ESTIMATING RAINFALL IN THE PHILIPPINES USING AN AUTOMATED INTERPRETATION OF FORECAST IMAGES

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Abstract

Flood forecasting is a process that relies on hydrologic models to predict water levels and flow rates in different basins. These hydrologic models depend on the predicted amount of water in rain clouds. A common form of this data for these models comes from color-configured forecast map images. These images are manually interpreted. However, manual interpretation is slow, tedious, and prone to error especially if there are numerous images. We propose a method to automate the interpretation of these images for a faster and more efficient means to predict the amount of water in the clouds. We identify two computational sub-problems: (1) localization and recognition of the region of interest (ROI), and (2) interpretation of the values in the ROI. We use the Speed-up Robust Features (SURF) technique to localize the ROI's, and a look-up table which makes use of Hue Saturation Value (HSV) color space. Experimental results show higher accuracy compared to the manual interpretation, and a significantly faster processing time.

Introduction

Flood forecasting has received renewed research interest in the wake of several flood-related disasters that had cost countless lives and billions of dollars worth of damage [1]. Flood forecasting involves a number of factors to consider. One factor is the amount of rainfall in an area. In the Philippines, rainfall prediction is done through images obtained from satellite-based forecast images. Although other technologies in existence can achieve similar results like Doppler radar (Chape, et. al., 2005), our proposed system is tailored to countries without such sophisticated systems. Examples of these are the Ensemble Tropical Rainfall Potential images (eTRaP), as shown in figure 1, and the Navy Operational Global Atmospheric Prediction System (NOGAPS) reports. These images are refreshed every 3 hours and manually interpreted for values at over sixty different gauge locations. Table 1 shows the range of rainfall intensities used by the Philippine Atmospheric and Astronomical Services Administration (PAGASA) [2].

Manual interpretation is slow, tedious, and prone to error, especially if there are numerous source images. This paper explores a method to automate the interpretation process for an improvement in the overall efficiency of flood forecasting. It addresses the problem in the context of image processing by dividing it into two main sub-problems. First, we have the problem of locating the region of interest in the map and secondly, we have the problem of color interpretation.

In locating the ROI, we use the SURF, an improvement over Scale-Invariant Feature Transform (SIFT) method that robustly detects features and geometric deformations which makes it ideal for localization. In eliminating the vertical and horizontal noise (latitude and longitude) in the image, we apply the Generalized Hough Transform (GHT) which can be used to find arbitrary shapes in an image especially lines.

Statement of the Problem

The aim of this paper is to create an automated system that will estimate the amount of rainfall in various points in the Philippines where range gauges are located. In order to create such system, there are mainly two requirements: (1) the system must correctly locate the region of interest, which in this case, is the Philippines (2) the system must accurately estimate the amount of rainfall based on the colors in the image.

Background Literature

Currently, there is no automated system that estimates rainfall in the Philippines. Until recently, PAGASA manually interprets forecast images by the guess-and-look method, whereby they guess the location of the rain gauge stations in the image and look at the amount of rainfall in those areas according to the configurations in the image. To give an example, figure 1 shows a sample rainfall forecast image that PAGASA uses for rainfall estimation.

As of now, there exists no single method that provides a complete solution to the problem, at least in the Philippines. Thus, there is a need to create a system that will cover all the essential processes, not only for the rainfall estimation, but for the interpretation of precipitation forecast images as well. The said system is the main objective of this paper.

Bay (2008) describes SURF as a novel detector-descriptor scheme used for feature computation and matching. It can correctly detect features with geometric deformation and localization errors which makes it robust. This also makes the method scale and rotation invariant. The algorithm for SURF includes a Fast-Hessian Detector, which has good performance as regards to running time and accuracy.

Ballard (1981) proposed the GHT that takes advantage of the parameterization of curves to form distinct shape characteristics. The curves are parameterized in the general line form:

$$\rho = x\cos\theta + y\sin\theta \tag{1}$$

where ρ is the perpendicular distance from the origin and θ is the angle with the normal. An implementation of the transform for image analysis uses an array called an accumulator that serves as classification bins that group pixels according to the parameters of a line. The bins with the highest values are used to describe the lines. GHT can be used to find arbitrary shapes in an image. Ballard describes a technique in his paper showing that shape boundaries can be used to create mappings between the image space and the Hough transform space. Complex shape mappings can be created from basic shape mappings that allow the GHT to be applicable for any arbitrary shape.

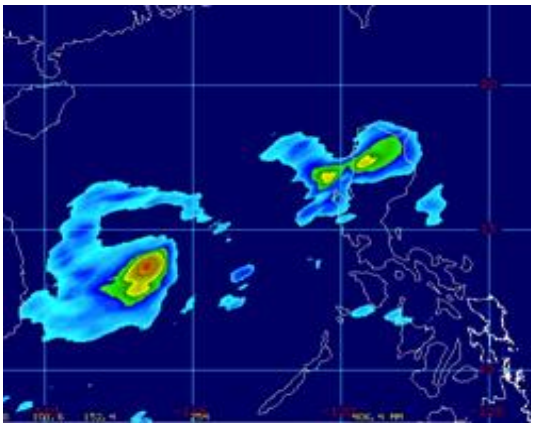

Figure 1. An example eTrap forecast image.

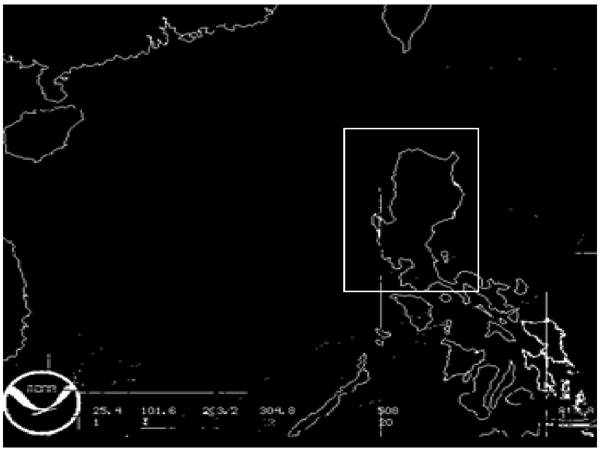

Figure 2. An example of an image after binarization, noise reduction, and localization.

Methodology

There are five sequential stages in the system. Firstly, image enrollment is required wherein for every given type of satellite image, the user has to input a sample so that future images of the same type can be processed faster and more accurately. The second stage involves color filtering to binarized the image so that localization of the region of interest can be performed. Once the image has been localized, it is then superimposed on the original image so that the colors can be interpreted correctly.

Image Enrollment

The first goal of the system is to localize the Philippines in the image, an example of which is shown in Figure 2. In general, this system is applicable to quantized satellite images wherein boundaries between water and land mass are outlined. Computers are sensitive to minor changes in the image such that it detects the slightest distortion. Because of this, the computer will not be able to recognize the Philippines on different map types. This problem must be addressed because the system must be able to handle images made using different models.

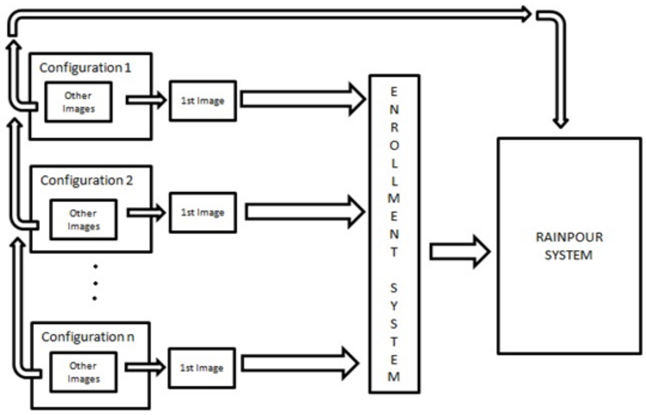

Figure 3. Image enrollment system.

A proposed method to solve this problem is the employment of an image enrollment system shown in Figure 3. The system registers the shape of the Philippines per model. The fact that these models have greater chances of generating the same shape of the Philippines is utilized by the system, thus making it more flexible and usable for larger input examples.

Users are asked to localize the boundaries of Luzon, the northern area of the Philippines, using the cropping tool. Only the area of Luzon is enrolled because it is as unique in shape as the Philippines and is sufficient for the localization of the country. By strategically specifying specific points along the boundaries of a shape, we can define a unique set of points that can be used to identify it. Also, there are models such as eTRaP where only the upper half of the Philippines is seen in the image (this is because the model focuses on the area of the typhoon rather than the stationary area in the map).

Color Filtering

The color filtering method requires the boundary color γ from the user, and a threshold α to apply to the values of the color. Color range limits P_{min} and P_{max} can be determined according to the following equations:

$$P_{min} = \gamma - \alpha, \qquad P_{min} \geq 0 \tag{2}$$

$$P_{max} = \gamma + \alpha, \qquad P_{max} \leq \delta_{max} \tag{3}$$

where δ_{max} is the color descriptor maximum. A filtering function *filter(A, SL, SU, C)* is applied to the source array A to get the filtered colors. SL and SU are the lower and upper boundary, each of which contains the range obtained from above in the number of color descriptors for the format used. C is the resultant array. *filter(A,SL,SU, C)* is given by:

$$C(I) = SL_0 \leq A(I)_0 < SU_0 \tag{4}$$

for a single-channel array,

$$C(I) = SL_0 \leq A(I)_0 < SU_0 \text{ and } SL_1 \leq A(I)_1 < SU_1 \tag{5}$$

for a two-channel array,

$$C(I) \text{ is set to } 0xff \text{ (all '1'-bits)} \tag{6}$$

if $A(I)$ is within the range and 0 otherwise.

Gridline Removal

Most precipitation images have grid lines that correspond to longitude and latitude to aid the reader in locating areas. However, these lines can add noise problems during localization because they occlude areas of interest. To circumvent this problem, Fisher (2011) proposes a feature extraction technique called the Hough Transform is used to find vertical and horizontal lines in the image. Found lines are then subtracted from the image which results in better performance of the system. The resulting binary image will serve as input to our next step which is localization.

Localization

To localize the Philippines, we use SURF. First, the filtered image and the enrolled template image are loaded. Next, the distinctive features in these images are gathered using Fast-Hessian method. This generates the SURF descriptors which are then used to match the features between the forecast image and the template.

The Fast-Hessian detector used by the SURF method is based on the Hessian matrix, where given a point $\chi = (x, y)$ in an image I, the Hessian matrix $H(\chi,\sigma)$ in χ at scale σ is defined as

$$\mathcal{H}(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix},$$

where $L_{xx}(\chi,\sigma)$ is the convolution of the Gaussian second order derivative $\partial^2 g(\sigma)/\partial x^2$ with the image I in point χ, and similarly for $L_{xy}(\chi,\sigma)$ and $L_{yy}(\chi,\sigma)$.

Color Interpretation

Initially, a table of pixel coordinates for the desired areas must be constructed. These coordinates are relative to the size of the template image discussed in the enrollment system section in this chapter. In the case of this study, the pixel coordinates are made to represent the ROI. A look-up table for the color ranges and their respective values is also created.

Since the images are represented in the form of pixel arrays, the individual gauge locations represented by pixel coordinates can be immediately accessed via indexing. When a gauge location is found in the image, the color information in that pixel is extracted and compared to the table previously created.

The human eye generalizes color information and does not see single pixel values in a specific pixel location. A person typically uses all the information he can get, present in the image to form conclusions. To prove this, upon seeing that a gauge is juxtaposed over a white boundary, a person will not interpret the amount of rain that will fall over this area to be that which is paired with a white color. He will use the colors around this boundary to make an approximation.

To emulate this, the method proposes a search around the neighboring pixels of the gauge located. The HSV color values of these pixels are extracted and interpreted and the average of these values are used as the final reading. colors within the range of the boundary and colors not registered in the table are ignored. This prevents the algorithm from using an extreme value in the average computation, otherwise it may yield to highly inaccurate readings.

Gonzales, et. al. (2004) defines the neighbor search average is calculated as $H(p)$ = the color values of a pixel p, $V(H(p)) = V(p)$ is the rainfall value function dependent on the image configuration and maps a pixel's precipitation value through the function $H(p)$, where $p_1 ... p_n$ is the Moore neighborhood of p_0 (8-connected pixels), and the $H(p_0 ... p_n)$ is not in set T. T is the set of integers z, such that $z\text{-}a < z < z\text{+}a$, where z is the given boundary color, and a is the given threshold value.

Experiments

Table 1. Rainfall Intensity Categories Used by PAGASA.

Category	mm./hr.	mm./3 hrs.	mm./6hrs.	mm./12 hrs.	mm./24 hrs.
Light	<2.5	<7.5	<15	<30	<60
Moderate	2.5--7.5	7.5--22.5	15--45	30--90	60--180
Heavy	>7.5	>22.5	>45	>90	>180

Localization

A total of 214 images were used for the eTRaP model and 53 images for the NOGAPS model. Out of the 214 eTRaP images, 202 were correctly localized, giving a 94.39% accuracy. Out of the 53 NOGAPS images, 48 were correctly localized, which resulted in a 97.96% accuracy.

Color Interpretation

Table 2. Performance on Different Experiments.

Criteria	Automated vs. Manual	Automated vs. Actual Data	Automated vs. Actual Data
Similarity (%)	96.20%	72.22%	70.37%
Discrepancies	4	30	32
Discrepancies (%)	3.70%	27.78%	29.63%

Color interpretation (rainfall estimation) was done on 108 pixel locations on correctly localized images. Table 2 shows the different accuracies achieved on different experiments.

Figures 2 to 4 show the intensity dispersion graphs for all the gauge points tested from given different intensity levels.

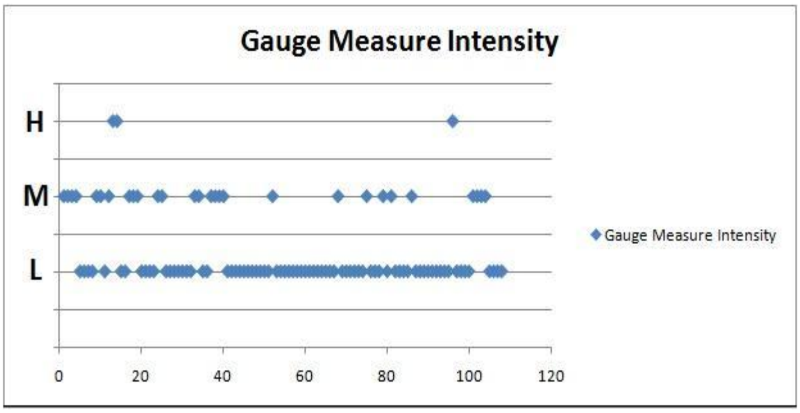

Figure 2. Intensity dispersion from different stations. The y-axis corresponds to heavy, moderate, and light rainfall intensity categories while the x-axis corresponds to the different rain gauge stations.

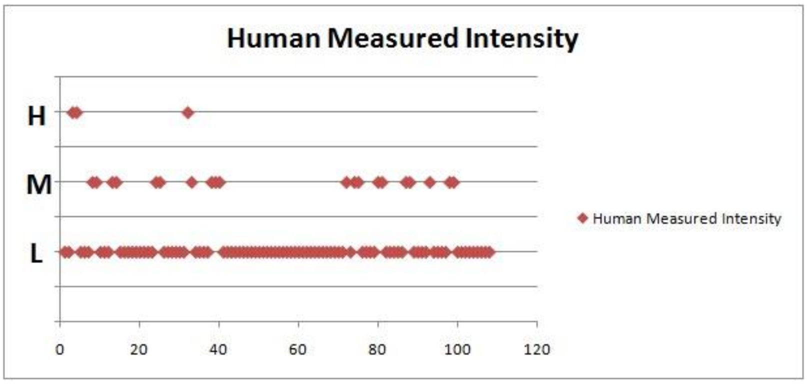

Figure 3. Human-measured intensity dispersion. The y-axis corresponds to heavy, moderate, and light rainfall intensity categories while the x-axis corresponds to the different rain gauge stations.

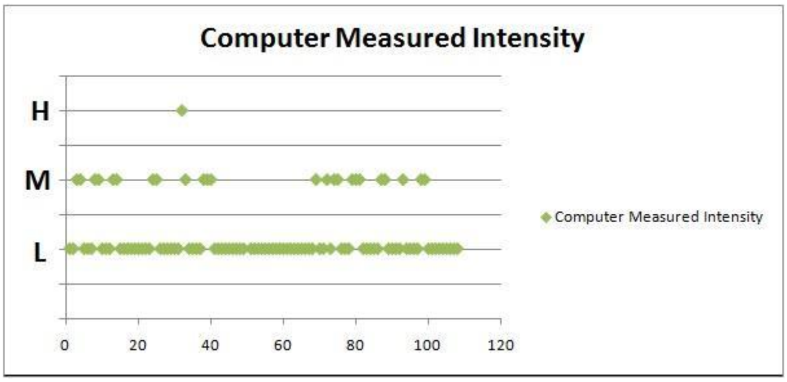

Figure 4. Computer-measured intensity dispersion. The y-axis corresponds to heavy, moderate, and light rainfall intensity categories while the x-axis corresponds to the different rain gauge stations.

Conclusions

This paper has shown that an automated solution for rainfall estimation can outperform the manual method both in speed and accuracy. The solution is flexible enough to accommodate new types of precipitation forecast images, which are freely available, given an image enrollment system. Images need only have 256 colors and 640x480 or less resolution. It has modest system requirements and therefore can be operated using relatively inexpensive resources, especially in countries which cannot afford expensive equipments.

This research can be extended further to consider localization techniques other than SURF. Other factors that aid in flood forecasting may also be taken into account such as terrain, soil properties, and vegetation. Haar training can also by used for localization for faster object detection [7]. Another object detection algorithm that may be employed for localization is done by Viola and Jones (2001). It resembles Haar-based functions but involves more complex computation.

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