VIDEO-BASED FLOOD AND SWASH MAPPING – AN APPLICATION OF DEEP-LEARNING TO NEARSHORE RESEARCH

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INTRODUCTION

Many of the 1 billion people living in coastal areas lower than 10 m above sea level worldwide are at risk from changing climate and increasing storm intensity. Efficient and accurate mapping of coastal inundation and wave runup is of societal significance, benefiting flood hazard mitigation and climate change adaptation. Conventional methods of flood monitoring rely on in-situ water level gages installed in rivers and along the coasts. Such field measurements are sparse, and thus are unable to resolve spatial variations of coastal flooding and wave runup on beaches and structures. Recent advances in computer vision technology powered by deep-learning algorithms enable real-time flood detection and quantification using photos and videos that are widely available from traffic cameras, webcams, social media, and un-crewed aerial vehicles (Jafari et al. 2021, Liang et al. 2023). Although use of video for flood monitoring is recent, videos from cameras mounted on shore-based towers have been employed for decades by the nearshore community to monitor the surf and swash zones and to quantify wave runup on the beach. However, automated edge detection methods used to track the moving edge of the swash typically require manual quality control post-processing, which restricts the ability to monitor wave runup over large numbers of transects and long periods of time. The goal of this study is to overcome the limitations of conventional methods of flood and swash monitoring by leveraging a new deep-learning framework for efficient mapping of inundation and swash motion at the water and land interface.

METHODOLOGY

A novel deep-learning framework is developed for flood and swash mapping based on videos of flooding and wave runup. The kernel of this system is a Convolutional Neural Network (CNN) model that leverages advanced algorithms, such as Adaptive Feature Bank (AFB) and Uncertain-Region Refinement (URR), for water and land or water and surrounding reference object segmentation (Liang et al. 2021, Liang et al. 2023). AFB-URR automatically adjusts the learned features from previous frames of video images to encompass changes of the object's appearance. This allows the CNN model to exploit the temporal correlations of video images and robustly propagate segmentation (masks) of water or other appearance of volatile objects to subsequent frames in long videos. The workflow (Fig. 1) of the video-based flood and swash mapping system using deep-learning algorithms takes a raw video (or an image) as the input. Depending on the source of the video, there are two pathways of water segmentation. For videos with unknown camera properties and configurations, the water region and reference objects are detected and segmented from the raw image and their interface is identified. Then, a template matching module aligns the detected object emergent in the flood water with its standard reference template, such as stop signs, houses, and humans, which is used to rectify the view angles and poses, and estimate the inundation depth (Liang et al. 2023). For videos with known camera viewing angles and poses, the second pathway of water segmentation is as follows.

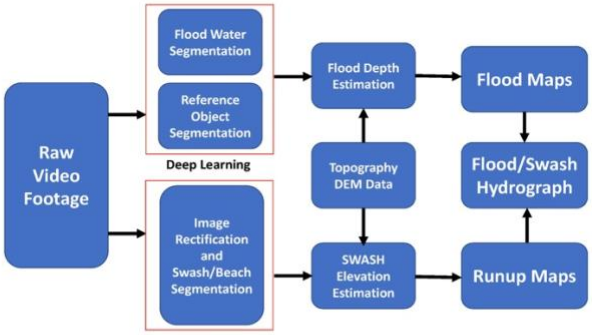

Fig. 1 Workflow of video-based flood and swash mapping system using deep-learning algorithms.

Frist, photogrammetry is used to rectify the raw video image to a reference plane. The contrast and brightness of rectified images are improved through an image enhancement algorithm. The processed video images are then segmented by the deep-learning algorithms to obtain horizontal swash motion followed by the conversion of the horizontal swash motion to the topographic data to obtain the vertical swash motion. After that, the 2% exceedance of wave runup in a random swash time series at any cross-shore transect can be obtained by performing a statistical analysis on the vertical swash time series along an entire shoreline covered by the video (Salatin et al. 2023).

RESULTS

Reconstruction of Tides from Videos in Boston Harbor

The flood and swash mapping system has been tested on several long videos to demonstrate its robustness in varying weather, illumination, and surf conditions. The first test uses publicly available video recording of tides in the Boston Harbor obtained with a camera mounted on the Tea Party Museum Ship. Continuous videos were downloaded one frame per ten minutes (Fig. 2 includes one frame of the downloaded video and the segmentation result). When no salient reference objects are detected in the video, the system allows users to adopt one of two interactive mechanisms for flood height estimation: (1) A user can select four points to represent the horizontal and vertical axes, then the system uses them to estimate a perspective transformation to calibrate the scene; and (2) a user can pick an arbitrary region in the scene as the reference. Adopting the second mechanism, a region on the background building was selected and tracked. Then, pixels in the videos were converted to physical units. Tracking water levels in these videos is challenging, due to two main reasons: (1) Different weather and illumination conditions result in continuous changes in the water appearance; and (2) the water regions are often occluded by other moving objects (e.g., ships, people). The flood mapping system effectively detected and segmented water regions in such situations (bottom panel in Fig. 1) where the reconstructed tides are in good agreement with the observations at the nearby tide station.

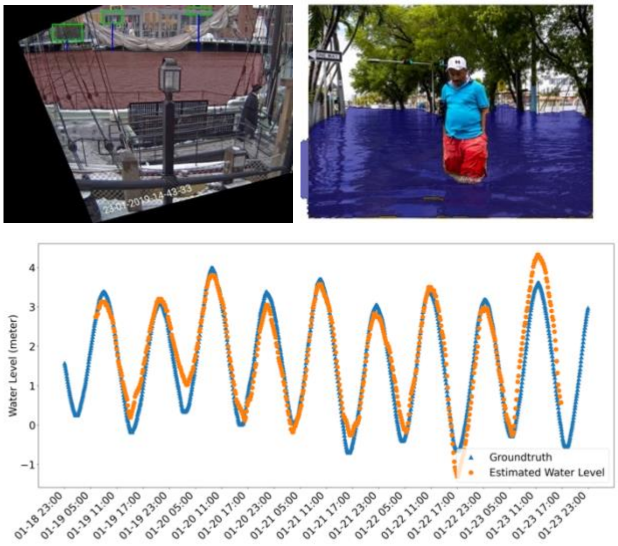

Fig. 2 Field tests of the flood mapping system. Left top panel shows the water segmentation (brown mask), reference marker (green boxes), and the reconstructed (red dots) and measured (blue curve) tides in Boston harbor in the bottom panel. The right top panel shows the segmented flood water (blue mask) and the reference object (person) during Tropical Storm Alex (2022) in Miami.

Quantifying Alongshore Variability of Swash Motion

One advantage of the novel swash mapping system is the ability to quantify alongshore variability of wave runup. The system was tested using videos on the Atlantic Ocean beach near Duck, NC to estimate swash excursions along the shoreline. The CNN model was trained with 16 images of the swash zone, and then used to estimate swash excursions for four 1-hour sets of 2 Hz images (Fig. 3). The spectra of swash excursions, significant swash heights, wave setup, and the 2% exceedance values of runup estimated by the CNN model agree reasonably well with those estimated by a scanning lidar (Fig. 3, bottom panel). Although the results are promising, improved image rectification and better synchronized topographic and bathymetric data would enhance the accuracy of wave runup estimated by the flood and swash mapping system.

CONCLUSIONS

A video-based flood and swash mapping system was developed by leveraging a novel deep-learning framework. The system agrees well with in-situ measurements of water levels in Boston Harbor and swash motion along an Atlantic Ocean beach. The new system is capable of adaptively detecting the appearance change of water in video images under dynamic or noisy and varying weather and lighting conditions. It is able to handle videos of urban flooding, as well as wave runup and rundown on the beach in combination with a digital elevation model of topography.

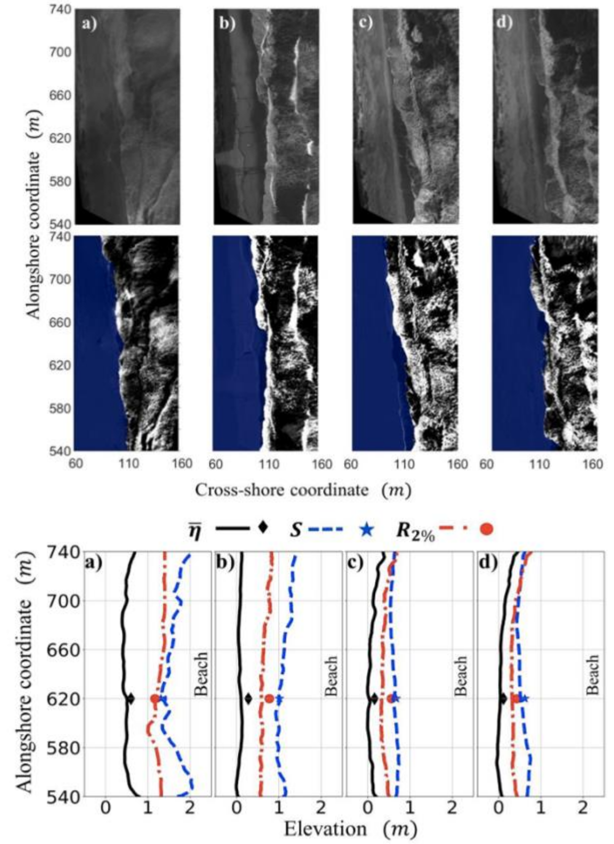

Fig. 3 Raw video frames (top panels) and segmentation of processed video frames (middle panels) for four test cases, and CNN- (curves) and lidar- (symbols) estimated runup significant swash height (dashed blue curves, blue stars), the 2% exceedance value of runup (dash-dotted red curves, red circle), and setup (solid black curves, black diamond) as a function of the alongshore coordinate (bottom panels).

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