AI-supported Citizen Science to Monitor High-Tide Flooding in Newport Beach, California

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Abstract

Monitoring High-tide Flooding (HTF) is challenging because HTF usually spreads widely and forms localized water accumulations depending on the natural processes and infrastructure. Stationary monitoring systems and satellite imaging have their certain limitations. To date, citizen science is considered as the most promising means to monitor HTF, which provides wide and continuous coverage of the community and real-time first-hand witness of the flooding event. Here, we present a flexible Artificial Intelligence (AI) -supported citizen science platform for HTF monitoring. Flood extent is identified through standard photogrammetry algorithms and a Computer vision technique called monoplotting, and water depth can be estimated using reference objects. In this paper, monoplotting is employed to establish a correlation between photos and the corresponding digital elevation model (DEM) data, allowing to map the flood extent and water depth to the DEM map to minimize the data uncertainty and enhance the data credibility, resolution, and overall value.

CCS Concepts: • **Computing methodologies → Artificial intelligence; Computer vision tasks; Scene understanding**.

Keywords: High tide flooding, computer vision, monoplotting, flood extent estimation

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1 Introduction

Relative sea-level rise is increasing flooding frequency worldwide [9]. Besides the emphasized extreme floods such as those from tropical storms, tidally driven flooding gives rise to shallow (several centimeters) and wide-spreading floods, which are far less documented, analyzed, and understood [11]. NOAA (National Ocean and Atmospheric Agency) reported that the relative seal-level rise along US coastlines has risen by 0.34 m since 1920 and about 4 centimeters higher than 2018; 75% of the 62 US East and Gulf Coast locations witnessed an accelerating increasing trend of HTF [12]. According to the report, New Jersey is one of the most affected states, where NOAA recorded 20 and 22 days of HTF at Sandy Hook and Atlantic City in 2017, and 14 days at Cape May in 2009. Last year, the national median HTF reached 4 days annually at the 98 monitored sites, and the New Jersey sites reported up to 11 days of HTF, much greater than the national median, and are projected to reach up to 160 days of HTF annually by 2050 [12]. The increasing trend of HTF is also evidenced by the evolving tidal ranges in the major US estuaries. Talke and Jay [13] compiled the tidal records of major estuaries and found the tidal ranges have doubled in certain locations.

As a major contributor to "nuisance flooding" or "sunny day flooding", HTF disrupts transportation, sewage, and other infrastructure systems, devaluates real estates, reduces income and jobs, exposes health hazards to heighten public health risks, and salinizes groundwater to deterioration coastal ecosystems [8]. Because HTF is a repeating and chronical hazard, the disruption heavily impacts on local economic activity. For example, in Annapolis, Maryland, HTF has reduced downtown visits by 1.7% in 2017, which costs $12 million revenue loss in 16 surveyed businesses [5]. The visits will further reduce by 24% with the projected sea-level rise of 12 inches and make major impacts on the local community [5]. These relatively more frequent, smaller floods may prove to be more costly at some locations than large, infrequent extreme events [8]. High-quality and wide-coverage data is urgently desired to support further and systematic environmental and social studies.

Monitoring HTF is challenging because HTF usually spreads widely and forms localized water accumulations depending on the natural processes and infrastructure. Stationary monitoring systems such as tidal and river gauges can only capture a small fraction of the occurrence due to their fixed location; satellite imaging is limited by orbits and spatial and temporal resolution, so the chance of capturing the short-term HTF with the right timing, acquisition location, and sufficient resolution is considerably low. To date, citizen science – an approach to collecting data through the participation of the general public [1] – is considered the most promising means to monitor HTF, which provides wide and continuous coverage of the community and real-time first-hand witness of the flooding event [8]. Moreover, HTF is more suitable to be studied by citizen science because of less weather constraints and better predictability. Besides the high value in education and outreach activities, citizen science has shown exceptional value in providing key data for earth observation, especially in collecting flooding data and supporting flood management. For example, systems have been developed to receive water level readings through mobile phone messages [7], web-based text inputs [10], and image uploading [6]. The present project is targeted to address the data gap of HTF observation using citizen science. In this study, a novel citizen-science based approach is proposed to develop a comprehensive map of flooded area containing information about flood extent and water depth. In this regard, flood extent estimation as one of the tasks of this approach, is elaborated and a sample result is presented for the recent HTF event in Newport Beach, California in July 2020.

2 Research Methods

In order to develop a flood map by means analyzing of photos and videos in social media the two different tasks of (i) estimation of flood water depth, and (ii) estimation of flood extent should be carried out by different methods.

2.1 Flood Water Depth Estimation

To further increase the value of citizen contributed data, we plan to develop a deep learning model to automatically assess water depths from collected photos using reference objects. This method would be more accurate than the manually estimation of water depth based on the approximate size of available objects in the photos because humans have difficulty to quantify water level by visual examination. According the method developed by Chaudhary et al. [3], it is proposed to consider k discrete levels for water depth in a way that level 0 indicates no flood water and level (k-1) means that the water level is beyond the average human height (170 cm). The classification is compared with reference objects of the average human height. Water depth can be gauged using the reference object such as car wheels, bicycles, curbs, human heights, traffic signs, safety cones, etc. A deep learning model will be trained to recognize the kind of the reference object such as safety cones, humans, or car wheels. The percentage of the object submerged will be converted to water depth using a database of typical object heights.

2.2 Flood Extent Estimate

There are some studies in the literature that working on the estimation of flood extent. In this regard deep learning models were employed to detect the flooded area in photos. By means of pre-trained neural network with logistic regression the flooding extent can be reliably detected in the photos after sufficient training [2]. However, this method is not able to convert the extracted information to geo-referenced data that can be presented in a map. In this regard, a major issue affecting citizen science's data reliability and credibility is the mismatch between the location of observed scene and the location of the data collection device, e.g. the mismatch between the location of the observed object used to estimate water depth and the location of smart phone. A computer vision technique called monoplotting is proposed to address this issue and also estimating flood extent. Using the monoplotting method, a correlation between the collected photo and the underlying Digital Elevation Model (DEM) or Digital Surface Model (DSM) can be established. In other words, the mentioned geolocation mismatching can be solved by developing a pixel-level correlation between the DEM (or DSM) and the contributed photo. In addition to this benefit, as the monoplotting is able to transform data of photo into the corresponding real-world geographical coordinate system, it allow to do further analysis such as estimating the extent of the flood if can be seen in the photo.

In the monoplotting technique, first the location and orientation of the camera are estimated through matching several Ground Control Points (GCP) (at least 6 points) in the image and DEM. Once these points are determined on the corresponding features such as street corners. Using an algorithm and solving a collinearity equation and standard photogrammetry algorithms in OpenCV, computer vision libraries in Python, the pose of camera is estimated. The process of matching the GCPs in this study is performed manually; however, in our future studies an optimization method will be developed to make the matching process semi-automatic. After the GCPs are matched, a pixel-to-pixel correlation between the DEM and the collected photo is established, and consequently, the geolocation of each pixel or feature in the image can be estimated. The information in the photo such as flood extent boundary and the location of reference objects for which water depth was estimated can be determined and mapped to the DEM using the pixel-level correlation.

2.3 Combining flood extent and water depth information

Once the water depth is determined for the reference objects available in a given picture, the geo-locations of those objects are obtained by monoplotting. The boundary points of the flood extent are also estimated using monoplotting. As

Figure 1. Social media photos from the high tide flood event in Newport Beach, California in July 2020

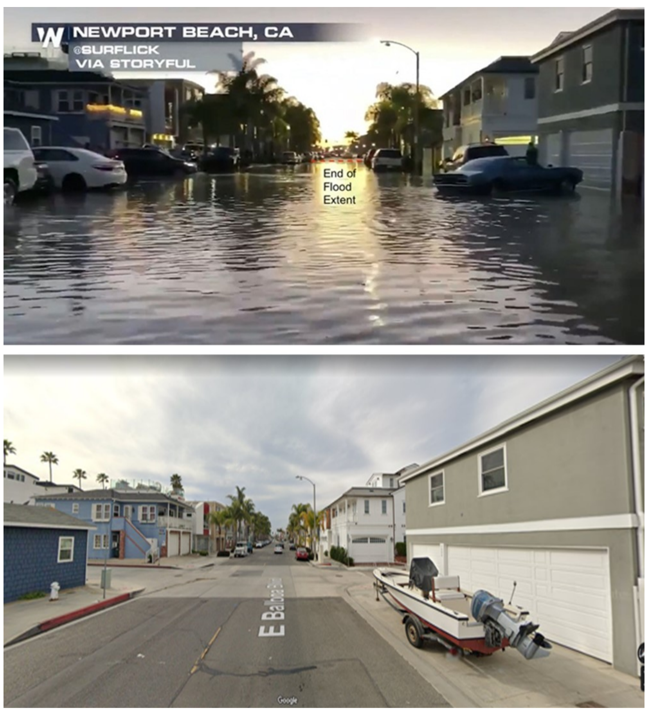

Figure 2. (a) A photo of a flooded street in the Newport Beach that shows the flood extent; (b) corresponding Google Map street view photo

the location of boundary and objects points are now available, they can be projected to the DEM. A flood water depth contour can be generated using the water depth and extent estimates. Assuming the boundary of the flood extent has water depth of zero, the reference-object based flood depth estimates from all the flood reports will be used collectively to develop a map of water depth. An optimization scheme will be implemented to produce a contour with the geo-referenced DEM. A regularization scheme will be adopted to encourage the optimization toward the assumption that the water surface is smooth, and flat.

3 Results

To demonstrate the feasibility of the proposed methods and explain its significance, we performed an analysis for a photo collected during the high tide flood occurred in Newport Beach, California in July 2020. The flood event was driven by a high tide event coupling high wind waves. Four photos, shown in Fig. 1, extracted from a video uploaded to social media. The photos were compared with Google maps street view photos and the address of the street was found. The process of finding the location for a large number of photos can be performed by means of deep neural network models based on matching the features in the photos and Google street view photos along the streets of the flooded area. The top left photo in Fig. 1 is selected for monoplotting analysis to estimate the flood extent. Because the photo in analysis is collected from social media, no GPS or camera meta data is available, so we performed the monoplotting using manually labeled 9 GCPs selected on street corners and building edges to determine the camera coordinate and direction. For this purpose, we used a high resolution DEM with 0.5-meter-cell size available in 2016 USGS West Coast El-Nino Lidar data [4].

After the location and orientation of the camera is determined, the flood scene is successfully reconstructed and confirmed by checking with Google Map, shown in Fig. 2. Also, the estimated location of the camera can be seen in Fig. 3 both in DEM and Google satellite images. The top photo in Fig. 2 shows the end of the flood extent (indicated by the red dash line) and the information from monoplotting can be used to map the line in DEM (Fig. 4). As a result, we can follow the sides of the street from the camera to the end of the flood extent to outline the inundation. Also, the water depth values of seven locations estimated manually using the car tires were mapped to the DEM in Fig. 4. The DEM-referenced flooding information demonstrates the feasibility of the proposed study and the potentials for improving the results by generating flood water depth contour show the value that AI techniques could add through visual data mining. In addition, the citizen science data was shown largely improved through the reduced geolocation ambiguity and high resolution details of the data analysis. Also note that extracting such information for water depth and camera location will be automatic with the aid of deep neural network models in our future studies. This will allow us to automatically process high-volume citizen science data and provide high-quality datasets in a wide and continuous timeline.

4 Conclusion and future work

The ongoing sea-level rise is driving an emerging type of flooding, High-tide Flooding (HTF), which occurs during a full-moon tide with or without prevailing winds or currents. Using citizen science and a flexible and Artificial Intelligence (AI)-supported platform for HTF monitoring, Flood extent

Figure 3. The estimated camera location shown both in DEM and Google satellite image

can be identified through a machine learning algorithm and water depth can be estimated using reference objects. In addition, a computer vision technique called monoplotting is used to establish a correlation between photos and corresponding DEM data, leading to relatively more precisely map the flood extent and water depth to the DEM map to minimize the data uncertainty and enhance the data credibility, resolution, and overall value. Although the presented method can be applied only for the regions where DEM is available for, it can provide unique datasets of HTF to support satellite missions to validate the flood and water body sensing. The study will advance citizen-science based data processing schemes, especially by involving AI techniques. Pilot studies will demonstrate the feasibility and value of using citizen-science data to validate and complement satellite-derived flood sensing.

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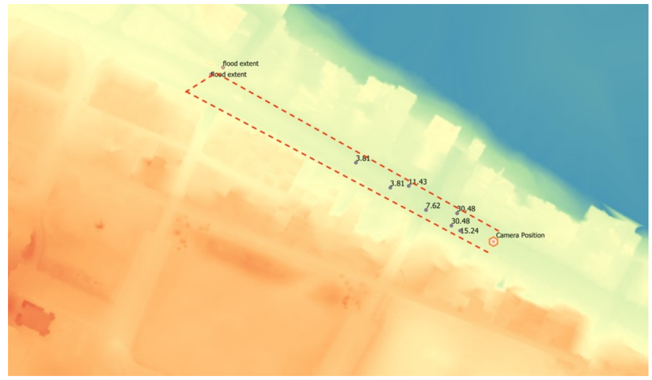

Figure 4. Determined flood extent and water depth (cm) using monoplotting and manual estimation

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