DEEP LEARNING TO UNRAVEL NONLINEARITY IN WAVE BREAKING USING WAVE FLUME VIDEO IMAGES

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INTRODUCTION

The behavior of waves, influenced by numerous factors, becomes markedly complex as they approach coastlines and interact with seabed geometries. Simultaneously, this process involves a range of phenomena, including wave breaking, which is one of the most iconic and influential. Wave breaking is not only pivotal in shaping coastal landscapes but also has far-reaching consequences for the design and safety of coastal infrastructure. Traditional research methods, including theoretical, experimental, and numerical approaches, have sought to elucidate the intricate relationships involved in wave breaking. However, the inherent nonlinearity and transient nature of this phenomenon pose substantial challenges to understanding its natures (Goda, 2010). Departing from conventional methodologies, our research leverages the advanced capabilities of deep learning to refine data acquisition techniques and decode the intricate patterns of wave breaking, thereby advancing predictive models and management strategies for coastal environments.

WAVE BREAKING INDEX AND BREAKER TYPE

In-depth analysis of the wave breaking index and breaker types is central to our inquiry. Wave breaking index, indicating breaking wave height and breaking water depth, is critical for estimating the scale and impact location of breaking waves. Owing to their highly turbulent nature, most wave breaking index formulas have been derived empirically. These empirical equations, while reproducible, are limited by the data range used and their complexity, often leading to reduced applicability and predictive accuracy. Similarly, traditional visual assessment methods for classifying breaker types, defined by their apparent and dynamic characteristics at the moment of wave breaking, typically involve a high degree of subjectivity and inconsistency due to reliance on the observer's expertise. Moreover, with the efficacy of the Iribarren number for verifying breaker types being challenged in recent research (Moragues and Losada, 2021), there is an emerging need for innovative classification methods. Our approach seeks to mitigate these issues by utilizing advanced computational techniques, establishing a new standard for accuracy and reliability in the classification and analysis of breaking waves.

BREAKTHROUGH FOR THE NONLINEARITY OF WAVE BREAKING

Even in highly controlled laboratory settings for regular waves, a surprising degree of variability in wave breaking behavior has been observed, emphasizing the significant nonlinearity of the phenomenon (Smith and Kraus, 1990). The instantaneous feature and intense energy field of wave breaking further complicate its analysis. While wave breaking exhibits considerable variation on spatial and temporal scales, most previous studies were constrained to using spatially discontinuous data from stationary sensors. To surmount these limitations, we have developed a non-intrusive methodology that captures high-resolution data across both spatial and temporal dimensions. Leveraging the robust capabilities of deep learning algorithms, we will extract and analyze features with unprecedented detail and precision, thereby establishing a new standard for accuracy and reliability in the classification and analysis of breaking waves.

SETTINGS FOR PHYSICAL EXPERIMENT

Experimental setup was systematically constructed in a wave flume, 6 meters long, 0.25 meters wide, and 0.4 meters high, to obtain multi-angle, high-fidelity video data that mirrors the diverse conditions of real coastal environments. We acquired side-view and top-view imagery, alongside incident wave data from three wave gauges located at the toe of the slope, covering a broad spectrum of wave periods (0.8, 1.2, 1.6, and 2.0 seconds). The captured images offer a temporal resolution of 120 frames per second and a full HD spatial clarity at 1920x1080 pixels. We modeled variable bottom slopes using acrylic materials at inclines of 1/10, 1/15, and 1/20 to effectively reflect the structural and seafloor slopes found in coastal zones. Figure 1 illustrates wave flume layout, showcasing the implemented gradients and measurements designed to replicate different marine terrains. In this environment, we captured approximately 170 videos, each about seven minutes long. We introduced a dye into the water to enhance the visual contrast, aiding in the deep learning analysis of wave motion. We also strategically positioned the slopes to ensure proper alignment with the camera perspective, guaranteeing that the flume frames did not obstruct the recording of the entire wave breaking process.

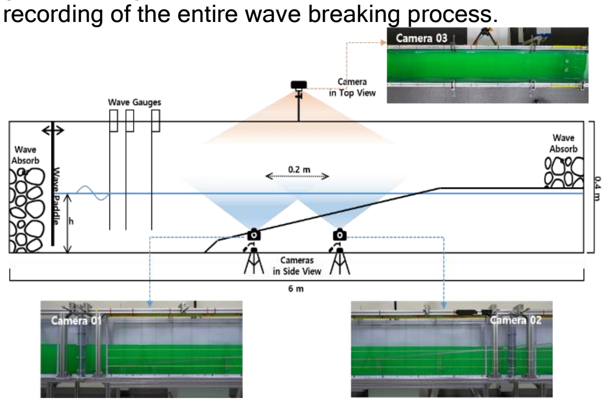

Figure 1 - Schematic diagram of the wave flume experimental design

DEEP LEARNING FOR WAVE SEGMENTATION

To extract wave breaking index and classify wave breaker types, it was essential first to extract water elevation from side-view video images. We converted pixel positions into real spatial coordinates, using fixed grids for perspective projection, with each pixel corresponding to 1 mm. Subsequently, we applied U-net based segmentation model (Ronneberger et al., 2015)–a deep neural network originally developed for medical cell tracking–to separate dynamic wave movements from static backgrounds, as shown in Figure 2. From now on, we will design another deep learning model utilizing the extracted water elevations as input data to estimate wave breaking index and classify breaker types. This ongoing work is expected to significantly enhance the quantitative analysis of wave breaking, setting a new benchmark in accuracy and reliability that far exceeds the capabilities of traditional observational techniques.

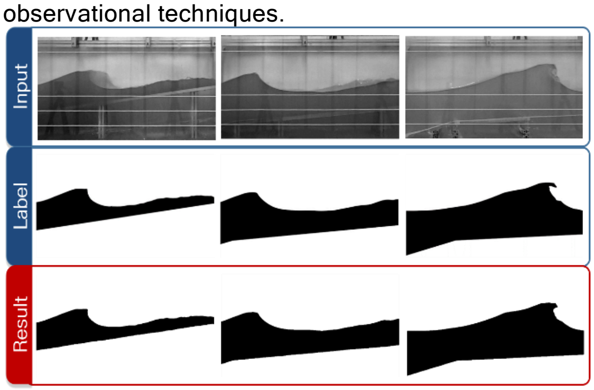

Figure 2 - Water elevation segmentation output using modified U-net based deep learning model

CONCLUSION

The application of deep learning in our wave breaking study marks a progressive development in coastal engineering, providing clarity on the processes involved and introducing new academic and practical insights. By employing consistent criteria for the extraction of wave breaking features through deep learning analysis, we aimed to minimize subjectivity, thereby ensuring greater objectivity in our findings and future applications while reducing dependence on specialized expertise. This approach also has the potential to enhance the value of video data and broaden the application of non-intrusive measurement techniques. The research carries important implications for the design and maintenance of coastal infrastructure and contributes to the sustainable management of coastal environments. Our findings are poised to make a substantive contribution to the field, illustrating the effective integration of sophisticated computational methods with conventional scientific inquiry.

ACKNOWLEGMENT

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