IOT BASE FLOOD MONITORING SYSTEM: A CRITICAL REVIEW

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ABSTRACT

Floods are among all natural disasters most often and devastatingly. The growing number of flood-related fatalities and financial losses worldwide every year requires a better response to flood threats. Interestingly, the recent decade has offered a number of research efforts studying how Internet-of-Things (IoT) network camera pictures and wireless sensor data might enhance flood control. This research includes a thorough literature evaluation of IoT-based sensors and computer vision applications for flood surveillance and mapping. This study highlights the principal computer vision algorithms and IoT sensor methods for monitoring floods, flood modelling, mapping and early warning systems in the literature, including water level estimates. The report also provides suggestions for further study. The research specifically offers strategies to better control and maintain coastal lagoons via the use of computer vision and IoT sensor approaches – an area not being examined in the literature.

KEYWORDS: IOT, Flood, Monitoring, Sensors

INTRODUCTION

Natural dangers such as floods, hurricanes, tsunamis and others pose a substantial threat to life and property worldwide. Such environmental hazards frequently end in catastrophes that entail serious economic loss, social disturbance and harm to urban environments, without appropriate monitoring and effective mitigating measures. Historical data have showed that the highest natural risk is the flood, accounting for 41% of all natural risks in the recent decade worldwide. In that time, alone over 1566 floods have affected 0.754 billion people throughout the globe, with 51.002 fatalities and estimated damage of $371.8 billion. In context, these data are solely responsible for the incidents of large-scale floods that were "reported," usually regarded as flood catastrophes. A flood catastrophe is defined as an overflow which disrupts or interferes substantially with human and social activities whilst the overflow is a water presence in generally dry regions. The worldwide effect of a flood would be more disturbing when these numbers included several additional small-scale floods in which less than 10 people have perished, 100 or more may have suffered, or when there is no state of emergency proclamation or need for international aid. The present scenario, however, requires for better techniques of monitoring and reacting to floods. In view of rising uncertainties connected with climate changes and the rising number of people living in places that are prone to floods, the necessity of enhanced flood control cannot be overemphasized.

There have been significant attempts worldwide to build cost-effective and comprehensive flood monitoring technologies. The typical technique is based on computer vision, which captures and processes pertinent pictures from current urban surveillance cameras in order to enhance flood decision-making. These sorts of cameras include inexpensive equipment costs and vast aerial coverage, allowing flood levels to be detected at various sites. The larger coverage offers the computer vision an edge over the conventional flood surveillance system, based on fixed-point sensors. Computer vision is based on image processing technology extensively used in several sectors, such as aerospace, medical, traffic monitoring and environmental object analysis. Research efforts to explore computer vision to enhance flood monitoring, flood mapping, the calculation of the debris flow and post-flood damage have increased during the previous decade. It is vital to evaluate the relevant literature and offer a constructively critical evaluation of scientific output, including the proposed direction of future study, to make appropriate use of this information and to promote quick advancement in research.

USE OF IoT FOR WATER LEVEL MONITORING

Monitoring water levels in early warning systems is of vital relevance and computer vision has shown to be effective. Image filtering plays a critical function in determining water levels in computer vision. For example, Yu et al. suggested using the approach of picture for tracking and detecting tiny water level changes. The difference approach is based on analysing the area of interest (ROI) between the previous and current frame and producing a water level utilising the Otsu threshold procedure. The picture collected from the river is first filtered using a Gaussian and average filter, which minimises the noise. The level of water is then measured from the y-axis of the edges. The experiment was conducted in one site alone. Because a threshold for the various filters changes under different illuminations, it is interesting to evaluate the resilience of this strategy by running the experiment at several places. Hiroi et al. presented a similar method to the differentiation procedure. The suggested remote sensing system likewise uses the differentiation method to monitor the water level through cameras. This strategy entails nevertheless collecting pictures at 10 minute intervals, comparing each succeeding image with the previous reading and then predicting the water level by logistic regression. The remedy was successfully tested at 13 different places and a reasonable increase in the water level was reliable and predicted.

SENSOR BASED WATER MONITORING

Several sensors are available to estimate water levels and hence improve early warning systems. The advantages and disadvantages of employing these sensors to monitor and measure water level were highlighted by Ba Teczyk et al. A pressure transducer is the earliest form of sensor On the negative, automated pressure transducers need calibration and are extremely responsive to any vertical movement as this may cause changes in hydrostatic pressure to compromise the precision of water level measurements. For air pressure monitoring, additional sensors may be necessary for adjusting the output of pressure transducers. Rangefinder sensors may be an excellent solution, but generally non-submersible equipment. Rangefinder sensors are cheap devices, making them economical, in particular if a vast region has to be monitored by numerous sensor nodes. However, Rangefinder sensors also need human calibration and rely on the distance from the water level measured. Rangefinder sensors are thus common in order to determine the distance from an item. Ultrasonic/rangefinder sensors essentially emit a signal and compute the time between sending and receiving signals like in the case of water level monitoring.

MONITORING THROUGH UAV

Some areas requiring regular monitoring are certainly more difficult to reach, but UAVs may give an economical alternative solution to real-time monitoring. UAV images can enable flood location, detection, segmentation and modelling. Feng et al. used drones to scan urban areas for flood prediction. The basis for UAV selection over static cameras was the easy collecting of data from various places. The paper offered a technique based on the merging of texture analysis and random forest algorithm to a hybrid technique. The total accuracy of the solution provided at the kappa level of 0.746 was 87.3%. The research shows that the accuracy of the photographs was raised by 11.2 percent as a result of the texture analysis. Important characteristics of this work include the employment of a UAV platform for the surveillance of complicated urban environments and the application of object-based information analysis (OBIA). Similarly pursuing a UAV-based texture and sliding box analysis, Popescu et al. offered a methodology. The picture was separated into sub-images and separated into two classifications, i.e. flooded or not inundated. The suggested method was assessed on 10 pictures and achieved 98,57 percent accuracy. Although the assessment of this approach may have benefited from the usage of a greater number of photos, this level of performance is regarded excellent.

CONCLUSION

This research conducted a thorough literature review of computer vision and IoT-based flood monitoring and mapping devices. The study indicated that a broad variety of applications support computer vision methods and the IoT-based sensor method to enhance flood surveillance and mapping. Some of these include early warning system, calculation of debris flow, flood risk management, flood mapping and surface water velocity, but are not limited to. It was noticed that the computer vision is favourable for a wider range and when it comes to water levels, each point in the field of view (FOV) may be regarded as a sensor, while IoT sensors are more accurate, but can provide just a point-sized measurement. Therefore, both computer vision and IoT sensors have weaknesses that may be solved by complementary usage by merging information from two distinct sources, hence improving the accuracy of the flood monitoring stations.

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