2024

BOOK OF ABSTRACTS

[EDITORS, EDITORS EDITORS]

[lorem ipsum dolore]

Heading

DGTMP’24 Nexus International Conference: Book of Abstracts

Coordinators

[lorem ipsum dolore]

Design and Layout

Maria Camila Marinho and [lorem ipsum dolore]

Cover

Sandra Filipe and Maria Camila Marinho

Publisher

[lorem ipsum dolore]

ISBN

[lorem ipsum dolore]

DOI

[lorem

Index | Table of Contents

Authors(s)	Title	Page

Article

Automated Wave Height Estimation and Overtopping Detection from Coastal Video Data

Ngene, T.[1,] *, Santos, F.[1], Abreu, T.[2], Silva, P.A.[3], Cunha, T.R.[4], Baptista, P.[1]

[1] Centre for Environmental and Marine Studies (CESAM) and Department of Geosciences, University of Aveiro, Aveiro, Portugal; ngene@ua.pt, fabioacsantos@ua.pt; renato.baganha@ua.pt
[2] Centre for Environmental and Marine Studies (CESAM) and Department of Civil Engineering, Polytechnic of Porto, Porto, Portugal; taa@isep.ipp.pt
[3] Centre for Environmental and Marine Studies (CESAM) and Department of Physics, University of Aveiro, Aveiro, Portugal; psilva@ua.pt
[4] 4) Department of Electronics, Telecommunications and Informatics, University of Aveiro – Instituto de Telecomunicações, Aveiro, Portugal; trcunha@ua.pt

* Correspondence: ngene@ua.pt; Tel.: +351920563022

Citation: To be added by editorial staff during production.

Academic Editor: Firstname Lastname

Received: date
Revised: date
Accepted: date
Published: date

Abstract: Coastal zones, prone to complex morphodynamic processes and extreme oceanic events, require continuous monitoring of parameters like wave height and overtopping events. Video monitoring systems have proven to be a reliable way to automatically detect, and extract features essential for effective coastal monitoring and management. This study compares and evaluates two methods for wave height estimation across various image regions and introduces a Deep Learning architecture for automatic wave overtopping detection, analyzing foam movement patterns in video data. For wave height estimation, the results show an average absolute difference of the significant wave height (Hs) of 0.1 meters between the two methods in the selected regions of interest (ROI), indicating strong agreement in the developed approaches. Regarding wave overtopping detection, the developed model demonstrates strong performance, achieving high precision (0.97) and specificity (0.97). It exhibits robust classification accuracy and generalization, as indicated by both an F1-score and an AUC-ROC (Area Under the Receiver Operating Characteristic Curve) of 0.94, highlighting its effective identification of wave overtopping events while minimizing false positives. These findings promise enhanced understanding of coastal dynamics, supporting effective infrastructure planning and disaster mitigation strategies, crucial for improving coastal management and resilience against natural disasters.

Keywords: Video-monitoring; Wave Height Estimation; Wave Overtopping Detection; Image Processing; Deep Learning

1. Background/Introduction

Coastal zones are integral to human development due to their economic and social importance. These regions experience dynamic processes over multiple temporal scales, ranging from short-term events like wave breaking and currents to long-term changes driven by climate variability. Owing to their economic value and level of urbanization, continuous monitoring is vital for understanding and forecasting the processes and impacts of human interventions, thereby ensuring coastal stability and sustainable development.

While traditional in situ measurements face challenges in cost and practicality under adverse conditions, video monitoring systems have emerged as cost-effective, reliable tools since the 1990s, offering continuous data collection and targeted observations despite operational limitations. Unmanned Aerial Vehicles (UAVs) are increasingly used in coastal monitoring due to their versatility, despite limitations in data acquisition time.

Coastal video monitoring systems have played a crucial role in morphodynamic studies, utilizing specialized image types like Timex, Variance, and Timestack. Traditional image processing methods involve techniques such as segmentation, edge detection, and texture analysis, but these can be limited by manual parameterization and environmental complexity. Recent advancements, particularly in Deep Learning (DL), have shown promise in coastal video analysis by automating the extraction of features from extensive video databases, thereby eliminating the need for manual intervention.

This study compares and evaluates two distinct methods for wave height estimation across different image regions or heights. Additionally, it introduces a novel DL architecture designed for automatic wave overtopping detection, leveraging video data to identify foam movement patterns. The integration of these methodologies is crucial for coastal management, offering validation for numerical models, enhancing wave condition monitoring, and providing essential data for predicting and preparing against coastal overtopping events. By combining these approaches, the study contributes to a comprehensive understanding of coastal dynamics and strengthens the foundation for effective coastal infrastructure planning and disaster mitigation strategies.

2. Materials and Methods

Within the scope of the NEXUS Agenda, a video camera was installed at the port of Sines. Operational since March 2024, the camera focuses on two primary goals: estimating wave heights and detecting wave overtopping at the harbor breakwater. The objective is to use the video camera installed in Sines for wave height determination and overtopping detection. However, since data from the system were not yet available (and there is insufficient data for overtopping detection), data from other locations were utilized to develop methods that will subsequently be replicated in Sines. Regarding wave height estimation, UAV video footage was captured at Costa Nova Beach on the western coast of Portugal. For overtopping detection, data from a coastal video monitoring station located at Praia dos Pescadores in Ericeira, also on the west coast of Portugal, were utilized.

2.1. Wave height estimation

For this part of the work, the video footage was obtained from Costa Nova beach at 4:15 pm on November 17, 2023, with a resolution of 3840x2160 pixels. Weather conditions during the UAV survey were favorable, with 11% cloud cover and a wind speed of 5 km/h. The wave height estimation methods employed relies on image feature segmentation, morphology, and image geometry analysis. Both methods were based on [1], which used a stadia rod to measure camera height, wave crest, trough, and still water level (SWL). Wave heights were estimated by manually extracting crest and trough points from a timestack image and scaling them with known world and image coordinates. However, this method is impractical for restricted nearshore zones and lacks automated wave crest and trough extraction. The first and second approaches use the same image processing techniques: extracting and inverting the dark areas of the image (representing wave height) to make them measurable. Wave features are measured in a symmetrical area around the optical axis. The conversion from image to world coordinates uses ground sampling distance (GSD) and camera properties like focal length and field of view. While [1] approach involves manually measuring wave crests and troughs, the second automates this process and adjusts the camera-to-image geometry for better wave height estimation.

2.2 Wave overtopping detection

Since June 2021, the Ericeira video system has been continuously capturing 10-minute videos during daylight hours, averaging 72 videos per day. The system's coverage includes the northern harbor breakwater, an area prone to overtopping. For wave overtopping detection, two primary types of deep networks were employed: Convolutional Neural Networks (CNN), specialized in extracting spatial features via convolution operations, and Long Short-Term Memory Networks (LSTM), re-nowned for their capacity to capture temporal dependencies and long-range relationships in se-quential data. The integration of CNN and LSTM within the CNN-LSTM architecture allows for concurrent processing of spatial and temporal information, rendering it extensively applicable in motion detection and classification tasks [2]. The study's methodology follows established Deep Learning procedures, including data acquisition, labeling, preprocessing, model training, hyperparameter optimization, and validation. Video footage was analyzed to extract image sequences at various times, seasons, and weather conditions. These images captured diverse foam movement patterns on a breakwater and were annotated for wave overtopping events. The dataset included 3058 labeled sequences, with 1584 showing wave overtopping and 1474 without. During the preprocessing phase, images underwent masking and cropping to isolate the specific area of interest for the study. Subsequently, they were resized to 224x224 pixels, dimensions compatible with the input requirements of the CNN employed, GoogLeNet [3]. After preprocessing, the model was trained using 85% of the videos, with the remaining 15% used for internal validation. Training involved adjusting weights over multiple epochs to improve accuracy. A CNN extracted spatial patterns from the videos, which were then analyzed by an LSTM to capture time-based relationships, enhancing detection of wave overtopping in coastal videos. Bayesian optimization refined the model's settings to maximize performance and accuracy, crucial for achieving optimal results. The final model architecture comprised a CNN (GoogLeNet) followed by a bidirectional LSTM (BiLSTM) with 1480 units evenly distributed in both directions (740 units each). This configuration integrated spatial and temporal information extracted from the videos, with the goal of accurately detecting wave overtopping events.

3. Results

3.1 Wave height estimation

For wave height estimation, the geometric correction was influenced solely by the image height, meaning that the image width had no impact on the region of interest (ROI). Consequently, a constant image width of 200 pixels was set along the optical axis. Three ROI positions were analyzed at image heights of 200-400, 400-600, and 600-800 pixels. The results demonstrate a good agreement between the two methods employed at the selected ROIs. Method 1 yields estimated H_s values of 1.37 m, 0.41 m, and 0.83 m, whereas Method 2 yields 1.47 m, 0.55 m, and 0.8 m, showing an absolute difference of 0.1 m. This demonstrates that either method can be utilized to estimate H_s in the non-breaking zone, depending on the camera and image parameters available for the application.

3.2 Wave overtopping detection

For wave overtopping detection, performance evaluation in-volved an external test set comprising 814 videos, of which 461 contained wave overtopping events and 386 did not. Similar efforts were made to ensure the representativeness and coverage of diverse conditions in the test set, mirroring those applied to the training videos. After applying the model to the test set, various performance metrics were computed to evaluate its effectiveness. The results obtained were highly satisfactory, with robust values for the calculated performance metrics: precision (0.97), recall (0.92), specificity (0.97), F1-score (0.94), AUC-ROC (0.94), and binary cross-entropy (0.21). These metrics suggest that the developed model exhibits robust capability in detecting wave overtopping events in coastal videos, demonstrating high precision and specificity. This indicates accurate identification of most wave overtopping events while minimizing false positives. Moreover, the low binary cross-entropy implies confident and well-calibrated predictions by the model. The AUC-ROC and F1-score affirm the model's effectiveness in consistently distin-guishing wave overtopping events from other coastal movements, emphasizing its strong perfor-mance in classification accuracy and generalization.

4. Discussion

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

5. Conclusions

Since their inception, coastal video-monitoring systems have proven to be highly effective and efficient tools for studying coastal zones, which, due to their propensity for complex morphodynamic processes, require continuous monitoring of parameters such as wave height and the quantification of events like wave overtopping. This study evaluates two wave height estimation methods and introduces a Deep Learning model for automatic wave overtopping detection using foam movement patterns in video data. The developed methods for wave height estimation are suitable for estimating Hs in the non-breaking zone, contingent upon the specifics of the camera configuration and prevailing environmental conditions. Further validation using hydrodynamic sensors is crucial to corroborate these findings across varied environmental conditions. This comprehensive validation approach aims to enhance the accuracy and reliability of wave height data, crucial for applications including coastal infrastructure design, climate change studies, and marine safety operations. The wave overtopping detection model showed promising results, supported by strong performance metrics. Configuring LSTM as a bidirectional layer (BiLSTM) notably enhanced the model's ability to capture complex temporal patterns in videos. Bayesian optimization for hyperparameter tuning significantly improved both accuracy and computational efficiency. However, challenges arose during evaluation, particularly in accurately detecting wave overtopping events later in the day due to their limited representation in the training set. Addressing this issue may require incorporating more diverse examples currently underrepresented in the dataset to further enhance model performance.

The integration of these methodologies enhances understanding of coastal dynamics and supports planning of infrastructure and disaster mitigation, emphasizing their practical relevance in coastal management and reinforcing strategies for resilience against natural disasters.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.". Authorship must be limited to those who have contributed substantially to the work reported.

Funding: Please add: "This research received no external funding" or "This research was funded by NAME OF FUNDER, grant number XXX" and "The APC was funded by XXX". Check carefully that the details given are accurate and use the standard spelling of funding agency names at https://search.crossref.org/funding. Any errors may affect your future funding.

Institutional Review Board Statement: In this section, you should add the Institutional Review Board Statement and approval number, if relevant to your study. You might choose to exclude this statement if the study did not require ethical approval. Please note that the Editorial Office might ask you for further information. Please add "The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board (or Ethics Committee) of NAME OF INSTITUTE (protocol code XXX and date of approval)." for studies involving humans. OR "The animal study protocol was approved by the Institutional Review Board (or Ethics Committee) of NAME OF INSTITUTE (protocol code XXX and date of approval)." for studies involving animals. OR "Ethical review and approval were waived for this study due to REASON (please provide a detailed justification)." OR "Not applicable" for studies not involving humans or animals.

Informed Consent Statement: Any research article describing a study involving humans should contain this statement. Please add "Informed consent was obtained from all subjects involved in the study." OR "Patient consent was waived due to REASON (please provide a detailed justification)." OR "Not applicable." for studies not involving humans. You might also choose to exclude this statement if the study did not involve humans.

Written informed consent for publication must be obtained from participating patients who can be identified (including by the patients themselves). Please state "Written informed consent has been obtained from the patient(s) to publish this paper" if applicable.

Data Availability Statement: We encourage all authors of articles published in scientific journals to share their research data. In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Where no new data were created, or where data is unavailable due to privacy or ethical restrictions, a statement is still required.

Acknowledgments: In this section, you can acknowledge any support given which is not covered by the author contribution or funding sections. This may include administrative and technical support, or donations in kind (e.g., materials used for experiments).

Conflicts of Interest: Declare conflicts of interest or state "The authors declare no conflicts of interest." Authors must identify and declare any personal circumstances or interest that may be perceived as inappropriately influencing the representation or interpretation of reported research results. Any role of the funders in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript; or in the decision to publish the results must be declared in this section. If there is no role, please state "The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results".

References

[1] J. Colvin, S. Lazarus, and M. Splitt, "Extracting nearshore wave properties from video: A new method for coastal estuaries," Estuar Coast Shelf Sci, vol. 246, Nov. 2020, doi: 10.1016/j.ecss.2020.107053.

[2] K. Xia, J. Huang, and H. Wang, “LSTM-CNN Architecture for Human Activity Recognition”, doi: 10.1109/ACCESS.2020.2982225.

[3] C. Szegedy et al., “Going deeper with convolutions,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 1–9. doi: 10.1109/CVPR.2015.7298594.