# Passive Acoustic Determination of Wave-Breaking Events and Their Severity across the Spectrum

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#### ABSTRACT

A passive acoustic method of detecting breaking waves of different scales has been developed. The method also showed promise for measuring breaking severity.

Sounds were measured by a subsurface hydrophone in various wind and wave states. A video record of the surface was made simultaneously. Individual sound pulses corresponding to the many individual bubble formations during wave-breaking events typically last only a few tens of milliseconds. Each time a soundlevel threshold was exceeded, the acoustic signal was captured over a brief window typical of a bubble formation pulse, registering one count. Each pulse was also analyzed to determine the likely bubble size generating the pulse.

Using the time series of counts and visual observations of the video record, the sound-level threshold that detected bubble formations at a rate optimally discriminating between breaking and nonbreaking waves was determined by a classification-accuracy analysis. This diagnosis of breaking waves was found to be approximately 70%–75% accurate once the optimum threshold had been determined.

The method was then used for detailed analysis of wave-breaking properties across the spectrum. When applied to real field data, a breaking probability distribution could be obtained. This is the rate of occurrence of wave-breaking events at different wave scales. With support from a separate, laboratory experiment, the estimated bubble size is argued to be dependent on the severity of wave breaking and thus to provide information on the energy loss due to the breaking at the measured spectral frequencies. A combination of the breaking probability distribution and the bubble size could lead to direct estimates of spectral distribution of wave dissipation.

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## 1. Introduction

#### a. Detection and measurement of wave breaking

The breaking of wind-generated waves is a frequent phenomenon at the ocean surface, playing a significant role in many oceanographical and meteorological processes. It is fundamental to air-sea interactions (see, e.g., Melville 1996), and is of great importance for maritime and coastal engineering applications. However, the understanding of breaking waves is still imperfect and their studies have been hampered by the absence of criteria for wave breaking and reliable instruments that could detect breaking events and quantify their properties. Furthermore, instrumentation measuring the energy loss due to breaking, particularly in rough field conditions, would be valuable.

Until recently, visual observations of breaking events were the only reliable means of breaking detection (Holthuijsen and Herbers 1986; Katsaros and Atakturk 1992; Babanin 1995; Banner et al. 2000). During the last decade or so, more technological means became available. These utilize the acoustic, optical, reflective, and other properties of breakers, distinguishing them from the more homogeneous background wave field. Without giving a comprehensive review of these methods, it is important to cite radar observations of the microwave backscatter from breakers (Jessup et al. 1990; Loewen and Melville 1991; Smith et al. 1996; Phillips et al. 2001), sonar observations of bubble clouds produced by breaking wind waves (Thorpe 1992), infrared remote sensing of breaking waves (Jessup et al. 1997), conductivity measurements of void fraction produced by breakers (Gemmrich and Farmer 1999; Lammarre and Melville 1992), and aerial imaging and its analysis to obtain wave-breaking statistics (Melville and Matusov 2002).

The new methods have demonstrated a reliable detection of breaking events. Some of them are also capable of describing the scales of breaking waves and even estimating energy dissipation due to breaking. Most of the methods, however, remain very expensive to deploy and the data analysis is time and resource consuming.

### b. Passive acoustic studies of wave breaking

Among the new breaking detection methods, passive acoustic determination of breaking and its properties have a potential advantage. The instrumentation (hydrophones) is relatively cheap, robust, and easy to maintain. The hydrophones are deployed below the surface and are solid-state devices, therefore escaping most of the destructive power of breaking waves. Once deployed, they can be operated on a long-term or regular basis and collect ready-to-process time series.

Passive acoustic measurements have been employed in a number of field and laboratory studies. They were pioneered by Farmer and Vagle (1988) in the field and by Melville et al. (1988) in the laboratory, who both showed that acoustic signatures of breaking waves can be used to identify the breaking events. Farmer and Vagle (1988) used a single hydrophone and found that the mean distance between the breakers and acoustic strength of the breakers depends on the wind speed.

Ding and Farmer (1994) further advanced the technique. They developed a directional array of hydrophones and a method to track individual breaking events out in the ocean. The directional array made possible measurements of the phase speed of breaking events, and showed it was related to the spectral scale of breaking waves (the wave period) and therefore to the spectral scale at which the dissipation occurs. Ding and Farmer obtained interesting statistics on the frequency and spacing of breaking occurrences; on breaking duration, dimension, and speed; and some temporal and directional spectral characteristics of breaking probability. They showed a number of distributions of the breaking probability as a function of event speeds and event directions (which are analogs of the wave spectrum frequency and direction), but did not attempt to relate the magnitude and shape of the distributions to the wave spectrum and thus to obtain the spectrum of energy dissipation.

Loewen and Melville (1991) extended and summarized results of the earlier laboratory studies. They used measurements of the acoustic pressure and concluded that duration of the hydrophone signal above a background noise threshold is proportional to the breaking wave period and that the acoustic energy radiated by breaking waves is proportional to the mechanical energy dissipated. These results provided a possible method of measuring temporal spectral scales of breaking events, and even the dissipation related to those scales, using a single hydrophone. In their study, the waves were made to break as a result of the natural evolution of wave packets, generated mechanically, with a preselected central frequency wave that eventually broke. Their method was effectively developed for a single-wave environment, and determination of the scales and energy losses of breaking waves in complex spectral environment was beyond the scope of their paper.

Felizardo and Melville (1995) further applied passive acoustics in the field, where breaking waves of all scales and various dissipation rates can be present at the same time. They argued that the dependence of ambient noise on the wind is indirect. They found correlations between the ambient noise level and wave parameters related to the incidence of wave breaking, and also between the total dissipation, estimated in a number of different ways, and the acoustic noise. No attempts to obtain a spectral distribution of the total dissipation were made. It should be mentioned that extending the Loewen and Melville (1991) approach into the multiscale wave environment may not be as straightforward as considering the duration of the hydrophone signal above a threshold. The acoustic energy radiated by a breaking event and even the threshold itself can be altered owing to multiple breakings nearby, or due to simultaneous breakings of different scales at the measurement spot.

A number of other passive acoustic techniques have been further developed to work on breaking detection and statistics. Bass and Hay (1997) and Babanin et al. (2001, hereinafter BYB) both used spectrograms of the hydrophone-recorded noise to detect breaking events. The identification of distinct crests in the spectrograms, spanning a frequency range from 500 Hz to 4 kHz, was argued to be a more reliable means of breaking detection in the complex spectral environment than the integrated ambient noise exceeding a threshold (BYB). The spectrogram method, however, was only applied for the detection of dominant breakers.

In summary, acoustic techniques have consistently showed the ability to detect breaking event signatures and, therefore, the ability to study breaking statistics. The techniques are, in principle, capable of distributing the breaking probability along the spectral scales of the corresponding breaking waves. This could be done in two ways. The breakers could be detected and statistics of their periods obtained; according to Loewen and Melville (1991) the statistics are proportional to the signal duration above the threshold. Alternatively, the phase speed of breakers, detected by a directional hydrophone array, could be related to the phase speed of waves with the corresponding frequency (Ding and Farmer 1994). Furthermore, it is possible to obtain the distribution of breaking wave energy dissipation along the spectral frequencies. As Loewen and Melville (1991) showed, once the breaking event is detected, the energy loss can be estimated by the amount of acoustic energy radiated.

However, no systematic studies have been made of the spectral distributions of the breaking probability, and no advances have been made in obtaining a spectral distribution of the dissipation. This is probably due to difficulties in applying the method of thresholding the integrated noise over background, in the spectral environment of real seas with multiple breakings at various scales. In real seas, the integrated background noise level will change, depending on wave and wind conditions, thus varying the threshold value (Ding and Farmer 1994). Even for stable wind-wave situations, the simultaneous presence of multiple wave scales can cause ambiguity in the detection of breaking events and, moreover, in measuring their duration or acoustic energy radiated. BYB synchronously detected the breakers by passive acoustics and by video recordings in the field, and showed that similar integrated noise above the background sometimes indicated a breaker and sometimes did not.

In the present study, a passive acoustic method of breaking determination using a single hydrophone was developed. Its key difference from the methods reviewed above was the analysis of very brief pulses, which as outlined in section 1d below, are associated with sound emission by individual bubbles. Our method shares both the advantages and some limitations of other passive acoustic methods reviewed above. Our method does rely on a discriminant (threshold) to trigger breaker detection and analysis and any such procedure will inevitably result in errors, as discussed in this paper. However, the statistical procedures developed in the present paper would permit a rigorous determination of discriminants from future field data, possibly leading to a universal discriminant.

Furthermore, analyses leading to estimates of breaking severity are inherently made in the frequency domain, rather than relying on relative magnitudes of the signal. In the present paper the term "severity" denotes the absolute energy loss from the wave system due to a wave-breaking event. It could include energy lost to work against buoyancy during air entrainment and the generation of mean currents as well as turbulent dissipation.

# c. Ambient sound in the ocean and its relation to bubble formation

The ambient sound level in the ocean at a given frequency may vary by 20 dB, increasing with the wind speed (Knudsen et al. 1948; Wenz 1962; Kerman 1988, 1992; Ding and Farmer 1994). Wind and wave effects are most marked in the 0.1–10-kHz band. The general mechanisms of sound creation in this band are understood, although their interrelationships are not. Wind pumps energy into the wave spectrum, causing wave growth, which can lead to breaking. The whitecapping from a breaker creates bubbles near the surface, and bubbles emit sound. However, it is known that the wind dependence is indirect. It is the hydrodynamic evolution of the wave spectrum that determines whether breaking occurs (Banner et al. 2000; BYB). Once breaking occurs, it is the primary source of the ambient noise in the ocean (Kerman 1988, 1992; Farmer and Vagle 1988; Felizardo and Melville 1995).

Subdividing the 0.1–10-kHz band allows more detailed explanations. In general, it is above 0.5 kHz that the wind-dependent component to the sound spectrum dominates (Wenz 1962). Furthermore, Bass and Hay (1997) and BYB showed that the sound spectrograms due to breakers become evident above 0.5 kHz. Theoretical work (Medwin 1989) suggests that the bubble formation process dominates the acoustic spectrum at frequencies greater than 0.5 kHz. From the basics of bubble acoustics (section 1d), 0.5–10 kHz corresponds to the natural emissions of millimeter-sized bubbles at near-surface depths. Frequencies around 0.1–0.5 kHz are likely to be produced by bubble clouds, not individual bubbles (Prosperetti 1988; Lu et al. 1990).

#### d. Passive acoustics of bubble formation

It has been well known since the time of Rayleigh (1917) that individual bubbles oscillate volumetrically with a natural frequency that depends on their size (see Leighton 1994, for a review), suggesting an obvious application to instruments analyzing bubbly flows. The simple harmonic solution to the Rayleigh–Plesset equation describing bubble acoustic oscillations shows that a single bubble's natural frequency is inversely related to bubble size, according to

$$\omega_0 = \sqrt{\frac{3\gamma P_0}{\rho}} \frac{1}{R_0} \tag{1}$$

(Minnaert 1933), where  $\omega_0$  is the radian frequency,  $\gamma$  is the ratio of specific heats of the gas,  $P_0$  is the absolute liquid pressure,  $\rho$  is the liquid density, and  $R_0$  is the equivalent spherical radius of the bubble. If the number of bubbles is assumed infinite, continuum approximations based on (1) permit overall acoustic properties of a bubbly cloud to be calculated (e.g., Commander and Prosperetti 1989; Duraiswami et al. 1998). The acoustic properties of bubbles have been the basis of several oceanographic instruments (e.g., Phelps et al. 1996; Terrill and Melville 2000) as well as industrial instruments (Duraiswami et al. 1998; Manasseh et al. 2001; Boyd and Varley 2001) although none are in widespread use. Most systems measure bubble-size distributions, relying on an active principle. Sound is sent into the water and the attenuation or reflection of the resulting signals is interpreted to infer the bubble-size distribution.

However, bubbles also passively emit sound at their natural frequency, that is, without being forced by an external sound field. As a bubble detaches from its parent body of gas, it produces an acoustic pulse. This may be due to a sudden compression of the trapped gas as the bubble pinches off (Manasseh et al. 1998). This "ringing" of the bubble may last less than 10–20 cycles; for example, for a 2-mm-diameter bubble (3-kHz natural frequency), the pulse can last less than 10 ms. While any disturbance may cause the bubble to ring, the highest-amplitude sounds are created when a bubble is pinched off (Chen et al. 2003). Many bubble creation events occur per second, during processes ranging from filling a glass to wave breaking. Although humans perceive this as a continuous noise, it is due to many discrete, brief events. An individual bubble's pulse becomes briefer as the bubbles are produced more closely to each other, and the frequency of the signal drops during the pulse, with the earliest acoustic cycles being closest to the natural frequency given by (1) (Manasseh 1997). It was shown by Manasseh et al. (2004) that these effects may be explained by interbubble acoustic interactions as the system becomes more "cloudlike." Furthermore, sound intensity drops rapidly with distance from the bubbles, which may be considered as monopole sources (Longuet-Higgins 1989; Leighton 1994).

These phenomena suggest that a sufficiently short time window triggered on a signal peak often contains data specific to a single, nearby, newly formed bubble (Manasseh et al. 2001). This implies that appropriately thresholded acoustic data can generate statistics as a function of time on both the number of bubbles produced and their size.

In the present study, sound frequencies above 0.5 kHz were considered, that is, those emitted by individual bubbles rather than bubble clouds. These frequencies were processed to capture the radii of some of the individual bubbles entrained into the water as a result of each wave-breaking event. It can also be argued that bubble size is related to the severity of the event, that is, the amount of energy lost by the breaking wave, and preliminary laboratory experiments are presented supporting this claim.

The paper is organized as follows. In section 2, the field experimental setup, signal conditioning method, and analysis procedure are described; a preliminary laboratory experiment relating breaking severity to the bubble size detected by the method is also outlined. In section 3, a passive acoustic method of detecting wave breaking is developed by cross-checking its predictions against visual observations. In section 4, calculations of the wave-breaking probability as a function of wave frequency are made. In section, 5 preliminary qualitative analyses of the breaking probability spectrum and breaking severity spectrum are presented. Conclusions are in section 6.

### 2. Experiment and basic data processing

The measurement and analysis procedures that we would propose based on the developments of the present paper were well summarized by an anonymous reviewer. The procedure is as follows.

- 1) A submerged hydrophone monitors sound continually.
- 2) A prior statistical classification-accuracy analysis has determined a sound pressure threshold optimally discriminating breaking from nonbreaking events. When the instantaneous sound pressure exceeds this predetermined level, a very brief pulse of sound is captured, assumed to be due to a single, freshly formed bubble.
- 3) The pulse frequency is rapidly measured and translated into the bubble's radius.
- Running statistics on the rate of detection of bubbles and the mean bubble size during breaking events are collected.
- 5) Each detected bubble is linked to the synchronous wave height record by means of a zero-crossing analysis, thus determining the period of the wave breaking at the time of the bubble detection and the wave period distribution of the breaking rate.
- 6) From laboratory experiments, the mean bubble size can be related to the wave-breaking severity.
- The rate of occurrence of the breaking events times their severity can be used to estimate wave energy dissipation due to breaking.
- 8) The wave period distribution of the dissipation rate is obtained.

The field experiment was carried out at Lake George, New South Wales, Australia, in 1997–2000. It was designed to simultaneously measure the source functions that drive the evolution of wind-generated waves in a finite-depth environment (Young et al. 2004). Measurements of wave breaking and whitecap dissipation, including passive acoustic measurements, were an integral part of the experiment.

#### a. Field experiment

The measurement site was an instrumented platform on Lake George. Full details are given in BYB and Young et al. (2004). Here, the relevant measurements are briefly summarized. The platform was located 50 m from the eastern shore, beyond the surf zone, and exposed to westerly winds that are the most frequent in the area and the corresponding longest wave fetches. Measurements were taken from a 10-m-long bridge on the side of the platform and covered a comprehensive set of synchronous readings in the atmospheric boundary layer, at the surface, in the water column, and at the bottom.

Approximately halfway along the bridge, an array of capacitance gauges was used to measure the water elevation, providing information on the frequencydirectional wave spectrum. Wave breaking and dissipation were recorded by a number of independent devices. A set of Sontek acoustic Doppler velocimeters (ADV) and a "Dopbeam" (Veron and Melville 1999) provided information on both temporal and spatial spectra of turbulence. They were used to profile rates of total turbulent kinetic energy dissipation from the surface to the bottom (see Young et al. 2004). Such profiles provide estimates of integrated-over-the-spectrum volumetric turbulent dissipation rates (Babanin et al. 2005) and may not readily give the total wave energy dissipation including the work done to entrain air. Although they were not used in the present paper, they may be useful in extensions of the current study as reference values for the spectrum of dissipation. In addition, an electronic marker enabled an observer to time stamp breaking and other events of interest.

Below the capacitance gauge array was a hydrophone measuring underwater noise. The hydrophone was calibrated, and in the 1–10-kHz band it was found to have a response of approximately -160 dB relative to 1 V mPa<sup>-1</sup>, varying from this by less than 10 dB. A video recording was made of the water surface around the wave gauges and hydrophone using a Panasonic Professional/Industrial Video model AG-7350, which has audio channel gain (recording levels) that are set by the user. The hydrophone signal was recorded on the audio channel of the videotape at a fixed gain, ensuring the camera and hydrophone data were recorded with the same time stamp.

Figure 1, reproduced from BYB, shows the setup of the platform and Fig. 2 shows a video frame with a breaking wave passing through the wave array (the hydrophone was located directly underneath). Synchronous measurements of the boundary layer wind profile were conducted by two vertical arrays of Aanderaa Instruments cup anemometers and wind vanes, which can be seen on the left side of Fig. 1. Six cup anemometers were positioned evenly on logarithmic spacings from 10 m above the mean water surface down to 0.5 m. Two vanes recorded wind directions near the top and second-from-the-bottom cups. Additionally, a Gill Instruments ultrasonic anemometer (21-Hz sampling frequency) was employed to supply information on highfrequency three-dimensional turbulent oscillations of the wind.



FIG. 1. Platform setup.

#### b. Signal conditioning

Acoustic data from the Lake George experiment had previously been analyzed by spectrograms (BYB). Well-defined peaks in the acoustic noise level were found, and by comparison with the coordinated video data the peaks were associated with wave-breaking events. For the present analysis, the video and hydrophone recordings were organized into 20-min segments according to the mean wind speed over the segment. Segments were chosen with relatively constant wind speeds.

The audio signal from the videotape was played back through an analog bandpass filter (Rockland model 852) passing frequencies between 0.1 and 30 kHz. The analog circuits of the videotape and playback recorder are not intended to reproduce signals above the human hearing limit of 15–20 kHz; thus, the upper-frequency



FIG. 2. Video frame.

limit merely eliminated electronic noise and the effective analog pass bandwidth was 0.1–20 kHz.

The analog-filtered signal was given a gain of 40 dB and digitized at 20 kHz by a datalogger (National Instruments DAQ-Pad 1200) connected to a PC's parallel port. The gain applied, together with the hydrophone's mean calibrated response (-160 dB relative to 1 V mPa<sup>-1</sup>), meant that 1 V as digitized corresponded to an order 1-Pa sound pressure level at the hydrophone. However, the present analysis was not anticipated at the time of the original experiment, so the precise gain set on the video recorder at the time of the experiment cannot be confirmed, although it was a constant. Hence, signals levels are only reported in this paper in volts, to emphasize that while the method is universally applicable, the precise optimum levels calculated in this paper may be specific to the present data.

Data were captured for a window 6 ms long; given the type of time-domain frequency analysis used [detailed below; see also Manasseh et al. (2001)], this window imposed a lower limit of 0.3 kHz. The 20-kHz sampling rate imposed a Nyquist upper limit to the frequency of 10 kHz. Thus, the final pass bandwidth was 0.3–10 kHz. Most of the pulses captured (over 95%) were between about 1 and 7 kHz [using (1), 1 kHz corresponds to 6-mm-diameter and 7 kHz to 1-mmdiameter bubbles]. This implies that eliminating signals below 0.3 kHz and above 10 kHz did not significantly bias the results.

The 0.3-kHz lower-frequency limit has a physical relevance: it eliminated hydrostatic pressure fluctuations corresponding to the passage of waves themselves. It is worth noting that the physics represented by (1) is unlikely to be valid as low as 0.3 kHz. Air bubbles in water do not exist in closed form above about 10-mm diameter (Maxworthy et al. 1996), that is, below about 0.6 kHz. Thus, if sounds in the low hundreds of hertz are generated by bubble acoustics, it is likely to be the collective oscillations of large clouds of bubbles vibrating as a whole (Prosperetti 1988; Lu et al. 1990). Owing to the filtering, this phenomenon would not be measured by the present analysis, but since Lake George is not an ocean environment with large breakers, it is less likely to occur.

#### c. Pulse processing

A pulsewise time-domain frequency analysis was applied to the digitized signals. The following procedure was applied, using StreamTone software. A full justification of the procedure is in Manasseh et al. (2001). A typical acoustic time series for a breaking wave system will be shown below (Fig. 5). Further examples of acoustic signals from similar complex bubbly flows can

be found in the literature (e.g., Leighton 1994; Manasseh et al. 2001; Manasseh 2004).

- 1) If the amplitude of the sound exceeded a given trigger level (discussed in detail below), a pulse was captured.
- 2) The length of the first period is estimated.
- 3) The first-period length is used to calculate a radius  $R_0$  using (1), assumed to be that of a "local" bubble near the hydrophone (section 1d).
- 4) The radius and detection time of each pulse are saved in a file.
- 5) Statistics on both the local radius  $R_0$  and the rate of pulse acquisition are calculated, over a record of duration *T* (a few minutes for initial tests, or the full 20-min segment length for the later analyses below).

The results included the following:

- 1) (a) the number of counts (or "number of bubbles detected") during the record duration T and (b) the count rate F (detected bubbles s<sup>-1</sup>);
- 2) (a) the mean local bubble radius  $R_0(\text{mm})$ , hereafter simply called *R* for brevity; and (b) the 95%  $\pm$  confidence interval on the bubble radius (mm).

The setting of the trigger level has an important influence on the results, particularly if the statistics are to be useful in the analysis of wave-breaking events. If the trigger level were too low, many pulses would be captured. Even if all these pulses corresponded to genuine bubble formations, they would not necessarily be bubble formations caused by wave breaking. Possible sources of error are discussed in appendix A. If the trigger level were too high, some wave-breaking events would be missed; possible causes are discussed in appendix A.

It is a common situation when an arbitrary "discriminant" controls a diagnostic test (Landis and Koch 1977; Huberty 1994; Fielding and Bell 1997) and a formalized method of optimizing the trigger level is discussed in section 3.

First, however, lower and upper limits defining a trigger-level range were determined. Table 1 shows a summary of main wind-wave parameters for records used in the present analysis. The lower limit was given by tests on the highest wind speed, which generated the highest count rates. The PC processing the digitized data was limited by its parallel port speed and could only process a maximum of approximately nine counts per second. (It must be emphasized that this is not a fundamental limit, merely a limit of the parallel-port logger used at the time.) Therefore, the lower limit was the trigger level that gave this "system maximum" count rate for the wind conditions generating the highest count rates.

TABLE 1. Summary of wave records used:  $f_p$ , peak frequency;  $H_s$ , significant wave height; and  $U_{10}$ , wind speed at 10-m height. Record number indicates the actual sequence wind speeds occurred in, e.g., 20 min, with an average of 15.0 m s<sup>-1</sup> immediately followed 20 min with an average of 19.8 m s<sup>-1</sup>.

No.	Record No.	$f_P$ (Hz)	$H_{s}$ (m)	$U_{10} \ ({ m m \ s}^{-1})$
1	311823.oc7	0.36	0.45	19.8
2	311845.oc7	0.33	0.40	15.0
3	311908.oc7	0.35	0.37	12.9
4	311930.oc7	0.38	0.34	12.8
5	312021.oc7	0.40	0.39	13.7
6	312048.oc7	0.37	0.37	13.2
7	312111.oc7	0.40	0.25	9.3

Saturation of the system was thus precluded. The upper limit was determined by statistical considerations. The *t*-test distribution asymptotes for counts above 30–50, facilitating statistical hypothesis tests. The segment with the lowest wind speed was analyzed as it had the lowest count rates. The highest trigger levels that still permitted 30 or more counts were found. This segment was also visually examined while the program was running in order to check if too many breaking events were being excluded. This check was a precursor to the more rigorous procedure described in section 3. The resulting trigger level range was 0.5–3.0 V.

The length of the segment analyzed also needed optimization. If the segment was too short, statistical confidence was harder to obtain; if it was too long, the method would be unproductive and any future instrument based on it would be of limited use. Three-minute subsamples of each segment were found to be sufficient for the trends reported in this section; the entire 20-min segments were analyzed for the results of section 3.

# d. General bubble radii trends and dependence on wind speed

Initial tests on the effect of trigger-level variations are shown in Fig. 3. The two extreme wind speeds and a midrange speed (record 3, Table 1) are shown. All of the measurements were for 3-min records (T = 180 s). Figure 3a shows the average bubble radius versus trigger level. Vertical bars indicate the limits of 95% confidence intervals. At each wind speed, once trigger levels exceed 1 V, the confidence intervals for the various trigger level overlap, implying that the trigger level does not systematically bias the bubble radius. The confidence interval increases with trigger level, owing to the drop in counts at higher trigger levels.

The curves for the three wind speeds are significantly different, suggesting a relation between the wind speed and the size of the bubbles created by the resulting



FIG. 3. Initial trigger level tests on 3-min samples for three wind speeds: 9.3 ( $\Box$ ), 12.9 ( $\odot$ ), and 19.8 m s<sup>-1</sup> (\*), for (a) the mean bubble radius *R* vs trigger level, with vertical bars for the 95% confidence limits on *R*, and (b) the count rate vs trigger level.

breaking waves. The difference between wind speeds seems clearest around 1.75 V. This is examined in more detail and at higher accuracy in section 3b.

Figure 3b shows the count rate versus trigger level. As expected, rates drop with increases in trigger level. Not surprisingly, there is also a relationship between wind speed and count rate, with higher rates as wind speed increases.

Further tests checked the influence of the trigger level on the scientifically relevant trends with wind speed (Fig. 4). Three-minute segments were used as before. Three trigger levels were studied. Figure 4a shows the mean bubble radius as a function of wind speed for the three trigger levels. The data at 3.0 V illustrate how statistically significant trends are obliterated if the level is raised too high, owing to small sample sizes. In section 3b below, data from the 1.75-V trigger level determined optimal by the formal classification-accuracy analysis will be isolated and shown later (Fig. 9a).

Figure 4b shows how the bubble rate increases as the



FIG. 4. Tests on 3-min samples at three trigger levels, showing scatter at nonoptimal trigger levels (entire datasets at optimal level shown in Fig. 9): 3 ( $\Box$ ), 1.75 ( $\bigcirc$ ), and 1 V (\*), for (a) the mean bubble radius *R* vs wind speed, with vertical bars for the 95% confidence limits, and (b) the count rate vs wind speed.

wind speed rises. Tests also confirmed that the choice of 3 min was reasonable; when six different 3-min records were taken from the same "average wind speed" segment, bubble count rates did vary, but bubble sizes were not statistically significantly different. A countrate variation on a time scale of minutes would be expected owing to longer-term variability of breaking rates due to wave groupiness (Donelan et al. 1972; Banner et al. 2000). However, mean bubble size would be expected to remain constant in a steady wave field, if, as discussed below, it is assumed to be related to the strength of individual breakers.

# e. Laboratory check on bubble radii trend with breaking severity

To examine the hypothesis that bubble size is related to breaking severity, the passive acoustic analysis was applied to data from a laboratory wave maker. Although a significant dataset remains to be analyzed,



FIG. 5. Typical acoustic time series showing grouping of sound pulses at breaking events. Note wave frequency is 0.75 Hz so that crests are about 1.33 s apart.

some preliminary results pertinent to the present paper are briefly reported.

Waves with a frequency of 0.75 Hz and various amplitudes were generated in a flume of width 1.215 m. The water depth was  $225 \pm 5$  mm above a sandy bottom. A vertical board 45 mm wide and 150 mm deep was placed about 10 m downstream of the wave maker; its top was  $30 \pm 3$  mm above the mean water level, so plunging breakers were forced to form over this barrier. Two capacitance probes measured the instantaneous water depth,  $640 \pm 5$  mm upstream of the board and  $560 \pm 5$  mm downstream of the board. A hydrophone (Bruel & Kjaer model 8103) with a diameter of 9.5 mm was mounted  $60 \pm 2 \text{ mm}$  downstream of the board with its tip 55  $\pm$  2 mm below the mean water level. The probes and hydrophone were approximately in the center of the flume width. A typical acoustic time series is shown in Fig. 5.

The acoustic signal was preamplified by a Bruel & Kjaer 2635 charge amplifier set to the hydrophone's calibration such that 1-V output represented exactly 100-Pa sound pressure amplitude. The signal was passed through a 400-Hz unity-gain high-pass filter and digitized at 40 kHz. The pulsewise processing described in section 2c was applied in real time on 5 min of data with a trigger level of 0.1 V (10 Pa). Of course, every wave broke, and the hydrophone was deliberately placed within a few centimeters of the bubble formation zone, so rather than determining the trigger level by a classification-accuracy analysis as described for field data in section 3, the criterion was simply to minimize variance in the processed data while keeping the

data collection time per run reasonably brief. Typically, 500–1000 pulses were acquired.

The difference between the water elevations upstream and downstream of the wave breaker were used to calculate the energy loss, a parameter assumed to represent the true breaking severity. The results are shown in Fig. 6, where the mean local bubble radius Ris shown with the 95% confidence interval calculated from the pulsewise processing. It can be seen that there is a clear, though not necessarily linear, increase in Rwith the loss of energy by the plunging breaker. At higher wave amplitudes than those shown, breaking increasingly occurred prior to the board and between the upstream probe and the board, so those conditions could not be used for the present analysis. While this preliminary result supports the contention that R can be a proxy for local breaking severity, much work is required to determine the true relationship between bubble size and breaking severity under a wider and more realistic range of breaking conditions.

#### 3. Determination of wave-breaking events

# a. Classification-accuracy analysis to determine optimum trigger level

The identification of when a wave breaks by an objective method is a key aim of the present study. Furthermore, the dependence of the initial field data analysis on an arbitrary parameter like the trigger level is an obvious limitation. Thus, an objective method of determining the optimal trigger level was sought for the specific case where the passive acoustic technique is to be used as a wave-breaking detector. Situations when an arbitrary discriminant controls a diagnostic test are common in the biological and medical sciences (Landis and Koch 1977; Huberty 1994; Fielding and Bell 1997; Kraemer et al. 2002). The present problem reduces to the optimization of a discriminant by comparison with an "absolute truth." The trigger level was the discriminant, while the visual observation of a breaker was assumed to be absolute truth.

Three-minute records were again used. These had been processed at various trigger levels as described in section 2c. Each 3-min record was then divided into 1-s intervals and each second was labeled with the number of pulses detected during that second. A matching list was constructed by detailed manual observations of the videotape over the 3 min. Each second during which wave breaking was visible was noted. Typically, of course, the wave-breaking event lasted more than a second so there could be several pulses per event. Any amount of whitewater noticeable in the vicinity of the hydrophone was classified as a breaking wave.



FIG. 6. Breaking severity assumed as bubble radius R against laboratory wave energy loss. Vertical bars are for the 95% confidence limits on R.

Contingency tables (e.g., Baldessarini et al. 1983; Agresti 2002) were constructed where the four possibilities are

- *a*—acoustic detection, a breaker visible;
- *b*—acoustic detection, no breaker visible;
- *c*—no acoustic detection, a breaker visible;
- *d*—no acoustic detection, no breaker visible.

For the diagnostic to be "good," the number of correct results a and d should be high while the number of false results b and c should be low. Four measures calculated from a, b, c, and d are commonly used to determine the effectiveness of a diagnostic (Landis and Koch 1977).

Sensitivity, the probability of acoustic detection if a breaker was visible (correct positive diagnosis), is given by

$$\frac{a}{a+c}.$$
 (2)

Specificity, the probability of no acoustic detection when no breaker was visible (correct negative diagnosis), is given by

$$\frac{d}{b+d}.$$
 (3)

The correct classification rate is the probability of correct positive detection and correct negative detection. In essence, this is the probability of "getting it right" and is given by

$$\frac{a+d}{N},\tag{4}$$

where N = a + b + c + d.

Kappa ( $\kappa$ ), a measure of agreement between different diagnostic methods (e.g., Landis and Koch 1977; Kraemer et al. 2002), is given by

$$\kappa = \frac{(a+d) - [(a+c)(a+b) + (b+d)(c+d)]/N}{N - [(a+c)(a+b) + (b+d)(c+d)]/N}.$$
(5)

It varies from zero to one and indicates the quality of the diagnosis relative to random guessing. A  $\kappa$  of zero is no better than random guessing, while unity is perfect. The following widely accepted ranges have been defined (Landis and Koch 1977) to help classify the effectiveness:

	$\kappa = 0.0$	poor,	
0.01	$< \kappa < 0.20$	slight,	
0.21	$< \kappa < 0.40$	fair,	
0.41	$< \kappa < 0.60$	moderate,	
0.61	$< \kappa < 0.80$	substantial,	and
0.81	$<\kappa < 1.00$	verv high.	



FIG. 7. Probabilities vs trigger level: correct classification rate ( $\Box$ ), specificity ( $\bigcirc$ ), and sensitivity (\*), for wind speeds of (a) 19.8, (b) 12.9, and (c) 9.3 m s<sup>-1</sup>.

Although  $\kappa$  is a popular descriptive statistic, its interpretation is still the subject of debate (Kraemer et al. 2002). For instance,  $\kappa$  can fail to be relevant if the prevalance of the measured event is low (Thompson and Walter 1988; Feinstein and Cicchetti 1990) (e.g., if there are many more intervals without breaking waves than those with breakers present).

Results of the classification-accuracy analysis are shown in Figs. 7 and 8. The basic trends are to be expected. Low trigger levels give a diagnostic that has high sensitivity, almost always detecting a breaker if there is one, but it has low specificity, with many false detections. Conversely, high trigger levels give a diagnostic with low sensitivity and high specificity. The correct classification rate generally peaks for midrange trigger levels, at approximately the intersection of the sensitivity and specificity curves. However, at the lower wind speed of 9.3 m s<sup>-1</sup>, there are many more nonbreaking periods present, so the correct classification rate is dominated by the specificity. The 19.8 and 12.9 m s<sup>-1</sup> wind speeds both have their maxima at a trigger level of 1.75 V.

The kappa values are shown in Fig. 8 and demonstrate a clear peak, again at the 1.75-V trigger level. This is evident for the 19.8 and 12.9 m s<sup>-1</sup> wind speeds, which have peak  $\kappa$  values of 0.43 and 0.52, respectively. These values are in the fair to moderate range (Landis and Koch 1977). Although the maxima for 9.3 m s<sup>-1</sup> indicates only slight diagnostic agreement, it does exhibit a peak at about the same 1.75-V trigger level. If there is a large discrepancy between the number of positives and negatives (which occurs at lower wind speeds), the kappa statistic can become irrelevant as noted above (Thompson and Walter 1988; Feinstein and Cicchetti 1990).

In summary, an optimum trigger level for detecting breaking waves exists. In the present dataset it is 1.75 V, in which case the probability of getting it right is approximately 70%-75% (Fig. 8).

### b. Analysis with optimal discriminant

Each 20-min segment was then examined in its entirety at the optimal trigger level of 1.75 V (except record 7 in Table 1, owing to corruption of the tape). Following the assumptions outlined in section 1, each pulse represented an individual bubble formation occurring near the hydrophone during a wave-breaking event. Results are shown in Fig. 9.

The increase in average bubble size with wind speed is now clear (Fig. 9a). An increase in bubble production rate with wind speed can be seen in Fig. 9b. There is a clear ordering of the wind speeds with respect to both the bubble rate and the mean radius, with quite high correlation. In summary, higher wind speeds generate breaking events more frequently, and the bubbles at higher wind speeds are larger. Similar trends of the mean bubble size with an independent variable have been found elsewhere (Manasseh et al. 2001; Zhu et al. 2001; Chanson and Manasseh 2003). Bubble size distributions typical of a plunging-jet system that may approximate wave-breaking processes are given in Chanson and Manasseh (2003).

These analyses at the optimal discriminant created a data file for each wind speed, listing all the sound pulses (bubble formations) that were detected. The list gave the time in seconds from the start of the segment of each detected bubble and its calculated radius. Further analysis of this file easily converted it into a time series with arbitrary time resolution. A resolution of S = 0.25 s was chosen to give a reasonable sampling rate along



FIG. 8. Kappa ( $\kappa$ ) vs trigger level for three wind speeds: 9.3 ( $\Box$ ), 12.9 ( $\bigcirc$ ), and 19.8 m s<sup>-1</sup> (\*).

the wave profile for the subsequent zero-crossing analysis. The result was a list given at each 0.25-s interval:

- 1) the number of bubble formations in each interval (usually zero or one, but occasionally greater than one) and
- 2) the size of the bubble detected, or an average if there were more than one.

# 4. Calculation of wave-breaking probability as a function of wave frequency

## a. Zero-crossing analysis and breaking probabilities

To obtain wave-breaking probabilities of individual waves at different frequencies, a zero-crossing analysis was applied. A time series of length t = 20 min of the surface elevation measured by the capacitance gauge was used for each wind speed (Table 2). From these, the period of each wave was calculated as follows. Times when the surface elevation crossed the mean or "zero" level were noted. Two consecutive zero upcrossings were analyzed and the time of the troughs preceding and following them were recorded. The difference between the trough times was taken as the period of that wave T, giving its frequency. Figure 10 (top panel) shows a 30-s section of the surface elevation data of record 1 (Table 1) used to calculate wave frequen-

cies. In Fig. 10, limitations of the zero-crossing analysis at small scales are quite obvious. These limitations and other issues with the zero-crossing analysis are discussed in appendix B. The synchronous passive acoustic wave-breaking data (section 3b) were then combined with the wave frequency data. Such bubble detection events are shown, for the same time series, in the bottom panel of Fig. 10. Occasional events that would correspond to negative surface elevations were excluded from the analysis to avoid possible ambiguity in detecting wave breakers when those events happened close to wave troughs. For each acoustically determined breaker, the frequency of the wave at the same time was extracted. The total number of breaking waves n(f) was found for each of the calculated frequencies. The total number of expected waves at each frequency N(f) = t/T. Thus, the probability that a wave of a given frequency would break,

$$b_T(f) = n(f)/N(f), \tag{6}$$

was found. In practice, in order to obtain n(f) and  $b_T(f)$ , the wave frequencies are effectively discretized into bands  $f \pm \Delta$ , where  $\Delta$  will be discussed below. This is, of course, because n(f) and  $b_T(f)$  are not spectral densities but statistical quantities, and there are no exact matches between measured wave periods and a given 1/f.



FIG. 9. Trends with wind speed at optimal trigger level, 1.75 V: (a) mean bubble radius and (b) count rate. Entire datasets used.

Since the set of wave records used in the present study is a subset of the records used by BYB to obtain breaking probabilities of dominant waves, a consistency check was performed to compare the  $b_T$  values from the two studies. In BYB the crests of enhanced energy in spectrograms were counted to give the *n* in (6). The spectrogram crests across the entire 500 Hz–4 kHz frequency band were only indicative of dominant waves

TABLE 2. Summary of results for entire segment tests:  $U_{10}$ , wind speed at 10-m height; R, mean local bubble radius; F, count rate; N, number of counts; and T, record duration. Record 7 (9.3 m s<sup>-1</sup>) was omitted owing to corruption of the tape.

		R	95% C.I.			
$U_{10} \ ({\rm m \ s^{-1}})$	No.	(mm)	$R \pm (mm)$	$F(s^{-1})$	N	$T(\mathbf{s})$
12.8	4	1.33	0.09	0.42	498	1198
12.9	3	1.49	0.08	0.57	680	1198
13.2	6	1.48	0.09	0.56	644	1198
13.7	5	1.43	0.08	0.54	644	1198
15.0	2	1.53	0.07	0.78	932	1198
19.8	1	1.77	0.07	1.55	1860	1198

breaking, as verified by the synchronized video. Thus, the total number of waves N was assumed to be

$$N = t f_p, \tag{7}$$

where as before t is the record duration and  $f_p$  is the spectral peak frequency for each wind speed.

In BYB it was suggested that the dominant breakers account for waves from a frequency bandwidth of

$$f = f_p \pm 0.3 f_p,\tag{8}$$

because this is the width of the spectral peak representing the modulation properties of the nonlinear groups that lead to dominant breaking (Banner and Tian 1998). In the present analysis, it was found that the bandwidth given by (8) slightly underestimates  $b_T$  rates compared to those of BYB. In Fig. 11, the two  $b_T$  rates are compared for a frequency bandwidth of

$$f = f_p \pm 0.35 f_p.$$
 (9)

Given the limited number of records (the BYB set consisted of 26 records), the comparison is very good, with a correlation of 93%; the mean ratio of the two is 1.01. This shows that the two methods consistently detect dominant breakers and suggests that a range given by (9) rather than (8) defines the spectral peak band driving the evolution of wave groups leading to dominant breakings.

#### b. Frequency distributions of breaking probability

The method now was applied to estimate the breaking probability at wave frequencies beyond the spectral peak, and to obtain the distribution of breaking probability  $b_T(f)$  with wave frequency. To do that, the number of waves at each frequency N(f) had to be redefined. It is clear that, if the waves of any given period 1/fare counted by the zero crossings in a wave record of duration t, the resulting count  $N_c(f)$  will be less than the nominal reference count N(f) given by (7), because in real seas, waves of periods different than 1/f will occupy some part of the duration t. It would not matter if the ratio  $N_c(f)/N(f)$  were constant across the frequency and therefore the crest count were simply proportional to the reference count. This is, however, not the case.

Banner et al. (2002) demonstrated that if the bandwidth  $\Delta f = \pm 0.3 f_c$  were chosen for a central frequency  $f_c$  in their experiment,  $N_c(f)/N(f)$  was about 0.65 at the spectral peak  $(f_c = f_p)$  and gradually decreased for higher frequencies  $(f_c > f_p)$ , asymptoting to 0.2 at  $f_c/f_p$ > 2. The ratio also depended on the choice of bandwidth. Therefore, to avoid this uncertainty, the break-



FIG. 10. Time series of water elevation: (top) zero crossings  $(\bigcirc)$ ; crests (+); and troughs  $(\times)$ . (bottom) Water elevation with superimposed histogram of count of detected bubbles within 0.25-s intervals at the optimal breaking-detection discriminant.

ing probability  $b_T$  used in the present paper was redefined as

$$b_T(f) = n(f)/N_c(f),$$
 (10)

where  $N_c(f)$  was the number of waves counted by the zero-crossing analysis within the bandwidth:

$$f = f_c + 0.1 f_p,$$
 (11)

with the set of central frequencies being

$$f_c/f_p = 0.8, 1.0, 1.2, 1.4, 1.6, 1.8, 2.0.$$
 (12)

Shown in Fig. 12 is the wave power spectrum created from the surface elevation data, and the breaking probability,  $b_T$  as a function of wave frequency for a 19.8 m s<sup>-1</sup> wind speed (record 1 of Table 1). The breaking distribution in the top panel of Fig. 12 was normalized so that it matches the spectral density at the peak frequency. This was done purely to make comparison of the two curves easier. The  $b_T(f)$  curve in the bottom panel is bracketed by two lines, which are the calculated 95% confidence intervals on  $b_T(f)$  (Walpole and Meyers 1978). Although the  $b_T$  curve only covers a fraction of the frequency spectrum, it is clear that the downward trend in breaking probability with wave frequency is statistically significant.

# 5. Application to wave-breaking probability and severity

# a. Lake George breaking probability: Analysis and discussion

Figures 13–14 present more derived analyses made convenient by the passive acoustic method. Even though these figures are only intended to demonstrate the potential of the passive acoustic method, it is worth pointing out some apparent features of the physics that have hardly been examined experimentally before.

In Fig. 13, distributions of  $b_T(f)$  are plotted versus relative frequency  $f/f_p$  for records 1–6 of Table 1, which correspond to different wave spectra developed under different wind speeds. In Lake George's bottomlimited environment, well-developed and even fully developed waves can be still strongly forced (Young and Verhagen 1996) and therefore are expected to break at the spectral peak.

The two higher wind speed cases clearly exhibit higher breaking rates across all of the spectrum (Fig. 13, top panel), whereas the other four records, with wind speeds below 14 m s<sup>-1</sup>, tend to merge. The dependence of  $b_T$  on the wind speeds is supposed to be indirect, via the dependence of the spectral density on the wind (BYB; Banner et al. 2000, 2002). Whatever the dependence, this plot suggests that much higher dissipation



FIG. 11. Comparison of breaking probabilities calculated by the present automated method and by a manual method (BYB).

rates for strongly wind-forced wave spectral components should be expected, owing to their frequent breaking for wind speeds such as those at 15 m s<sup>-1</sup> and above.

Out of the six wave records analyzed, only the first one (19.8 m s<sup>-1</sup> mean wind speed) corresponds to full development for the given water depth (I. R. Young 2005, personal communication). Therefore, although the waves are strongly forced, the wave spectrum will not develop further: the total wave energy will not grow and the spectral peak will not shift to lower frequencies. Since both the wind and the nonlinear interactions keep pumping energy into those lower frequencies, it must be rapidly dissipated at the lower frequencies due to interaction of the longer waves with the bottom and subsequent breaking. This is shown by the upper curve in Fig. 13: nearly 100% breaking is measured for frequencies below the spectral peak.

Breaking rates  $b_T(f)$  normalized by their respective spectral densities P(f) are shown in Fig. 13 (bottom panel). At the spectral peak, these normalized breaking rates collapse together very clearly, and stay separated both above and below the peak. Detailed investigations of the connection between breaking rates and the spectrum are beyond the scope of the present paper. However, according to Fig. 13 (bottom panel), if there is a linear or quasi-linear dependence of  $b_T$  on P(f), it would only be applicable at the spectral peak. Away from the spectral peak other effects make the dependence of  $b_T$  on P(f) nonlinear.

# b. Lake George breaking severity: Analysis and discussion

Though the laboratory results in section 2e are preliminary, there was a further, supporting suggestion that mean bubble size R is related to breaking severity. This was simply the correlation in Fig. 9 between R and wind speed, coupled with the inferred, though admittedly indirect, link between wind speed and breaking severity. Higher wind speeds imply both more frequent and more severe breaking. Since R does not depend on how many waves broke, the correlation in Fig. 9 points to a relation between R and severity. Assuming R is a valid proxy for local breaking severity, further derived analyses of the Lake George data are shown in Fig. 14.

In Fig. 14, the three subplots demonstrate a dependence of the severity-related parameters on wave frequency. The mean bubble size distribution with wave frequency, R(f), shows that the largest bubbles were produced by breakers at the highest wind speeds and the smallest bubbles were produced under the lightest winds. These details expand and reinforce the spectrally averaged result of Fig. 9.

It was suggested above that the larger bubbles correspond to more severe breakers. If so, the product of the mean bubble size R(f) and the breaking rate  $b_T(f)$ 





FIG. 12. Wave power spectrum and breaking probability vs wave frequency f: (a) wave power spectrum P(f) and (b) wave-breaking probability  $b_T(f)$ .

should be related to the respective dissipation rate at f. The dissipation rate will have other dependencies, including the properties of the wave spectrum that do not necessarily involve bubble formation. The distribution of  $b_T(f)R(f)$  is shown in Fig. 9b, and  $b_T(f)R(f)$  normalized by the spectral density P(f) is shown in Fig. 9c. The characteristics of these distributions are similar to those of  $b_T(f)$  in Fig. 13.

Two points are worth noting. First, the breaking severity appears quasi-linear with wind speed at the spectral peak. Second, as observed in section 5a for the breaking probabilities, the breaking severity is higher below the spectral peak than at the spectral peak, for the fully developed Lake George waves.

### 6. Conclusions

A simple passive acoustic method of analyzing breaking waves was developed, based on isolating individual pulses of sound from the underwater noise created by breakers. The method has two basic outputs as a function of time: the count rate of bubble detections, and

FIG. 13. Breaking probabilities vs wave frequency f normalized to the peak frequency  $f_p$  for (a)  $b_T$  and (b)  $b_T$  normalized by the spectral density P(f): 12.8 ( $\Box$ ), 12.9 (\*), 13.2 ( $\nabla$ ), 13.7 ( $\diamond$ ), 15.0 ( $\times$ ), and 19.8 m s<sup>-1</sup> ( $\bigcirc$ ).

the average bubble size near the hydrophone (the mean local bubble size). The outputs can be generated in an automated fashion in real time.

The method's first output, the detection rate, can be appropriately "trained" by a classification-accuracy analysis to identify when waves break, enabling further analyses. In this present first attempt, the identification of breaking waves was found to be approximately 70%-75% accurate once the classification-accuracy analysis had determined an optimum discriminant. This detection of breakers was then used to determine breaking probability as a function of wave frequency. Checks showed this had a correlation of 93% with earlier laborious manual calculations on the same sequences (BYB), suggesting that the automated and manual methods share a similar classification accuracy. The present results showed that the probability of a wave breaking is higher for the highest wind speeds across all of the spectrum.

The classification-accuracy analysis detailed here ought to be applied in further field experiments, covering a wider range of wind-wave environments than



FIG. 14. Breaking severity analyses vs wave frequency f normalized to the peak frequency  $f_p$  for (a) breaking severity assumed as bubble radius R, (b) product of breaking severity R and breaking probability  $b_T$ , and (c) product of breaking severity R and breaking probability  $b_T$  normalized by the spectral density P(f): 12.8 ( $\Box$ ), 12.9 (\*), 13.2 ( $\nabla$ ), 13.7 ( $\diamond$ ), 15.0 ( $\times$ ), and 19.8 m s<sup>-1</sup> ( $\bigcirc$ ).

were available in Lake George. If in each future field experiment, synchronized surface video and underwater audio records were made with the same equipment and settings (e.g., with the hydrophone the same distance below the surface and the camera the same distance above), the classification-accuracy analysis could be repeated on several datasets from a wider range of sea state environments than studied here. If the classification accuracy of 75% is not worsened, it would suggest the discriminant (in sound pressure amplitude at the hydrophone) has a universality.

The method's second output, the mean local bubble size, was found to increase with wind speed. Since breaking severity—the energy lost in a breaking event—is thought to be related to wind speed, it could be inferred that bubble size was related to breaking severity. This inference was reinforced by a laboratory experiment, showing the mean local bubble size determined by the present method increasing with breaking severity. Thus, it is possible that the method could also be used to measure breaking severity.

Although the results are preliminary, examples of how this method might be exploited were developed. The breaking probability and severity were found to be nearly linearly dependent on the spectral density at the spectral peak; this sort of dependence is not supported at other wave frequencies. For the fully developed Lake George waves, the breaking probability reaches nearly 100% at frequencies below the spectral peak, and dropped for frequencies higher than the spectral peak. This indicates a physically realistic result: for this environment, the wave spectrum development was arrested by interaction with the bottom. It is possible that combinations of the breaking probability and breaking severity distributions could lead to direct estimates of the spectral distribution of wave dissipation.

The method has promise for easy, real-time application in an ocean-monitoring context, utilizing standard hydrophones. However, the data presented here are not universal and are subject to some uncertainties that may bias the method, such as a propensity to detect signals from larger breakers farther away. Substantial research is required to advance this method, probably including systematic laboratory and ocean studies of the sounds under breaking waves.

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# APPENDIX A

#### **Errors Inherent to the Method**

Variations in wave conditions were an important source of random error. From observations of the video

17		Capillary	Gravity waves		
$({\rm m}{\rm s}^{-1})$	No.	coverage (%)	"Chop"	"Swell"	
9.3	7	20	Small only	None	
12.8	4	90	Prevalent	Occasional	
12.9	3	90	Occasional	Prevalent	
13.2	6	70	Prevalent	Rare	
13.7	5	70	Prevalent	Rare	
15.0	2	100	Very prevalent	Very prevalent	
19.8	1	100	Heavy	Heavy	

 TABLE 3. Qualitative descriptions of wave conditions based on video record observations.

record, it was clear that there was a broad spectrum of wavelengths ranging from "swell" to "chop," and small capillary waves. Qualitative observations indicated that the types of waves varied from segment to segment; a brief description is provided in Table 3.

The larger waves found at higher wind speeds produce a more energetic breaking event. Indications are that the corresponding bubbles generated are larger (Fig. 9) and larger bubbles are known to produce higher-amplitude sounds (Pandit et al. 1992; Manasseh et al. 2001). This means that the hydrophone is able to detect larger breaking waves from farther away. Therefore, there is a higher probability of detecting larger waves. Although there are methods of correcting for such biases (Chanson and Manasseh 2003), these were not applied in the present, comparatively simple analysis. Also, there would be a poorer specificity (more false negatives) because sounds from distant out-ofview breakers could be associated with the local, nonbreaking wave. The converse problems would occur for the smaller, less energetic breakers. A more detailed study determining the smallest breakers detectable at the optimal discriminant as a function of distance from the hydrophone would help reduce these uncertainties.

In comparing the breaking data with the wave height data (section 4), it appeared that, at times, breaking was predicted when a trough was present at the array measuring the height. There was a slight separation between the location of the hydrophone and the capacitance gauges, suggesting a trough could have been at the array while a breaking crest was above the hydrophone. However, the separation is only of the order of 10 cm and, thus, not large enough to be the cause of this error. Rather, it may be due to the hydrophone detecting loud breakers some distance out of view.

Another issue is bubble generations caused by interactions of waves with the supports of the pier housing the equipment. Occasions were noted when large wave crests were passing the supports and sound pulses were being detected. Possibly, bubbles could have been generated from the wave entraining air in its interaction with the supports. Although this was not frequent enough to significantly alter the results, anomalies became obvious when comparing the breaking data with the wave height time series.

#### APPENDIX B

#### **Issues with the Zero-Crossing Analysis**

The  $b_T(f)$  curve is shown up to a wave frequency of 0.7 Hz because it was found that the present zerocrossing analysis becomes noisy above that level. Random shifting of the breaking detection time series relative to the wave signal was used to find the frequency where the noise of the zero-crossing procedure began to have an impact. A manual wave-by-wave analysis revealed that the present passive acoustic method is nonetheless capable of detecting waves as short as 6 cm (5 Hz) breaking near the hydrophone. The automated analysis, however, has to rely on both the acoustic method and the zero-crossing procedure. The zerocrossing procedure cannot consistently resolve short waves riding larger ones.

Since the passive acoustic method can detect small breakers, the frequency interval of  $b_T$  distributions could potentially be extended if the zero-crossing procedure were improved. A better bandpassing procedure can force the short waves to zero-cross and thus be detected. A superior alternative, preserving the wave shape, would be a riding-wave removal (RWR) method (Gemmrich and Farmer 1999; Banner et al. 2002). An ambiguity, however, would be introduced if multiple wave scales were present simultaneously: is it the long wave, or the short one riding it that is the breaker? This could be overcome by combining the analyses of RWR and passive acoustic data, but this refinement of the procedure is beyond the scope of the present paper.

#### REFERENCES

- Agresti, A., 2002: *Categorical Data Analysis*. 2d ed. John Wiley and Sons, 734 pp.
- Babanin, A. V., 1995: Field and laboratory observations of wind wave breaking. Second Int. Conf. on the Mediterranian Coastal Environment, Vol. 3, Tarragona, Spain, 1919–1928.
- —, I. R. Young, and M. L. Banner, 2001: Breaking probabilities for dominant surface waves on water of finite constant depth. *J. Geophys. Res.*, **106**, 11 659–11 676.
- —, I. Young, and H. Mirfenderesk, 2005: Field and laboratory measurements of wave-bottom interaction. *Proc. 17th Australasian Coastal and Ocean Engineering Conf. and the 10th Australasian Port and Harbour Conf.*, Adelaide, Australia, Engineers Australia, NCCOE, and PIANC, 293–298.
- Baldessarini, R. J., S. Finklestein, and G. W. Arana, 1983: The predictive power of diagnostic tests and the effect of prevalence on illness. *Arch. General Psych.*, 40, 569–573.
- Banner, M. L., and X. Tian, 1998: On the determination of the

onset of wave breaking for modulation surface gravity waves. *J. Fluid Mech.*, **367**, 107–137.

- —, A. V. Babanin, and I. R. Young, 2000: Breaking probability for dominant waves on the sea surface. J. Phys. Oceanogr., 30, 3145–3160.
- —, J. R. Gemmrich, and D. M. Farmer, 2002: Multiscale measurements of ocean wave breaking probability. J. Phys. Oceanogr., 32, 3364–3375.
- Bass, S. J., and A. E. Hay, 1997: Ambient noise in the natural surf zone: Wave breaking frequencies. *IEEE J. Oceanic Eng.*, 22, 411–424.
- Boyd, J. W. R., and J. Varley, 2001: The uses of passive measurement of acoustic emissions from chemical engineering processes. *Chem. Eng. Sci.*, 56, 1749–1767.
- Chanson, H., and R. Manasseh, 2003: Air entrainment processes of a circular plunging jet: Void-fraction and acoustic measurements. J. Fluids Eng., 125, 910–921.
- Chen, L., R. Manasseh, A. Nikolovksa, and C. Norwood, 2003: Noise generation by an underwater gas jet. *Proc. Eighth Western Pacific Acoustics Conf.*, Melbourne, Australia, WC21\_1-4.
- Commander, K. W., and A. Prosperetti, 1989: Linear pressure waves in bubbly liquids: Comparison between theory and experiments. J. Acoust. Soc. Amer., 85, 732–746.
- Ding, L., and D. M. Farmer, 1994: Observations of breaking surface wave statistics. J. Phys. Oceanogr., 24, 1368–1387.
- Donelan, M. A., M. S. Longuett-Higgins, and J. S. Turner, 1972: Whitecaps. *Nature*, 239, 449–451.
- Duraiswami, R., S. Prabhukumar, and G. L. Chahine, 1998: Bubble counting using an inverse scattering method. J. Acoust. Soc. Amer., 104, 2699–2717.
- Farmer, D. M., and S. Vagle, 1988: On the determination of breaking surface wave distribution. J. Geophys. Res., 93C, 3591–3600.
- Feinstein, A. R., and D. V. Cicchetti, 1990: High agreement but low kappa. I: The problem of two paradoxes. J. Clinical Epidemiol., 43, 543–549.
- Felizardo, F. C., and W. K. Melville, 1995: Correlation between ambient noise and the ocean surface wave field. J. Phys. Oceanogr., 25, 513–532.
- Fielding, A. H., and J. F. Bell, 1997: A review of methods for the assessment of prediction errors in conservation presence/ absence models. *Environ. Conserv.*, 24, 38–49.
- Gemmrich, J. R., and D. M. Farmer, 1999: Observations of the scale and occurrence of breaking surface waves. J. Phys. Oceanogr., 29, 2595–2606.
- Holthuijsen, L. H., and T. H. C. Herbers, 1986: Statistics of breaking waves observed as whitecaps in the open sea. J. Phys. Oceanogr., 16, 290–297.
- Huberty, C. J., 1994: *Applied Discriminant Analysis*. John Wiley and Sons, 466 pp.
- Jessup, A. T., W. C. Keller, and W. K. Melville, 1990: Measurements of sea spikes in microwave backscatter at moderate incidence. J. Geophys. Res., 95, 9679–9688.
- —, C. J. Zappa, M. R. Loewen, and V. Hesany, 1997: Infrared remote sensing of breaking waves. *Nature*, 385, 52–55.
- Katsaros, K. B., and S. S. Atakturk, 1992: Dependence of wavebreaking statistics on wind stress and wave development. *Breaking Waves*, M. L. Banner and R. H. J. Grimshaw, Eds., Springer, 119–132.
- Kerman, B. R., 1988: Sea Surface Sound: Natural Mechanisms of Surface Generated Noise in the Ocean. Kluwer Academic, 639 pp.

- —, 1992: Natural Physical Sources of Underwater Sound: Sea Surface Sound. Kluwer Academic, 749 pp.
- Knudsen, V., R. S. Alford, and J. W. Emling, 1948: Underwater ambient noise. J. Mar. Res., 7, 410–429.
- Kraemer, H. C., V. Periyakoil, and A. Noda, 2002: Kappa coefficients in medical research. *Stat. Med.*, 21, 2109–2129.
- Lammarre, E., 1994: Void-fraction measurements and soundspeed fields in bubble plumes generated by breaking waves. *J. Acoust. Soc. Amer.*, **95**, 1317–1328.
- —, and W. K. Melville, 1992: Instrumentation for measurement of void-fraction in breaking waves: Laboratory and field results. *IEEE J. Oceanic Eng.*, **17**, 204–215.
- Landis, J. R., and G. G. Koch, 1977: The measurements of observer agreement for categorical data. *Biometrics*, 33, 159– 174.
- Leighton, T. G., 1994: *The Acoustic Bubble*. Academic Press, 613 pp.
- Loewen, M. R., and W. K. Melville, 1991: Microwave backscatter and acoustic radiation from breaking waves. J. Fluid Mech., 224, 601–623.
- Longuet-Higgins, M. S., 1989: Monopole emission of sound by asymmetric bubble oscillations. Part 1. Normal modes. J. Fluid Mech., 201, 525–541.
- Lu, N. Q., A. Prosperetti, and S. W. Yoon, 1990: Underwater noise emissions from bubble clouds. *IEEE J. Oceanic Eng.*, 15, 275–281.
- Manasseh, R., 1997: Acoustic sizing of bubbles at moderate to high bubbling rates. *Experimental Heat Transfer, Fluid Mechanics and Thermodynamics*, M. Giot, F. Mayinger, and G. P. Celata, Eds., Edizioni ETS, 943–947.
- —, 2004: Passive acoustic analysis of complex bubbly flows. Proc. 16th Int. Congress of Chemical and Process Engineering, Prague, Czech Republic, 202\_1-8.
- —, S. Yoshida, and M. Rudman, 1998: Bubble formation processes and bubble acoustic signals. *Proc. Third Int. Conf. on Multiphase Flow*, Lyon, France, 1.
- —, R. F. LaFontaine, J. Davy, I. C. Shepherd, and Y. Zhu, 2001: Passive acoustic bubble sizing in sparged systems. *Exp. Fluids*, **30**, 672–682.
- —, A. Nikolovska, A. Ooi, and S. Yoshida, 2004: Anisotropy in the sound field generated by a bubble chain. J. Sound Vibration, 278, 807–823.
- Maxworthy, T., C. Gnann, M. Kürten, and F. Durst, 1996: Experiments on the rise of air bubbles in clean viscous liquids. J. *Fluid Mech.*, **321**, 421–441.
- Medwin, H., 1989: Bubble sources of the Knudsen sea noise spectra. J. Acoust. Soc. Amer., 86, 1124–1130.
- Melville, W. K., 1996: The role of surface wave breaking in air-sea interaction. Annu. Rev. Fluid Mech., 28, 279–321.
- —, and P. Matusov, 2002: Distribution of breaking waves at the ocean surface. *Nature*, **417**, 58–63.
- —, M. Loewen, F. Felizardo, A. Jessup, and M. Buckingham, 1988: Acoustic and microwave signatures of breaking waves. *Nature*, **336**, 54–56.
- Minnaert, M., 1933: On musical air bubbles and the sound of running water. *Philos. Mag.*, 16, 235–248.
- Pandit, A. B., J. J. Varley, R. B. Thorpe, and J. F. Davidson, 1992: Measurement of bubble size distribution: An acoustic technique. *Chem. Eng. Sci.*, 47, 1079–1089.
- Phelps, A. D., D. G. Ramble, and T. G. Leighton, 1996: The use of a combination frequency technique to measure the surf zone bubble population. J. Acoust. Soc. Amer., 101, 1981–1989.
- Phillips, O. M., E. L. Posner, and J. P. Hansen, 2001: High range

resolution radar measurements of the speed distribution of breaking events in wind-generated ocean waves: Surface impulse and wave energy dissipation rates. *J. Phys. Oceanogr.*, **31**, 450–460.

- Prosperetti, A., 1988: Bubble-related ambient noise in the ocean. J. Acoust. Soc. Amer., 84, 1042–1054.
- Rayleigh, Lord, 1917: On the pressure developed in a liquid during the collapse of a spherical cavity. *Philos. Mag.*, 34, 94–98.
- Smith, M. J., E. M. Poulter, and J. A. McGregor, 1996: Doppler radar measurements of wave groups and breaking waves. J. Geophys. Res., 101C, 14 269–14 282.
- Terrill, E. J., and K. W. Melville, 2000: A broadband acoustic technique for measuring bubble size distributions: Laboratory and shallow water measurements. J. Atmos. Oceanic Technol., 17, 220–239.
- Thompson, W. D., and S. D. Walter, 1988: A reappraisal of the kappa coefficient. J. Clinical Epidemiol., 41, 949–958.
- Thorpe, S. A., 1992: Bubble clouds and the dynamics of the upper ocean. *Quart. J. Roy. Meteor. Soc.*, **118**, 1–22.

- Veron, F., and W. K. Melville, 1999: Pulse-to-pulse coherent Doppler measurements of waves and turbulence. J. Atmos. Oceanic Technol., 16, 1580–1597.
- Walpole, R. E., and R. H. Meyers, 1978: Probability and Statistics for Scientists and Engineers. Macmillan, 580 pp.
- Wenz, G. M., 1962: Acoustic ambient noise in the ocean: Spectra and sources. J. Acoust. Soc. Amer., 34, 1936–1956.
- Young, I. R., and L. A. Verhagen, 1996: The growth of fetch limited waves in water of finite depth. Part I. Total energy and peak frequency. *Coastal Eng.*, 29, 47–78.
- —, M. L. Banner, M. A. Donelan, A. V. Babanin, W. K. Melville, F. Veron, and C. McCormick, 2004: An integrated study of the wind-wave source term balance in finite-depth water. J. Atmos. Oceanic Technol., 22, 814–831.
- Zhu, Y., J. Wu, and R. Manasseh, 2001: Rapid measurement of bubble size in gas-liquid flows using a bubble detection technique. *Proc. 14th Australasian Fluid Mechanics Conf.*, Adelaide, Australia, Adelaide University, 270\_1-4.