# A PROBABILISTIC MODEL FOR FLOOD DETECTION IN VIDEO SEQUENCES

*Paulo Vinicius Koerich Borges*$^{*\nabla}$, *Joceli Mayer*$^{*}$, *Ebroul Izquierdo*$^{\nabla}$

LPDS - Dept. of Electrical Engineering, Federal University of Santa Catarina, Brazil.$^{*}$
MMV - Dept. of Electronic Engineering, Queen Mary, University of London, UK.$^{\nabla}$

**ABSTRACT**

In this paper we propose a new image event detection method for identifying flood in videos. Traditional image based flood detection is often used in remote sensing and satellite imaging applications. In contrast, the proposed method is applied for retrieval of flood catastrophes in newscast content, which present great variation in flood and background characteristics, depending on the video instance. Different flood regions in different images share some common features which are reasonably invariant to lightness, camera angle or background scene. These features are texture, relation among color channels and saturation characteristics. The method analyses the frame-to-frame change in these features and the results are combined according to the Bayes classifier to achieve a decision (i.e. flood happens, flood does not happen). In addition, because the flooded region is usually located around the lower and middle parts of an image, a model for the probability of occurrence of flood as a function of the vertical position is proposed, significantly improving the classification performance. Experiments illustrated the applicability of the method and the improved performance in comparison to other techniques.

## 1. INTRODUCTION

In the past few years automated retrieval of events in newscast videos has received great attention by the research community [1, 2], as broadcasters have strong interest in creating large digital archives of their assets for reuse. A significant amount of time and money is spent by news networks to find in their archives events related to a fresh event that has just happened. In this context, catastrophe related news are one of the most common topics that require automated retrieval, and this task is subject to a number of large research projects [3, 4]. In the catastrophe news, flood events are one of the most common subjects, along with bombings and fire. Efficient detection of flood in video contents has proved to be an important research topic in the last few years [3, 5, 6], with application not only in video retrieval but also in surveillance in security systems [5], aiming at early detection of flooding and consequent reduction of financial losses.

In this paper we propose an efficient visual based event detection method for identifying flood in videos. Most of the visual based flood detection proposed in the literature are applied in satellite image analysis [7, 8]. However, these algorithms are focused on aerial-like images, which have specific characteristics which are not always valid for flood detection in ground shots, making them unsuitable for video retrieval or surveillance applications.

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In contrast, the proposed method is applied for retrieval of flood catastrophes in news content, such that there is great variation in lightness, camera position or background/foreground scene, depending on the video instance.

The method exploits visual characteristics that are very often present in flood regions. In addition to the common brownish flood water, because of the bright reflection present in water smooth surfaces, these regions usually present low saturation. Also, in parts which contain rippling effects caused by rain or by the water flow, a texture is often present. The image is divided in blocks of size $J \times J$ and for each block these features are evaluated, such that each block receives a score given by the probability of containing flood. If several high score block are spatially connected, a flood image is assumed. To help determining the block score, we propose a probabilistic model for the position of flood in an image. This is based on the fact that flood regions are much more present in lower/middle parts of images than in the upper parts, which usually contain sky or buildings. Based on this, the contributions presented in this paper can be listed as follows:

$(i)$ We exploit the fact that flooded regions generally fit into one of two characteristics: they have either a brownish color, which is the water color itself, or they have light gray characteristics, when the water is reflecting buildings or the sky. The first case has well defined color and the second presents very low saturation. Because these two cases are usually spacially interlaced, a connected component analysis is used to refine the result.

$(ii)$ From a training set, a probabilistic model is employed for the color distribution and for the saturation. The relationship between the averages for each color channel is used as a detection metric.

$(iii)$ We propose a model for the spatial distribution of flood in the image, which we show to be well represented by a non-central chi-square distribution.

$(iv)$ Because of the water flow and rain a rippling effect is often present in water regions, which varies from frame to frame. We analyze this change using a difference metric from frame to frame, in potential flood regions.

$(v)$ The features are combined with the Bayes classifier to achieve a practical low detection error rate.

This paper is organized as follows. In Section 2 we discuss color and dynamic flood characteristics, proposing efficient discrimination features for flood. In Section 3 we present a probabilistic model for the spatial distribution of flood in an image. In Section 4 we propose a patch-based analysis for the feature extraction. In Section 5 we present experimental results, followed by relevant conclusions in Section 6.

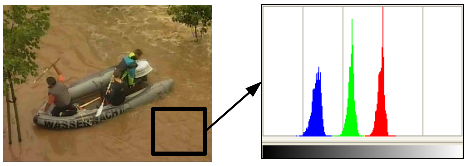

**Fig. 1**: Histogram of brownish flood inside the black square, for the red, green and blue channels.

## 2. STATISTICAL CHARACTERISTICS OF FLOOD

Flood has very characteristic visual signatures. Color, texture, and water flow of flooded regions are all essential features for efficient classification. In general, in addition to color, a region that corresponds to flood can be captured in terms of the statistical characteristics of the pixels in the region, and their change from frame to frame in a video sequence. Due to water flow, the texture of a flooded region often presents a stochastic motion, which depends on surrounding environmental factors such as current strength and rain.

Based on these factors, in the following we propose several useful features for detecting flood, explaining the physical characteristics to validate their applicability.

### 2.1. Color

Based on an experimental analysis of flood images and in accordance to [5], two distinct visual features were observed for a flood surface: the surface presents either a smooth darker region (the water color itself, usually brownish) or it presents strong reflective spots which are usually much brighter than the surrounding. These spots are caused by the water rippling and the reflection of bright objects on the water.

#### *2.1.1. Brownish Water*

For the first case, we noticed that, for a given flood pixel $f(m,n)$ in an image $f$ we have

$$f_R(m,n) > f_G(m,n) > f_B(m,n) \tag{1}$$

where $f_R$, $f_G$ and $f_B$ are the red, green and blue channels representation of $f$, respectively. A typical histogram of a brownish region is given in Fig. 1.

Let $\bar{f}_R$, $\bar{f}_G$ and $\bar{f}_B$ represent the sample average of the pixels in a flooded image region, for the red, green and blue channels, respectively. Interpreting $\bar{f}_R$, $\bar{f}_G$ and $\bar{f}_B$ as random variables and making use of the central limit theorem [9], we employ a Gaussian model for these variables, such that $\bar{f}_R \sim \mathcal{N}(\mu_{f_R}, \sigma^2_{\bar{f}_R})$, $\bar{f}_G \sim \mathcal{N}(\mu_{f_G}, \sigma^2_{\bar{f}_G})$ and $\bar{f}_B \sim \mathcal{N}(\mu_{f_B}, \sigma^2_{\bar{f}_B})$. Based on these assumptions, a color based detection metric $D_C$ is given by:

$$D_C = D_{C_R} D_{C_G} D_{C_B} \tag{2}$$

where

$$D_{C_R} = p_{\bar{f}_R}(\bar{f}_{R_{obs}})/p_{\bar{f}_R}(\mu_{f_R}) \tag{3}$$
$$D_{C_G} = p_{\bar{f}_G}(\bar{f}_{G_{obs}})/p_{\bar{f}_G}(\mu_{f_G}) \tag{4}$$
$$D_{C_B} = p_{\bar{f}_B}(\bar{f}_{B_{obs}})/p_{\bar{f}_B}(\mu_{f_B}) \tag{5}$$
$$\tag{6}$$

where $p_x(x_0)$ represents the evaluation of the probability density function of a random variable $x$ at value $x_0$. In this case, $\bar{f}_{R_{obs}}$ represents the average value in the red channel of an observed region. If $\bar{f}_R$, $\bar{f}_G$ and $\bar{f}_B$ can be assumed independent, $D_C$ can be interpreted as the degree of confidence (represented by a probability) that a set of pixels represent a flood region (based only on color analysis).

#### *2.1.2. Light Gray Water*

For the second case, because of the gray appearance of the reflections, the saturation tends to a low value. The saturation detection metric is:

$$D_S = \bar{f}_S \tag{7}$$

where $\bar{f}_S$ is the average of the saturation channel of the HSV representation of $f$.

### 2.2. Texture

At the same time that a light gray flood region presents low saturation, these regions also present intensity variations (lighter or darker gray). For this reason, to avoid having gray objects like gray skies (which are very common in flood images) and buildings included in the classification, we include the entropy as a measure of texture. The entropy metric is given by:

$$D_E = \text{Entropy}\{f_V\} \tag{8}$$

where $f_v$ is the 'value' channel of the HSV representation of $f$. Experiments illustrate that using $D_E$ in the flood detection process improve the performance of the algorithm.

### 2.3. Feature Combination

Considering a stochastic interpretation of the features in this work the Bayes classifier [10] is employed to combine the features, although it is clear that different classifiers could also be tested.

Although some features have better classification power than others, because all the discussed features are useful to discriminate flood from non-flood, combining them increases the distance between these two classes, and consequently reduces the detection error rate [10], at the expense of increased computational complexity.

## 3. SPATIAL DISTRIBUTION OF FLOOD

One important characteristic of flooded regions is that they are usually located in the lower and middle parts of an image. From on a set of 85 images $f_i$, $i = 1 \ldots 85$ containing flood (a few examples are given in Fig. 3, we manually segmented the flood regions, setting the 'flood pixels' to 1 and the 'non-flood pixels' to zero, as illustrated in Fig. 4. We refer to the segmented images as $f_{s_i}$. Let $s$ be a new image given by the sum of all the segmented images, such that $s = \sum_{i=1}^{85} f_{s_i}$. Projecting the pixels in $s$ to the vertical axis, we obtain histogram presented in Fig. 5, as a function of the vertical position (where 0 represents bottom of the image).

From this figure we observe the relationship between the vertical position and the probability of occurrence of flood in a given part of an image containing flood.

Using a histogram based PDF estimation [11], we notice that the distribution in Fig. 5 is well represented by a non-central chi-square distribution [12] with 2 degrees of freedom and non-centrality equal to 4, as illustrated in Fig. 6. We use this information to weight the confidence from the result of the visual analysis.

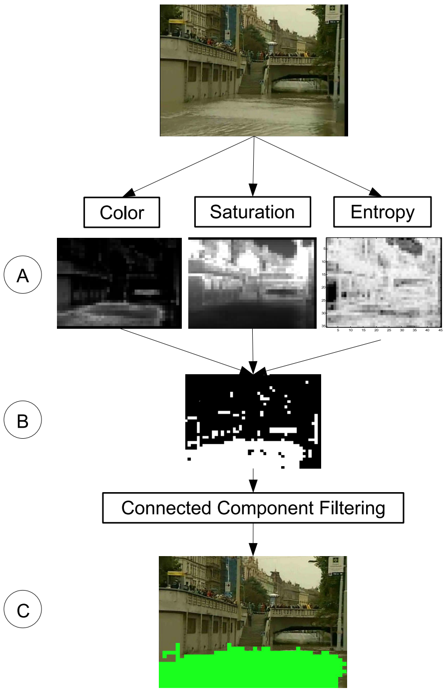


**Fig. 2**: Block Diagram of the process.

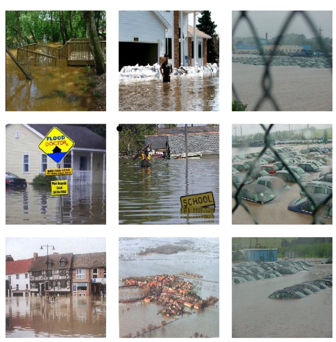

**Fig. 3**: Illustration of flood containing images.

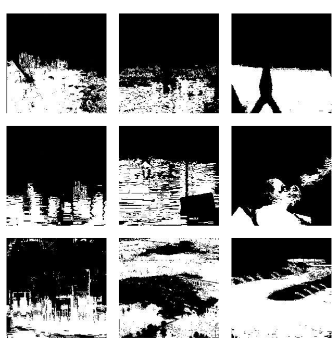

**Fig. 4**: Illustration of flood segmentation.

## 4. PATCH BASED FEATURE EXTRACTION

Because of the dependence between position and probability of occurrence of flood stated above, we employ a patch based approach

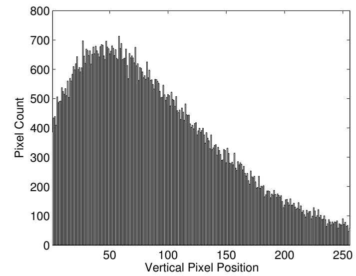


**Fig. 5**: Histogram of the projection of $s$ on the vertical axis as function of the position, where 0 represents the bottom of the image.

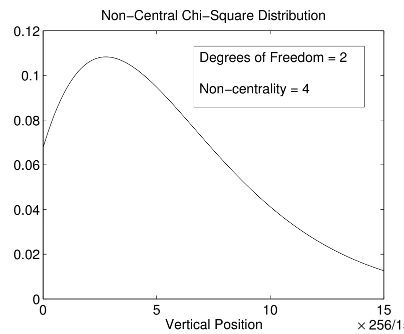


**Fig. 6**: Plot of a chi-square probability density function for comparison with Fig. 5

to the classification, performing the visual analysis separately on blocks of size $J \times J$ in the image. The image is initially divided in blocks and each block receives a score $S_f$ for the probability of being flood, according to the result of a Bayes based classification using the features discussed in Section 2. The confidence on this score is then increased or reduced depending on the position of the block in the image. This increase/reduction is computed according to a chi-square function, as discussed in Section 3.

### 4.1. Patch Score Map

Using the confidence score from the visual analysis and spatial location, we generate a patch score map (PSM) for the image each of the features (color, saturation, entropy) is formed. An instance of PSM's is illustrated in stage "B" in Fig. 7. In order to have a final decision on whether or not the image is flood related, we find the connected component image [13] among components with high score.

If the energy of the connected component PSM is above a given threshold $\lambda_{PSM}$, the frame is assumed as containing flood. Else, it is assumed that the image does not contain flood.

## 5. EXPERIMENTS

In the experiments, we used as a test set a selection of videos from the MESH [3] database of news content. This database is formed of several instances of catastrophe related videos from the Deutsche Welle network, containing several news reports related to flood events. They include different kinds of flood environment such as country, city, daylight and dark lighting. This diversity is convenient to evaluate the performance of the system under different lighting and qual-

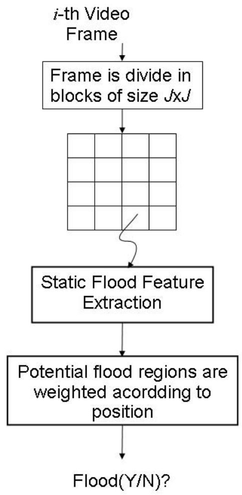


**Fig. 7**: Patch score map.

**Table 1**: Experimental error rates.

| Features Used | False-Positive | False-Negative |
|---|---|---|
| Color | 16.2% | 7.5% |
| +Saturation | 6.2% | 4.7 |
| +Entropy | 4.5% | 4.0 |
| +Position | 0.9% | 0.46 |

ity conditions. The video selection also contains many shots of objects with flood-like appearances such as gray buildings and skies, for example.

The video resolution is $768 \times 576$ and the frame rate is 25 frames per second (fps). There are approximately 532 minutes of video (or 798,000 frames).

The frames are classified as "contains flood" or "does not contain flood," as discussed in Section 4.1. For training the system, 75 instances of flood in video sequences were used.

The results using the features discussed are presented in Table 1. This tables shows the false positive (wrongly assume the presence of flood) rate and the false negative (wrongly assume the absence of flood) rate. The rows corresponding to each feature represents the error rates when that feature only is used to classify flood from non-flood. The row 'Chi-Square' corresponds to the results when all the probabilistic non-central chi-square model is used.

The results described in [14] and [15] yield error rates similar to the system proposed here. However, [15] assumes the camera is stationary and [14] makes use of frequency transforms and motion tracking, requiring more computational processing time, making them unsuitable for video retrieval.

## 6. CONCLUSIONS

In this paper we have exploited important visual features of flood not previously discussed in the literature, using a probabilistic model for the position of the flood region in images. We combined color, contrast and entropy, along with their dynamic change from frame to frame. In contrast to other methods which extract complicated features, the features discussed here allow very fast processing, making the system applicable not only for real time flood detection, but also for video retrieval in news contents, which require faster than real-time analysis. The experiments illustrate the applicability of the method, with an average false-negative rate of 0.46% and a false-positive rate of 0.9%.

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