A SYSTEM FOR THE ANALYSIS OF IMAGES CONTAINING ATMOSPHERIC DISCHARGES-SAIDA

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***Abstract*—** *This paper describes a system that is able to detect and classify images of lightning discharges stored in video files. The system uses Edge Detectors and Mathematical Morphology to detect images of lightning discharges, and the classification is done using an Artificial Neural network (ANN). The system was implemented in C Language and using the OpenCV library, and was tested with 20 video files, containing 63 lightning discharges previously manually detected. Results showed that 95% of the lightning discharges present in the video files were detected and the number of discharges was correctly computed, and that the artificial neural network classified the detected events with a success rate of 90%.*

Keywords— Image Processing, Computer Vision, Artificial Neural Networks, Lightning Discharges.

1 Introduction

Lightning discharges are highly associated to thunderstorms strength, and information about the type, strength and number of the discharges can be useful to many government departments and companies. Aircraft companies can use it to suspend high-risk activities (like fueling) and re-route aircrafts around hazardous thunderstorms, while forestry's departments can deploy crews in fire outbreak regions to reduce fire spread; government departments use this information to warn local population about incoming thunderstorms, reducing material and human losses. Also, it is possible to define regions with high lightning occurrence, which can be then avoided to both construction and storage of inflammable materials (Vaisala, 2013).

The study of lightning discharges is not only relevant to a thunderstorm event: scientists study how the rate of lightning strikes produced within a hurricane's eyeball is tied to the changing strength of that hurricane, and volcanoes can create lightning strikes due to the friction of dust clouds create in its eruption.

The development of video cameras allowed scientists around the world to study lightning with more precision, its behavior, and discover cloud-to-atmosphere lightning, among other discoveries. These studies allow risk areas determination and local population warning about possible disasters. However, the continuous monitoring creates a huge amount of data to be processed by a human being: this process is slow and tiresome, which justifies its automation.

The goal of this paper is to describe an automated system that is able to analyze video files, detect lightning discharges, extract relevant information (position, lightning level, number of strokes) using image processing and computer vision techniques and classify the lightning discharge using Artificial Neural Network techniques.

This paper is organized as follows: Section 2 describes the techniques used by the system; Section 3 describes related work and Section 4 presents the proposed system and results; finally, Section 5 concludes this work.

2 Image Processing and Classification

In this work, three techniques commonly applied in image processing and classification were used: Edge Detection, Mathematical Morphology and Artificial Neural Networks.

"Edge detection is the name for a set of mathematical methods which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities" (Wikipedia, 2013a). An edge operator (or filter) is usually a small image (or mask) that, when convoluted over the original image, will produce a new image in which only the edges will remain.

Several edge operators exist: The Roberts operator, which is one of the first edge detectors proposed. The Prewitt and the Sobel operators, which compute an approximation of the gradient of the image intensity function (the difference between both is how the approximation is made); and the Canny Operator (Canny, 1986), which is considered the optimal edge detection algorithm.

In order to detect lightning discharges, several edge operators were tested. As result, we decided to use the Canny operator to detect the event's borders, even in noise presence. The canny filter's idea is to calculate the convolution between the image and the Gaussian function derivative, and afterwards, derivate the result: this operation results in a binary image, where high values indicate border presence, and low values indicate weak borders (or inexistent). Figure 1 shows the Canny Edge Detection operator applied to an image.

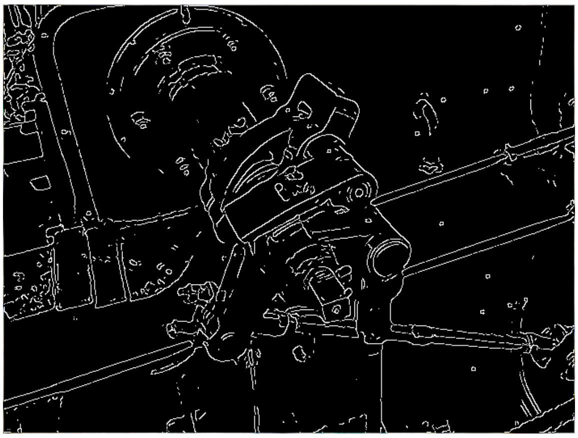


Figure 1: Canny operator applied to a color photograph of a steam engine (from Wikipedia, 2013a).

Mathematical Morphology (Serra, 1983) is a powerful technique for shape processing and analysis, in particular for those applications where geometric aspects are relevant. It defines a set of operations – the application of a small mask over an image – producing a different image. The basic operations of this technique are:

- Erosion: using this operation with a small mask, the original image will be eroded, i.e., lines and objects will loose its borders and get thinner.
- Dilatation: is the opposite of erosion: using it will make objects get dilated, i.e., objects and lines in the image will get thicker.

Mathematical Morphology defines several operators, and a whole mathematical theory for the combination of these. In this work, only dilatation is used.

Figure 2: A shape (in blue) and its morphological dilation (in green) and erosion (in yellow) (From Wikipedia, 2013).

An Artificial Neural Network – ANN – (Haykin, 1994) is a mathematical model inspired by the study of biological neurons. An ANN is composed of processing units (neurons) connected between themselves and grouped in layers. The first layer is known as “Input” layer, which is where the system receives the external information. Each neuron processes its information and sends his response to the next layer’s neurons. This process repeats until a response is created at the last layer, the “Output” layer. Figure 2 shows an artificial neural network, with 2 hidden layers.

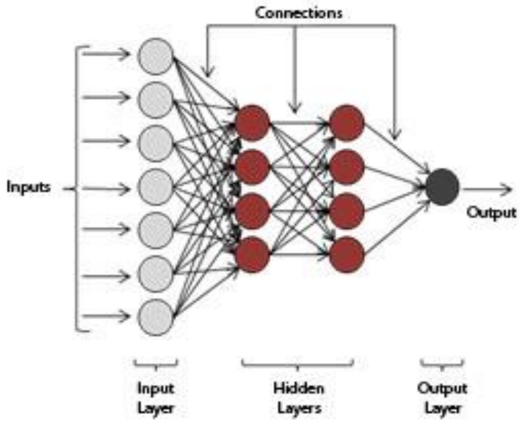


Figure 3: Artificial Neural Network example, with 2 hidden layers.

The *Backpropagation* algorithm (Rumelhart et al, 1986) is used to train a Multi-layer perceptron artificial neural network: it consists in presenting pairs of examples of correct classifications, in order to compute an error between the neural network’s response and the desired response. This error is backpropagated to the neural network’s neurons, changing the neurons connection weights. The process is then restarted, using the newly computed connections. This process repeats until the error is minimum, or the number of these cycles (each one is called “epoch”) reaches a limit.

3 Related Work

The computer vision and artificial intelligence focus in the development of systems able to both detect and classify objects in images with precision, and in an autonomous way. A first system that used images to detect lightning was proposed by Santos Filho et al. (2005). It was composed of a number fixed video cameras, that allowed the localization of the events, and an omnidirectional camera to capture a panorama image of the sky. It was used to continuous monitor the atmospheric discharges.

The first system that was able to detect and classify lightning images was developed by (Gin et al., 2009), using the Sobel edge detector and decision trees. The work developed by Crivelaro et al. (2010, 2011) focused in studying many Computer Vision and Artificial Intelligence methods to classify lightning discharges found in images. His works compared many techniques, such as Support Vector Machines, K-Means, Nearest Neighbors, and concluded that the best method for classifying a lightning image is the Artificial Neural Network.

Other computer vision application can be found in several areas, from medical imaging to robotic guidance. Unfortunately, there are very few groups working on the classification of lightning images, as this is a new area of study.

4 The Developed System

The developed system can be split in two modules: Detection and Classification modules. The first one uses computer vision techniques implemented in the OpenCV Library (2013) to eliminate irrelevant events (birds, noises, etc) and uses two main algorithm to detect lightning discharges and lightning flashes: the Shape (Canny) and Brightness algorithms. The second module uses an Artificial Neural Network (ANN) to classify lightning discharges as horizontal and vertical. The developed neural network uses the *backpropagation* algorithm and the MLP (Multi-Layer-Perceptron).

The two modules are described in the following Sub-sections.

The videos used in this project were acquired by seven video cameras, disposed in a 360º loop at Centro Universitário da FEI, São Bernardo do Campo, Brazil, that continuously recorded lightning events during the summer of 2011 and 2012. In this period, several convective storms were recorded.

4.1 Detection Subsystem

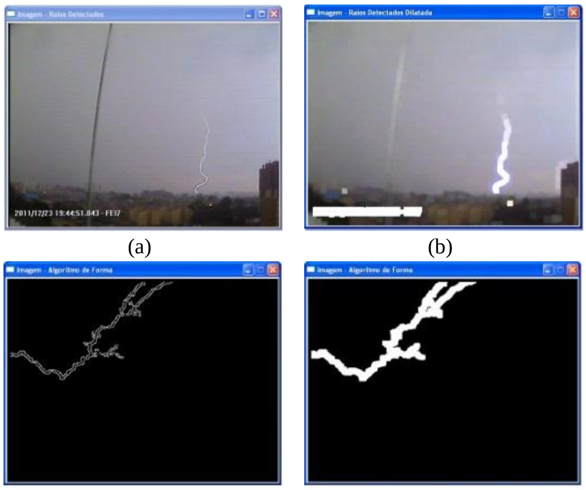
The detection module of the system works as follows.

Initially the system detects if there are significant differences between frames in a sequence, indicating that something, still not classified, occurred. Whenever there is a significant difference between two consecutive frames, it means that the detection algorithm must process the actual frame. One imaginary line known as "horizon line" excludes all the pixels beneath it from the actual image, because they have irrelevant information, like trees, roads, buildings, etc. The user determines the horizon line's position. Figure 4 shows one image used to help the user define the horizon line.

Figure 3: Image created by the system to help the user define the horizon line's position. The horizon line is in red.

After an event is detected, the dilatation algorithm is applied. The dilatation algorithm selects all the pixels in the image as little groups, and converts them to a medium color level, reducing noise and amplifying differences in normal images (RGB), and amplify and fill present objects in binary images. The dilatation was used by the cvDilate function in OpenCV.

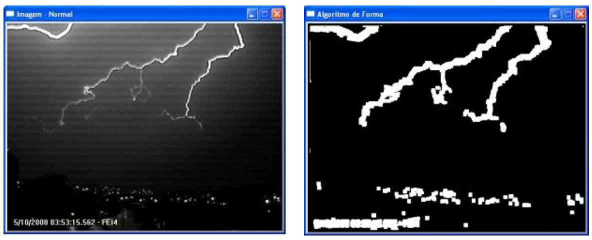
Figure 5 shows one normal image containing one lightning discharge (Fig. 5a) and its dilatation (Fig. 5b). It's possible to see that the lightning discharge was amplified. Figure 5c shows a binary image containing one lightning discharge, which was dilated (Fig. 5d). After the dilatation, the lightning discharge channel was filled.



(a) (b) (c) (d)

Figure 5: (a): Normal image containing one lightning discharge, (b): Dilated image, (c): Binary image containing one lightning discharge and (d): Dilated image.

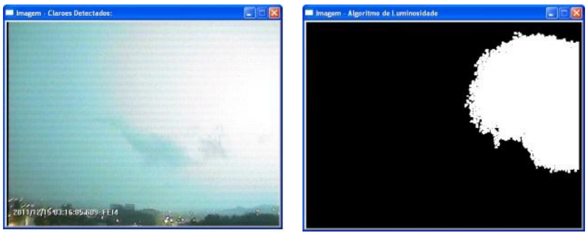
The next algorithm is the shape algorithm, used to detect all the objects in the image. This algorithm is used to detect the lightning discharge, since the lightning discharges creates a well-defined shape in the sky. The algorithm method is based on the Canny algorithm, which calculates the convolution between the processed image and the Gaussian derivative, G'(x). The convolution smooth the images borders, which is necessary to detect the relevant borders. The result is then derivate using the Sobel operator matrices (Sobel, 1990), creating a binary image that contains all the relevant borders detected. Figure 6 shows an image processed by the shape algorithm.



(a) (b)

Figure 6: (a): Normal image containing one lightning discharge and (b): Dilated shape algorithm.

After the shape detection, a brightness algorithm is applied in the image to detect the brightest regions of the image, because the brightness level is associated to the lightning flashes occurrence. Its method consists of calculating the number of pixels that exceeds determined brightness threshold, starting from the brighter (level 255, which, in the RBG scale, means white) and going to the darker (level 0, which means black). If a high amount of pixels exceeds the threshold, the image is binarized, where the brighter pixels become white pixels, and the other ones become black pixels. This process is necessary to detect and classify lightning flashes. Figure 7 shows the brightness algorithm passed in an image containing one lightning flash.



(a) (b)

Figure 7: (a): Normal image containing one lightning flash and (b): Dilated Brightness algorithm.

The shape and brightness algorithm's returned images might have irrelevant information that must be removed before the classification part. A background filter is passed in the returned images, which contains all the background elements positions previously manually detected. Figure 8 shows a normal image (Fig. 8a) and its respective filter image (Fig.8b).

(a) (b)

Figure 8: (a): Normal image and (b): Manually created image.

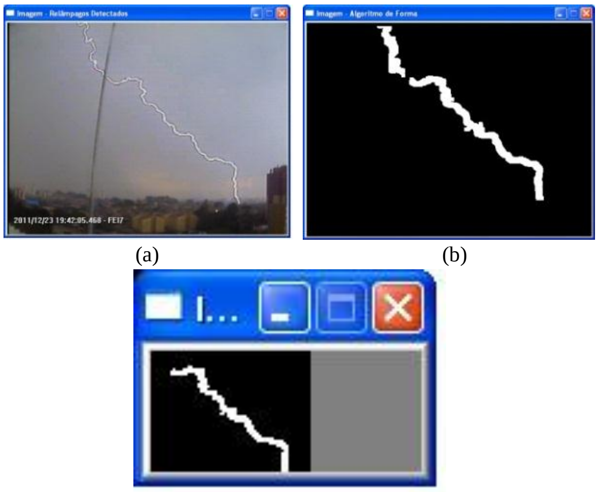
The system loads the filter's image depending of the video file being analyzed, and then binarizes and dilates it. All the white pixels detected in the filter's image are excluded from the shape and brightness algorithms. Figure 9 shows the background filter's image binarized (Fig. 9a) and dilated (Fig. 9b).

The filter image must be generated manually to improve the system efficiency. If there is no image to use, the system filters the shape algorithm using the brightness algorithm.

Before the lightning discharge classification, the shape algorithm's returned image must be resized to 65x49 pixels, and the lightning discharge must be centralized. This process reduces the neural network processing/learning time, and improves the neural network result. The 65x49 pixels size was chosen because it is proportional to the initial image and it has a central pixel, which facilities the lightning's centralization. The neural network receives the resized image and then classifies it as vertical lightning or horizontal lightning. The images' resizing an auxiliary algorithm, because the returned image was distorted using OpenCV's function only. Figure 10 shows an image's resizing and Figure 11 shows a block diagram of the detection subsystem.

(a) (b)

Figure 9: (a): Background filter's image binarized and (b): Background filter's image binarized and dilated. All the white pixels will be excluded from the shape and brightness algorithms returned images. There's a slight difference in height.



(a) (b)

(c)

Figure 10: (a): Normal image with one lightning discharge, (b): result of the Shape algorithm and (c): lightning resized and centralized.

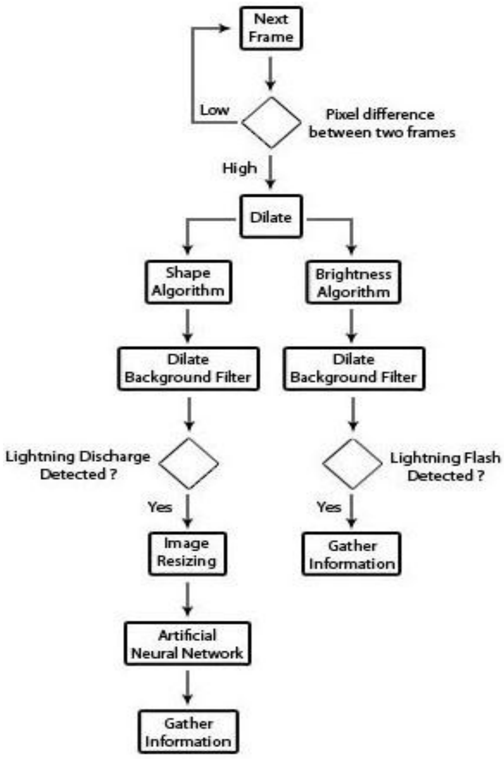
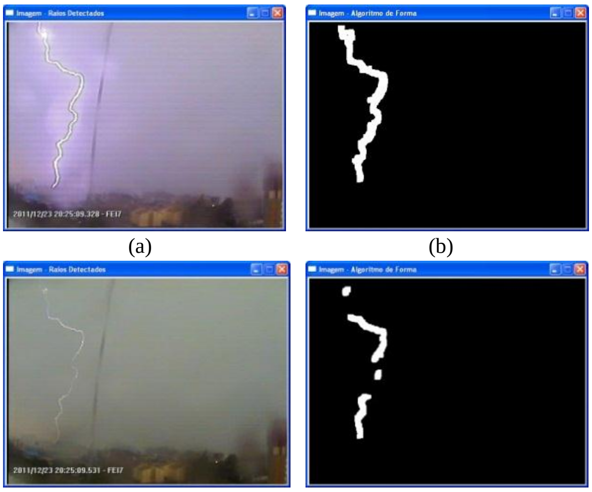
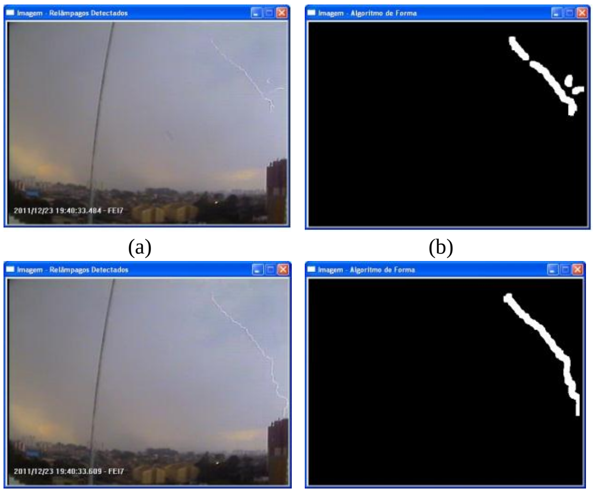


Figure 11: Diagram of the detection subsystem developed.



(a) (b) (c) (d)

Figure 12: (a): Normal image containing one vertical lightning discharge, (b): Shape algorithm result, (c): Normal image containing the same lightning discharge after 4 frames and (d): Shape algorithm result after 4 frames. The system knows that it is the same lightning event.



(a) (b) (c) (d)

Figure 13: (a): Normal image containing one lightning discharge, (b): Shape algorithm, (c): Normal image containing the same lightning after 2 frames and (d): Shape algorithm after 2 frames. The system is able to detect that it is the same lightning event.

4.2 Classification Subsystem

The resized images that are the result of the Detection module are passed to the neural network to be classified as horizontal and vertical lightning. In this project, the neurons use the sigmoid function to process de data.

The backpropagation, Multi-layer Perceptron Artificial Neural Network was trained with 2 image groups. The first group, containing 42 images with 57 lightning discharges (one image can have more than one lightning), was previously classified by a teacher, and then passed to the neural network, while the second group, containing 33 images with 42 lightning discharges was used to test the training efficiency. These images were previously manually detected, and processed by the classification module before being passed to the neural network. The ANN was tested with one to five hidden layers, with up to 50 neurons each. The best configuration achieved a success rate of 95%, with one layer containing 20 neurons, and a *learning* of 0.01. This configuration was implemented in the developed system.

After the lightning's classification, the system detects the number of strokes of each lightning strike, and other important information (brightness, frame which the lightning strike was detected) as well. The developed system compares the position of each already detected lightning strike with the recently detected lightning strike, to detect if the positions match each other. If this happens, the system knows that it's the same lightning. Figure 12 shows a lightning strike, which was detected 2 times.

This process also detects if the lightning strike is increasing or decreasing (appearing or disappearing from the image) by comparing the number of pixels detected by the shape algorithm in each frame. In Figure 12, the lightning discharge is also classified as a decreasing lightning.

Another feature of this procedure is that the system is able to verify if the shape algorithm, by any reason, isn't able to detect the lightning's entire channel. Figure 13 shows one lightning discharge detected 2 times. In the first detection (Fig. 13a), the shape algorithm couldn't detect the entire lightning channel (Fig. 13b) due to its intensity, which made the system classify this frame as containing multiple lightning discharges. After 2 frames (Fig. 13c), the lightning discharge intensified itself, which made the shape algorithm able to detect the lightning's channel entirely (Fig. 13d). The system updates the previous gathered information and considers it as only one lightning discharge, avoiding errors. This process works with increasing/decreasing lightning discharges.

The last procedure consists on creating folders to save all the information gathered from the video file. The system saves the lightning strike images, with and without background, and creates a text file containing all the information gathered. The lightning discharge is classified as vertical/horizontal, increasing/decreasing, and number of discharges. Both lightning discharges and flashes are saved in JPEG images, containing the event's duration (in frames) and intensity. The system also saves the number of events detected in each video file.

4 Conclusions

The system was used to detect, classify and count the number of strokes of each lightning discharge acquired from September 2011 to June 2012, and was used to classify the type of lightning flashes in images from July 2012 to August 2012.

The lightning discharges detection using the shape algorithm and the lightning flash detection showed good result, with a margin of error of 5% in detection.

The background filter reduced the irrelevant information gathered by both algorithm, and removed almost all noises detected from manual reduction.

The image's resizing to 65x49 pixels, proportionally, and centralizing the lightning discharge in the image to the neural network's classification increased its performance. The neural network's classification as horizontal or vertical lightning showed a margin of success of 95% in the second group.

The artificial neural network was trained with many configurations to test the difference in its performance. The neural network's training using a high number of neurons and layers didn't showed good results for all sizes of images, while the training using binary images with a lower amount of neurons and layers showed better results.

The developed system was tested with 20 video files, containing 63 lightning discharges previously detected. Results showed that no event was lost, and the classification module achieved a margin of 90% (10% error containing both false negative and false positive), using the neural network best configuration found. Besides that, the information gathered (light level, position, number of discharges), was also correct.

The developed system needs, on average, 5 minutes to process each video file (with size varying from 1 to 2GB), while the manual process needs more than 30 minutes for each file, depending on the number of lightning discharges, noise, and other variables.

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