a finite number of scaled mother wavelets (i.e., WT resolution). The latter issue has two possible solutions. One is to increase the resolution of the WT analyses, a solution that is computationally costly and hence decreases the speed of data processing. A second possible solution is oversampling of the $\eta(t)$ signal at a higher frequency to “smooth out” the subsequent WT analysis results, a solution that is preferable in terms of computational costs and complexity and is the one chosen in this work. The selected sampling frequency required for data smoothing is

discussed below in view of the analyzed signal characteristics. All signal processing tasks and calculations discussed here were performed using the MATLAB software package. The procedure, in general, was as follows:

- Pretreat the $\eta(t)$, including oversampling if needed, and identification of individual crests and general wave record characteristics.
- Obtain the $F(t)$ signal using the PTM, followed by conditioning of the $F(t)$ to simplify detection of breakers at or near crests.

FIG. 6. Frames extracted from Lake George project video corresponding to different experimental conditions: LGD is Lake George daylight, LGH is Lake George high U_{10} , and LGN is Lake George night time.

FIG. 7. Data treatment stages and detection energy maps. The $F(t)$ signal is filtered with a cutoff filter of 30 Hz and enhanced by $\eta(t)$ multiplication. Data from the (top) JA and (bottom) LGH sets are presented, using the F3 mother wavelet. All data points corresponding to negative water surface elevations are nulled (the middle trace in both sets).

- Apply the WT on the $F(t)$ signal, using the selected mother wavelet, to yield a detection energy map.
- Quantify the detection energy E of each wave crest in the record.
- Discriminate between detection energy values corresponding to breaking and nonbreaking crests using an energy value threshold relative to the maximum energy $E_{\max}$ of the examined record.

The steps listed above are detailed below. Since the developed method aimed to enable accurate detection of breakers in a single wave gauge record, we began by processing the water surface elevation

fluctuations records $\eta(t)$ obtained by a single wave gauge.

a. Pretreatment of the surface elevation fluctuations signal

In this stage, the dominant wave period/frequency of the record and all crests appearing above the mean water level were identified using the zero-crossing method. In addition, the Lake George datasets were oversampled from a sampling frequency of 25 to one of 300 Hz to ensure production of smooth detection energy maps by the subsequent application of the WT of

FIG. 8. Detection method algorithm diagram.

$F(t)$, as discussed above. Oversampling was performed by means of spline interpolation.

b. Obtaining the instantaneous frequency variations by PTM

Next, the instantaneous frequency variations of $F(t)$ were obtained by Eq. (3). Since breaking was expected to be detected at or close to the waves' crests, the $F(t)$ signal was “enhanced” to allow easier detection of patterns associated with breaking by the WT. A low-pass filter was applied to $F(t)$, with a cutoff frequency of $f_{\text{cut}} = 10f_p$, where f_p is the dominant frequency of the surface elevation fluctuations record obtained previously. Then, assuming higher waves in the ensemble are more susceptible to breaking, the $F(t)$ signal was “amplified” by multiplication by the corresponding-in-time values of $\eta(t)$. Such “amplification” leads to more prominent appearance of patterns of the instantaneous frequency variations associated with higher crests. Since we were interested only in the crest regions as potential candidates for breaking detection, the $F(t)$ was then nulled for all instances corresponding to negative surface elevation (Fig. 7, middle plots).

c. Wavelet transform

Applying the WT on the modified $F(t)$, using the selected mother wavelet, we obtained the so-called wavelet spectrum of the analyzed record. Then, we examined a two-dimensional map of the detection energy E , which constitutes the absolute value of $\Im(a, b)$ [see Eq. (4) and Fig. 7, bottom plots]. The wavelet spectrum represents the distribution of the signal energy at all frequency bands with the variation of the scanning parameter b over time. A better match between the wavelet and the scanned section of the analyzed signal translates into higher values of detection energy (higher wavelet

coefficients), indicating a higher level of matching to the pattern associated with breaking. On the other hand, nonbreaking but steep waves are also marked by relatively high, yet lower than the former, energy values. The first precaution that needed to be taken after obtaining the E map was the exclusion of any erroneous results that might have been generated by boundary data points of the $\eta(t)$ signal. Because the experimental record started and ended at arbitrary instances of the wave-field evolution, the $\eta(t)$ signal might include abrupt start or end records. These instances are mistakenly translated into very high E values, and so the variation of E map values corresponding to these instances must be either smoothed or removed from the detection energy map. Variations in time of E at each pseudofrequency were then low-pass filtered with a cutoff frequency equal to double the dominant wave frequency f_p . This was done to eliminate energy fluctuations associated with small amplitude variations in $F(t)$, which represent local irregularities and measurement noise present in $\eta(t)$. This process resulted in a smoothed detection energy map that presented one continuous E signature for each crest in the examined record of waves (Fig. 7, bottom plots). At this point, the selection of crests represented by E values above a specific threshold constituted the detection of crests exhibiting breaking. The selection of such a threshold is discussed next.

d. Detection energy threshold

Each crest was assigned a detection energy ranking that equaled the mean value of E values in the vicinity of the corresponding crest. The detection energy threshold was then selected from among the ensemble of the ranking values of all crests in the examined record, as a fraction amount of the highest energy value E_{max} in the ensemble. This way, the threshold is universally applicable for any

TABLE 2. Dataset statistics as produced by visual detection.

Dataset name	SA	SB	JA	JB	SW1	SW2	JW1	JW2	LGN	LGD	LGH
Total no. of crests N_c	278	335	287	310	275	282	284	313	2076	5022	609
No. of breaking crests N_b	30	26	17	26	32	36	26	22	94	246	56
Percentage of crests breaking (%)	10.8	7.8	5.9	8.4	11.6	12.8	9.1	7.0	4.5	4.9	9.2

examined record of water waves, and is not case specific. Validation and performance tests detailed in next section were performed on the available data records. A threshold of $0.6E_{\max}$ was determined to produce the most accurate detection of breaking waves, well exceeding a positive detection rate of 90%. Figure 8 presents the overall detection method algorithm diagram.

5. Validation and performance test

Validation of the developed method for the detection of breaking waves from single wave gauge records was conducted using the datasets acquired in the laboratory wind-wave flume and in the Lake George experiments (see section 3 and Table 1 for details). These data represent a wide variety of types and spectral widths of breaking waves. The datasets were processed by implementing the detection method elaborated in above section 4, and algorithm performance was tested against the results of the visual detection performed on the available synchronized video records. We next describe the test routine and examine the detection method performance in terms of its ability to detect breaking waves at a high success rate, while keeping the false detection rate at a minimum.

A coefficient of performance (CP) was devised to quantify method performance. While processing the video records, each wave crest out of a total of N_c individual crests in each dataset was visually classified as breaking (label 1) or not breaking (label 0). Table 2 presents statistics for all identified crests and the number of visually detected breaking crests for each examined dataset. The total number of crests in the laboratory datasets was around 300, with 7%–13% of crests identified as breaking. The Lake George datasets contained a number of crests that runs well into the thousands, with only 4% to 9% of crests identified as breaking.

Each dataset was processed using the detection method eight times, and each time the detection energy threshold $E_{\max}$ was set to a different value, specifically 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9. Crests with detection energy values that exceeded the set threshold were classified as breaking (label 1), and the rest were classified as nonbreaking (label 0). The algorithm results were then

compared with those of the visual identification, and the comparison was summarized in a detection efficiency table (Table 3). Wave crests whose identification by the algorithm as breaking and nonbreaking is in agreement with the visual detection results add a unity value to the a_{11} and a_{00} cells of the detection efficiency table, respectively. Crests detected by the algorithm as breaking but were not visually detected as such add a unity value to the a_{10} cell, while those detected as nonbreaking by the algorithm but as breaking by the visual detection add a unity value to the a_{01} cell. The CP for the currently used detection energy threshold is, therefore, calculated as

$$CP = \frac{a_{00} + a_{11}}{a_{00} + a_{01} + a_{10} + a_{11}}. \quad (13)$$

The detection performance of the tested method was considered to be successful when the resultant CP exceeded a value of 0.9.

Figure 9 presents CP distribution for all 11 datasets, as computed for each detection energy threshold using different mother wavelets. The highest CP values, $CP > 0.95$, were attained at detection energy threshold values of $0.6E_{\max}$ for all examined cases. The CP values dropped rapidly with decreasing threshold, as the amount of falsely detected breakers increased. The decrease in performance at threshold values greater than $0.6E_{\max}$ is due to the decreasing number of positive detections. This confirms that the wavelet-based pattern recognition approach is able to deal both with the waves' scaling issues and with the variability in the leeward side shapes of breaking waves. Figure 10 presents the ratio of detection of false positives (a_{10}) to the total breaking crests detected by the algorithm $N_{\det}$ at each energy threshold. A careful correlation between the results provided in Fig. 9 and Fig. 10 reveals the F2 mother wavelet to be the best overall performing wavelet, with a

TABLE 3. Detection efficiency table.

		Visual detection	
		0	1
Algorithm-based detection	0	a_{00}	a_{01}
	1	a_{10}	a_{11}

FIG. 9. Coefficient of performance of breaker identification distribution implementing different energy thresholds and using different mother wavelets: (top) F1, (middle) F2, and (bottom) F3.

positive detection rate exceeding above 90% and less than 15% false positive detection rate, at $0.6E_{\max}$.

6. Conclusions

To address the challenges of research into breaking water waves, a new breaking-wave detection method that is independent of human decisions was developed

and tested. The new method was designed to be cost-effective in terms of instrumentation, allowing detection of breakers in records of instantaneous water surface elevation fluctuations obtained by a single wave gauge. The algorithm used is cost-effective in terms of data analysis, implementing a combination of PTM processing of the surface elevation fluctuations records with a pattern recognition algorithm. The main principle of operation

FIG. 10. Rate of detection of false positive breakers over the total number of breakers identified by the algorithm, implementing different energy thresholds and using different mother wavelets: (top) F1, (middle) F2, and (bottom) F3.

is the identification of the formation of a bulge on the breaking wave crest. Based on works of Zimmermann and Seymour (2002), Irschik et al. (2011), and Itay and Liberzon (2017), manifestation of the bulge in the $\eta(t)$ instantaneous frequency variations was identified and a wavelet transform-based pattern recognition algorithm was devised to allow accurate detection of breakers. Validation and performance tests were conducted using both laboratory and open-sea data, including mechanically

generated and wind-forced waves. These tests allowed us to devise a set of parameters for which the method achieves high positive detection rates (over 90% for the datasets examined here), alongside low false positive detections rates for two of the examined mother wavelets. Although high detection rates were demonstrated for the datasets examined here, additional validation tests, using experimental data and numerical simulations, are still needed to fine-tune the devised method

parameters and examine the method's performance in various wave-field setups. Of special interest is the performance of the proposed method in open-sea wave fields of various spectral widths and in wave fields that exhibit double-headed spectral shapes as in the case of wind-generated waves that coexist with swell. While the Lake George data used to test the algorithm in this work are of relatively narrow spectral width (0.1–0.15), we expect similarly good performance of the algorithm also with wave fields of much higher spectral widths. This is due to the fact that the devised method relies on the detection of the irregularity forming on the leading side of an actively breaking wave in the local instantaneous frequency signal, and uses appropriate wave specific normalizations for signal conditioning, including crest vicinity separation. Hence the presence of a wide variety of wave lengths should not pose a significant limitation for the developed detection method.

The detection method algorithm, first presented by Itay and Liberzon (2017), was developed further to allow accurate detection under a wide range of experimental conditions, and appropriate routines for data processing were devised. A preprocessing method was established, followed by a relative detection energy threshold approach. Implementation of the latter eliminates the need for detection threshold calibration for each experimental condition, as many previously developed instrumental detection methods require. This in turn, pending additional validation tests including detailed algorithm sensitivity and uncertainty analysis using numerical modeling of the waves fields, opens the possibility of implementing the proposed method in any possible experimental setup, be it laboratory or open sea. The ability to detect breaking waves in highly irregular wind-forced wave fields is especially promising. Such ability is essential for improving the current method of experimental research on wind-wave interactions and will allow more accurate quantification of the wind-wave momentum transfer budget and its redistribution in the wave field. Investigation of coastal-zone wave fields and the associated sediment transport and forces exerted on structures is also expected to benefit from the improved and cost-effective breaking-wave detection method presented here.

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