Detection and Estimation of the Extent of Flood from Crowd Sourced Images

Geetha M, Megha Manoj, Sarika A S, Muktha Mohan and Sethuraman N Rao

***Abstract*—An algorithm which estimates the extent of flood from random, crowd sourced images is proposed. It uses color based segmentation with brown color to segment out the flood water. The average brown color intensity, largest brown area, as well as water depth found out by comparison with human bodies detected, together contribute to the final estimation of the extent of flood. The algorithm, since it deals with normal images rather than satellite images or video sequences, can be used widely to explore flood affected areas so that adequate help can be supplied. This method can also be used in flood detection systems run in order to carry out rescue operations enabling us to lend our support for flood victims. Moreover, the fact that the existing work in this area deals with videos and satellite images mainly adds to the novelty of this work.**

***Index Terms*—color based segmentation, depth estimation, extent of flood, human body segmentation**

I. INTRODUCTION

In this new era, where technological advancements happen at a fast rate, we find solutions to a large number of problems faced by people around the world out of which natural calamities pose a major threat. Flood is one of the most dangerous of these hazards. It is the rise in the level of water leading to submerging of the land areas, especially the low lying areas, due to heavy downpour. It leads to lose of life and property. There has been government involvement in providing shelter to flood victims. Moreover, scientists have been researching for effective methods to deal with the damage caused. The rescue operations and basic amenities provided to victims must reach to heavily submerged area first. Here comes the importance of systems detecting the flood affected areas.

As an alternative, this is an approach where rather than just detecting flood affected areas we compute the extent of flood from random crowd sourced images.

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It can tell the extent of flood without a video sequence or satellite images like it is usually done. Here, a color based segmentation is used to segment out the water. The brown color intensity of the water part along with its depth with proportion to humans detected is then analysed to estimate the extent of flood.

Thus, by this method estimation of the extent of flood from the given flood scene is possible which enables us to send adequate help to people in these areas, helping people to cope up with the situation.

II. RELATED WORKS

There are not many works specifically focusing on this problem. Most of the existing works deal with video sequences as well as satellite images. Since our problems deals with normal camera images, it constitutes an entirely different work. Some of the above mentioned works are detailed below.

In "Flooded area detection using UAV images[1]" by A. Sumalan, D. Popescu and L. Ichim, an unsupervised technique for the detection of flooded areas using images acquired by a fixed-wing unmanned aerial vehicle (UAV) is explained. The proposed methodology for the detection of the flooded areas considers the development of an algorithm based on k means clustering and texture analysis using co-occurrence matrix. But, they focus only on UAV images whereas a system that uses normal images increases the usability by common people.

"A Probabilistic Model for Flood Detection in Video Sequences[2]" by Paulo Vinicius Koerich Borges, Joceli Mayer and Ebroul Izquierdo proposes a method which is applied for retrieval of flood catastrophes in newscast content, which present great variation in flood and background characteristics, depending on the video instance. are texture, relation among color channels and saturation characteristics. The method analyses the frame-to-frame change in features like texture, relation among color channels, saturation characteristics and the results are combined according to the Bayes classifier to achieve a decision (i.e. flood happens, flood does not happen). In addition, a model for the probability of occurrence of flood as a function of the vertical

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position is also proposed. But, here comes the significance of our method where we deal with images than videos. Dealing with moving scenes are even more complicated and so, we employ our algorithm to estimate the extent of flood from normal camera images for ease.

In "A Novel Approach to Urban Flood Monitoring Using Computer Vision[3][4]" by RamKumar Narayanan, VM Lekshmy, Sethuraman Rao and Kalyan Sasidhar, the captured images of partially submerged static structures such as buildings, lamp posts etc. are geo-tagged and uploaded to a server. The feature matching algorithm, SIFT finds the corresponding matching feature points between the captured and a reference image at the server. The flood line is then estimated and drawn against the reference image. Since the orientation need not match rightly every time with the reference image, it is not a reliable method.

III. PROPOSED METHOD

The proposed architecture mainly focuses on colour based segmentation on random images unlike the existing methods which handles satellite images and videos. The extent of flood in a flooded area is closely related to the intensity of brown colour of the water area segmented out. The depth of the water along with the estimated brown colour intensity contributes to the estimation of the extent of flood depicted in the given image. Fig.4 illustrates the components involved, starting from the module of preprocessing, after which largest brown area segmentation takes place. This is followed by the estimation of water depth which along with the average brown colour intensity and largest brown area, figures out the extent of flood in the scene. This section details all the steps involved.

A. *Preprocessing*

To enhance the features needed for further processing, we employ two steps:

1) *Gamma Correction:*

It controls the overall brightness of the image. First, the image pixel intensities are scaled from the range [0, 255] to [0, 1.0]. From there, the output gamma corrected image is obtained by applying the following equation:

$$O = i^{1/G} \tag{1}$$

where 'i' is the input image, 'G' is the gamma correction value and 'O' is the output image.(See Fig.1)

Fig. 1: Original Image followed by Gamma corrected Image with gamma value = 0.5

2) *HSV Conversion:*

Hue, Saturation, Value represents color shade, amount of gray colour and brightness of the image respectively. Since, the R,G,B components are correlated with the amount of light hitting the object, image discrimination on the basis of these components are difficult. So, HSV descriptions are more relevant and HSV color space is the most preferred color space for colour based image segmentation. Here, a range for brown colour is defined, pixels falling within this range are masked, thereby highlighting the brown coloured area (See Fig.2).

B. *Largest Brown Area Segmentation*

From the detected brown coloured areas, the largest area has to be found out for further processing. This segmented out region is taken for further analysis of extent of flood.

Thresholding is the simplest method of segmentation and operates upon grayscale images.All the pixels in the image

Fig. 2: Image masked and segmented within the specified brown range

Fig. 3: Thresholded image highlighting brown areas

that has value more than the threshold value specified, are changed into 255 as shown in Fig.3. Here, we implement two modes of thresholding, namely binary thresholding and Otsu's thresholding.

Binary thresholding accepts the threshold value given by the user. If it is a bimodal image, Otsu's thresholding comes into effect and automatically calculates the threshold value from the image. If not, binary thresholding takes its place.

After thresholding the image, the complete set of continuous points are found out, each set forming a contour. Here, the horizontal, vertical and diagonal segments are compressed and only their end points are taken to form contours.All such contours(external contours) are found out from the thresholded image and are stored as a list.

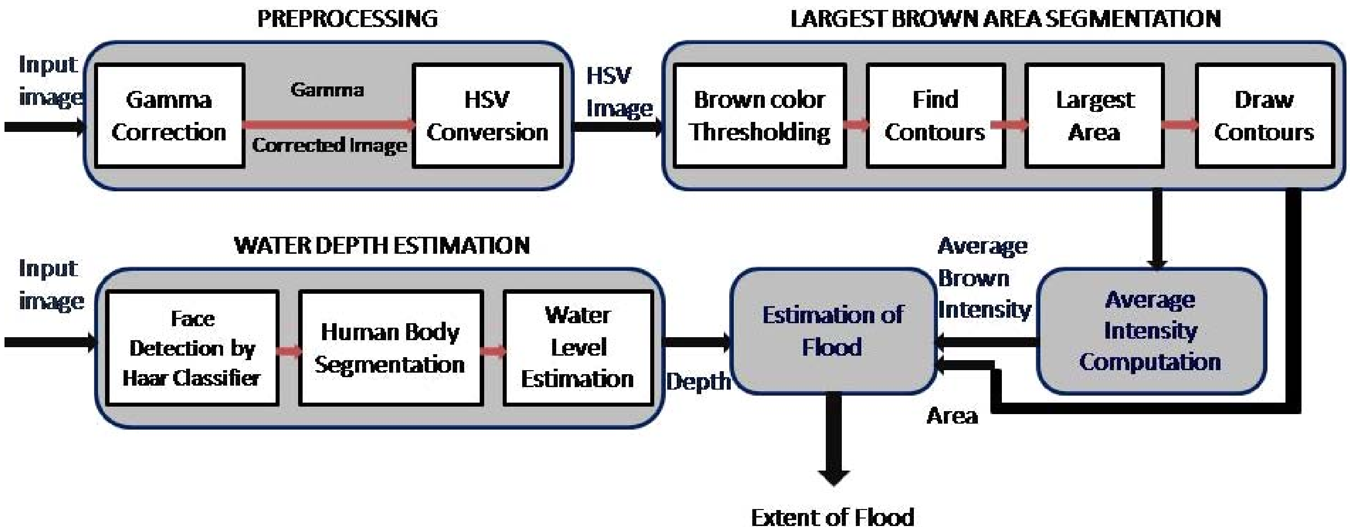

Fig. 4: Proposed Architecture

Fig. 5. Contours represented by green colour, where the thick lines show largest contour whereas thinner lines show the other contours

The most prominent property of contours, namely area is taken into consideration. The area of each and every contour is retrieved to take the largest among them. The largest contour area, is taken as the prominent region in the image and is given as an input to the last module of estimation of flood. Using this area, the percentage amount of flood water is calculated by formula (2).

$$\text{Flood water amount} = \frac{\textit{largest area}}{\textit{image size}} \times 100 \qquad (2)$$

The largest contour thus identified is drawn and highlighted to depict the result in the image clearly as shown in Fig.5. Moreover, the average or mean of the segmented image pixels is taken as average brown colour intensity which is fed to the final module of estimation of flood.

C. *Water Depth Estimation*

Water depth visualised in the given image is one of the significant factors contributing to the final output, i.e the estimated extent of flood. Face is detected by haar classifiers. It is an effective face detection method proposed by Paul Viola and Michael Jones. It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. Further, features are extracted from them. It is then used to detect faces in other images.

Here, the pre-trained classifier is loaded to detect the faces in the given image (front faces).

A rectangle is drawn over each face detected highlighting them. Starting with each of the faces detected, bounding boxes are drawn in proportion to the rectangle drawn for face detection. This segments out the human body approximately to four regions namely torso, waist, knee and feet. The brown color intensity in each region is computed. Then, the corresponding region to the maximum brown area is selected to estimate depth. The various proportions of human body along with the final result is depicted in Fig.6.

D. *Estimation of Flood*

The water depth, colour intensity and largest contour area are all significant factors contributing to the estimation of extent of flood and percentage of submerged area. After comparing the levels of human body with water and taking into account the largest area computed already, the extent of flood is estimated which forms the final desired output.

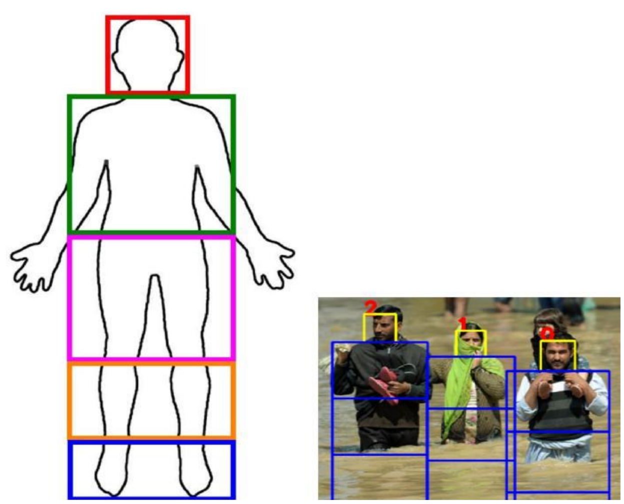

Fig. 6: Faces are detected and human bodies are segmented

```
Algorithm 1 Proposed Algorithm
Result: Extent of Flood
Input: Image img
processed = Preprocess(img)
area = LargestArea(processed)
if area < thresholdarea then
    Low contour brown area, flood not detected
    exit(1);
else
    intensity = AvgIntensity(processed)
    depth = WaterDepth(img)
    if depth <= thresholddepth then
        No flood
        exit(1);
    else
        Display "flood water percentage = (area / size) *100 "
        extent = EstimateFlood(area,depth,intensity)
        Display extent
    end
end
Function Preprocess(img):
    gc = gammaconversion(img)
    h = hsvconvert(gc)
    Define brown color range
    segimage = segmentwithinbrown(h)
return segimage
Function LargestArea(processed):
    Find the contour with maximum area
    Draw the largest contour to highlight it
return largestarea
Function AvgIntensity(processed):
    Mask it with largest contour found
    Compute the average BGR intensity of this contour
return intensity
Function WaterDepth(img):
    Detect the faces using haar classifiers
    Draw human body bounding boxes for segmentation
    Calculate intensity of brown color in each bounding box
    Compare the brown area in each segmented human body
      region as below:
    if brownarea >= thresholdarea then
        Calculate depth
    else
        depth=low
    end
return depth
```

The water depth calculated along with the brown color intensity in the bounding boxes together play the major role in determining the level or extent of flood as high, medium or low. Through trail and error, thresholds are fixed for intensity,depth as well as area in order to assign them different levels of flood.

The proposed algorithm is explained below which details the various processes contributing to the final output. The algorithm is described in two parts separating the module of estimation of flood from the main module.

The proposed algorithm details the major computations of the factors contributing to the final module of estimation of flood. These include the largest contour area with brown colour, average brown color intensity of the area and depth of the water.

By empirical research, we have obtained the maximum and minimum threshold. By continuous trial and error, we have classified the flood extent as high, medium and low within these threshold values.

```
Algorithm 2 EstimateFlood
Result: Level of Flood
Input Parameters: area, intensity, depth
if area < thresholdarea then
    No Flood exit(1)
else
    if intensity>= max then
        if depth==high then
            return (high flood)
        else if depth==medium then
            return (medium flood)
        else
            return (low flood)
        end
    else if intensity>= min and intensity < max then
        if depth==high then
            return (medium flood)
        else if depth==medium then
            return (medium flood)
        else
            return (low flood) end
    else
        if depth==high then
            return (medium flood)
        else if depth==medium then
            return (low flood)
        else
            return (low flood)
        end
    end
end
```

IV. RESULTS AND PERFORMANCE EVALUATION

The model is tested on the obtained dataset and the results are formulated. The performance of the model is analysed and efficiency is estimated. The detailed analysis of the performance of the proposed algorithm is necessary to have an idea about our work and the improvements what we can do to make it better in the near future. Further details are given below:

A. *Dataset*

Large number of crowd sourced and random flood scene images are collected to form our dataset. They are in fact collected randomly after performing a thorough search. Since the model has to be tested against flood and non-flood scenarios, a total of 205 images are tested, out of which 104 are flood scene images and 101 are non flood images. The results obtained after testing with each image is analysed and some are given below:

B. *Results*

The proposed method is tested on a variety of images ranging from flood scenes and non flood scenes. In most of the cases, human faces and bodies have been correctly detected improving its efficiency. Each of the intermediate processes and their results applied on some of the input images are shown below in Fig 7.

The images tested are classified into flood and non flood categories by the flood detection system. Flood scene images

Fig. 7: Sample input images going through the process of gamma correction, brown color segmentation, thresholding, largest contour detection, face detection and human body segmentation for estimation of the extent of flood.

are correctly classified into flood category and can be incorrectly classified into non flood category. Same can happen with non flood scene images where they can be correctly and incorrectly classified into non flood and flood categories respectively(Fig.8).

Fig. 8: Green bordered images show the correctly classified images and red bordered images show the incorrectly classified images by the system

A confusion matrix(see Table I) is developed from these classifications which points to the efficiency and accuracy of the proposed method. There are 104 flood scene images out of which 85 are correctly classified into flood category and the rest are incorrectly classified into non flood category. On the other hand, there are 99 non flood scene images and 86 of them are correctly grouped into flood category. Remaining of them are misclassified as flood scenes.

TABLE I
Confusion Matrix

	Flood	Not Flood
Flood	85	19
Not Flood	13	86

TABLE II
Accuracy Table

Image Name	Largest Area	Percentage of Flood Water	Percentage Submerged	Extent of Flood	Flood	Not Flood
Img 1	18224.0	4.680	87.5	0.33	Yes	
Img 2	1201.9					Yes
Img 3	133637.0	29.217	70.5	0.40	yes	
Img 4	87238.0	27.236	65.2	0.45	Yes	
Img 5	35239.5	13.140	82.3	0.60	Yes	
Img 6	46426.5	42.868	75	0.55	Yes	
Img 7	113.6					Yes
Img 8	108656.5	35.369	83	0.75	yes	
Img 9	34.5					Yes
Img 10	42538.0	55.681	87.5	0.87	Yes	

C. *Performance Evaluation*

An accuracy table(Table II) is maintained citing some of the test images that we used for testing our model. The table keeps record of the largest brown color area segmented out, the percentage of flood water in the given image computed by taking the fraction of the largest area in the image, percentage submerged and extent of flood. It also mentions whether the system classified it into flood or non flood scene.

In Img 1, all the faces are accurately detected. Img 2 which is a non flood scene image is classified into non flood category. Img 3, Img 4 and Img 5 are correctly classified into flood category, all the faces are detected, human bodies are segmented out and extent of flood is calculated. In Img 6 and Img 10, faces are detected and flood extent is displayed correctly. Similarly, images 7, 9 and 8 are correctly grouped into not flooded and highly flooded scenes respectively.

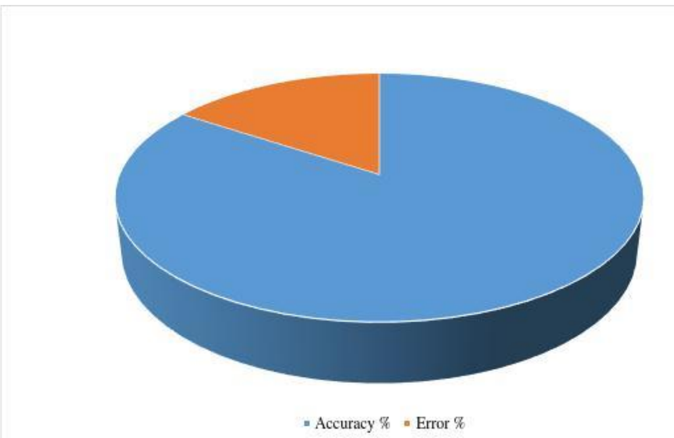

Fig. 9: Accuracy Graph

$$accuracy\ rate = \frac{Number\ of\ correctly\ classified\ images}{Total\ number\ of\ images} \times 100$$

$$error\ rate = \frac{Number\ of\ incorrectly\ classified\ images}{Total\ number\ of\ images} \times 100$$

The pie chart above(Fig.9) depicts the accuracy rate and error rate obtained by the model after testing with the available dataset. The high accuracy rate compared to the low error rate throws light on the accuracy of the algorithm devised for estimation of the extent of flood from normal crowd sourced images.

V. CONCLUSION

The extent of flood is estimated from crowd sourced random images with simple color segmentation and depth analysis. This result obtained from images can prove useful for sending help to flood affected areas. The percentage of submerged area and amount of flood water is approximated from the image. We plan to extend our work considering more factors like vehicles and human body parts relative to the water level and calculate the flood extent so that the accuracy is improved.

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