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Using Computer Vision Techniques to Generate Embedded Systems for Monitoring Volcanoes in Ecuador with Trajectory Determination

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Abstract: Ecuador is a country with a great number of volcanoes, 27 active in the part continental and insular, of which three are in full process eruptive by which the government Ecuadorian estimated necessary the monitoring constant of them volcanoes of the territory, however, all the process is manual both the analysis of images as the of data. By that arises the need of creating a system embedded that allow control an or several functions with resources limited and in conditions environmental hostile doing the processing and analysis of images through software free of way autonomous. By this reason is created an algorithm that will allow detect the presence of flows as well as the trajectory of them themselves for which is necessary mitigate in the possible the noise inherent to the processing digital of images in order to generate alerts in case of exist a phenomenon volcanic.

Key words: Volcanic phenomena, embedded systems, artificial vision, autonomous, noise inherent, exist

INTRODUCTION

The vision artificial or commonly called vision by computer is the science and technology that allows to the "machines" see, extract information of the images digital, solve any task or understand the scene that have in front. The vision by computer acts on a representation of the reality that it provides information on, colors, brightness, forms, etc. (Liu *et al*., 2015).

Currently, the applications of it vision artificial are extensive and van from the field of the industry (check defects within a process, count bottles, interpret a TAC medical...) and the field of the medicine (search and count of cells), until systems more complex that allow to the robots move is in an environment unknown, passing by the reality augmented, the recognition of patterns among others many applications (Liu *et al*., 2015; Khaloo and Lattanzi, 2015).

This research has resulted in the development of a system of automatic monitoring in real time where the core of its operation is the algorithm that allows for the detection of the trajectories of emissions and pyroclastic flows. This algorithm is based in several principles such as the transformed of hotelling, filters of edge, binarization, etc.

MATERIALS AND METHODS

State of art: Is obvious that the vision artificial has several applications less ambitious that the construction of robots autonomous (Elmer *et al*., 2015). These applications are very varied according to the need for each region, for example, in Mexico it is working on a satellite for the monitoring of the Popocatepetl volcano which began more than 2 years, there is not much information on the subject of automatic monitoring of volcanoes through artificial vision systems is performed this research which aims to build a robust application to generate useful information for users with the help of technology. This research considers the following aspects that are presented in Fig. 1.

Ecuador has an infrastructure of both monitoring volcanoes located in strategic places to have an overview of the status of the volcano and for determine exactly which direction the lava flow is directed, the current problem is that video evaluators are maintained earrings of the behavior of the volcano the 24 h, being a purely manual process.

The stages of a system artificial is observed in the Fig. 2, these phases not always followed of way sequential but in sometimes is necessary realimentarlas towards back (Halfawy and Hengmeechai, 2014).

Capture: Acquisition of digital images through some type of sensor is used a camera with sensor CCD because the research is based in their easy reproducibility in addition to present features relevant and necessary as robustness facing the noise produced in environments hostile or by changes of light.

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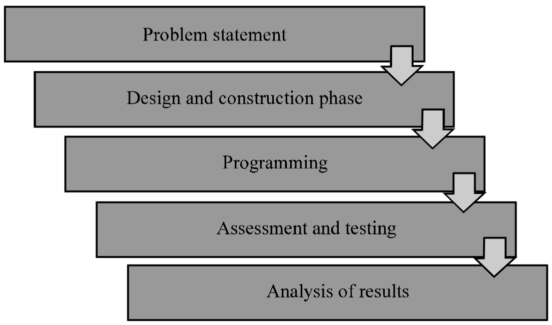


Fig. 1: Research methodology

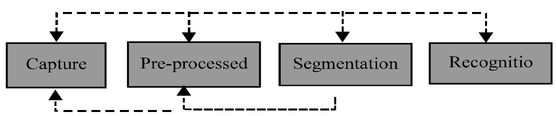


Fig. 2: Stages that make up a vision system artificial

Pre-processed: Prepare the image by removing the non-useful parts and/or enhancing the parties of interest, using the thresholding and binarization to separate the background of the image to focus us in the cone of the volcanoes in addition also reducing the information and therefore, the computational consumption.

Segmentation: Isolate elements of interest for its subsequent interpretation, through operations morphological for obtain relevant specific characteristics.

Recognition: Distinguish the different objects segmented according to their characteristics, framing areas that are of interest to analyze them using the hotelling transform to describe their paths in the case of pyroclastic flows (Georgakopoulos *et al*., 2013).

Following these stages the algorithm contains the following operations that are considered more important within the program Open CV and Python for the treatment of images.

Operations basic: Thresholding, binarization.

Filtered: Transformed of hotelling, filters detectors of edges.

Segmentation: It uses techniques based on segmentation using morphological transformations as binary erosion, dilation and closure.

Hotelling transformed (PCA): Analysis of Components main (PCA), also known as transformed of hotelling is a transformation that allows reduce the information redundant in the images through the use of algorithms statistical-mathematical present inside the software free. The objective of this technical is reduce all the information unnecessary contained in a original set of N bands to a smaller set of new bands or components (Axelsson and Sorensen, 2013). Any image can be represented as a matrix in which the intersection of a column with a row corresponds to one pixel. Bearing in mind this feature can be carried out on it operations and statistical-mathematical transformations, principal component analysis is to reduce several bands synthesizing the redundant information.

The objective general of the PCA is reduce a group of variables and transform it in a joint smaller without losing a part significant of the information original. Thanks to the use of this technique it is possible to increase the computational efficiency because it reduces the dimensionality of the data of the image on which we work. In addition, from a statistical point of view, it facilitates the interpretation of shafts of variability in an image which is of great importance to locate those traits that are present in the vast majority of bands and those that are specific to some group of these (Piotr *et al*., 2015).

Calculation of main components in the image: Should be considered a number of variables ($x_1, x_2, ..., x_p$) in a group of individuals or objects on which it is intended to calculate, from them, a new set of variables $y_1, y_2, ..., y_p$ uncorrelated among themselves, whose variances are decreasing gradually. Each y_j (where $j = 1, ..., p$) is a linear combination of the $x_1, x_2, ..., x_p$ original, that is to say:

$$y_j = a_{j1}x + a_{j2}x_2 +, ..., + a_{jp}x_p = a_j^1 x \quad (1)$$

Being our vector a, $a^1_j = (a_{1j}, a_{2j}, ..., a_{pj})$ vector of constants and:

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_p \end{bmatrix}$$

Obviously, if what we want is maximize the variance, a simple way to achieve this could be increasing coefficients a_{ij}. Therefore, to keep the orthogonality of the transformation is restricted that the module of the vector $a'_j = (a_{1j}, a_{2j}, ..., a_{pj})$ is:

$$a^1_j a_j = \sum_{k=1}^{p} a^2_{kj} = 1 \quad (2)$$

To calculate the first component is must $a_1$choose, so, y_1 have a variance that is greater possible, taking into account the restriction $a'_1 a_1 = 1$. The second component is achieved by calculating a_2, so that, the variable y_2 is uncorrelated with y_1. From equally they are selected, $y_1, y_2, ..., y_p$, uncorrelated each other of way that there is increasingly less variance between the random variables of the process (Nazarbakhsh and Manaf, 2014).

Extraction of factors: We try to choose a_1 of such way that will maximize the variance of y_1 with the restriction of that $a'_1 a_1 = 1$:

$$\text{Var}(y_1) = \text{Var}(a'_1 x) = a'_1 \sum a_1 \quad (3)$$

The method more used to maximize a function of several variables that must meet restrictions is the method of the multipliers of LaGrange. One of the big problems is in maximize the function $a'_1\Sigma\ a_1$ with the restriction $a'_1\ a_1 = 1$. Is can observe that the unknown is a_1(the vector that is our unknown and us gives the combination optimum linear for the process).

Percentage of variability: Actually, each Eigenvalue corresponds to the variance of its component y_i that is defined by the eigenvector a_i, that is, Var $(y_i) = \lambda_i$. If we add all the eigenvalues we obtain the total variance of the components:

$$\sum_{i=1}^{p} \text{Var}(y_i) = \sum_{i=1}^{p} \lambda_i = \text{traza}(\Lambda) \quad (4)$$

Since, the matrix is diagonal but by the properties of the trace operator, traza (Λ) = -traza$(A'\Sigma A)$-traza $(\Sigma A'A)$-traza (Σ). Because $Aa' = 1$ to the be A orthogonal, reason by which:

$$\text{traza}(\Lambda) = \text{traza}(\Sigma) = \sum_{i=1}^{p} \text{Var}(x_i) \quad (5)$$

Calculation of components main obtained based on the matrix of correlations: In them variables original standardized we calculate the components that is variables with mean of 0 and variance of 1. This process is similar to take those components main that belong to the matrix of correlations. Reason for which is the components are eigenvectors of the matrix of correlations and are not the same as the covariance matrix. If you act in this way, you are given the same degree of importance to all variables (Gomes *et al.*, 2016).

In the matrix of correlations all the elements that make up the diagonal are 1. The sum total of all the eigenvalues is p and the proportion of variance collected by the autovector j-esimo component is:

$$\frac{\lambda_i}{p} \quad (6)$$

Identification of the components main: The transformation of components main can be easily understood taking into account only two variables, if represent graphically them values of them points of the image of form two-dimensional defining the two variables as axes of abscissas and ordinate we will obtain the diagram of dispersion of the Fig. 3. The points of dispersion have a typically elongated shape, showing some correlation or dependency between both bands.

Therefore, the PCA shows us the address at which the data show more variance. The size of each vector own itself is encodes in the value own corresponding e indicates how much vary them data along the component main. The center of all the points in the set of data is the start of them vectors own. The vectors own in the matrix of covariance when calculating the components main show the direction of the axes of minimum inertia (main) and them values own are directly proportional to the variability.

With the information obtained through the Hotelling transform we can calculate the trajectories according to the variance of the components main obtained which allows us to segment an area belonging to the flows

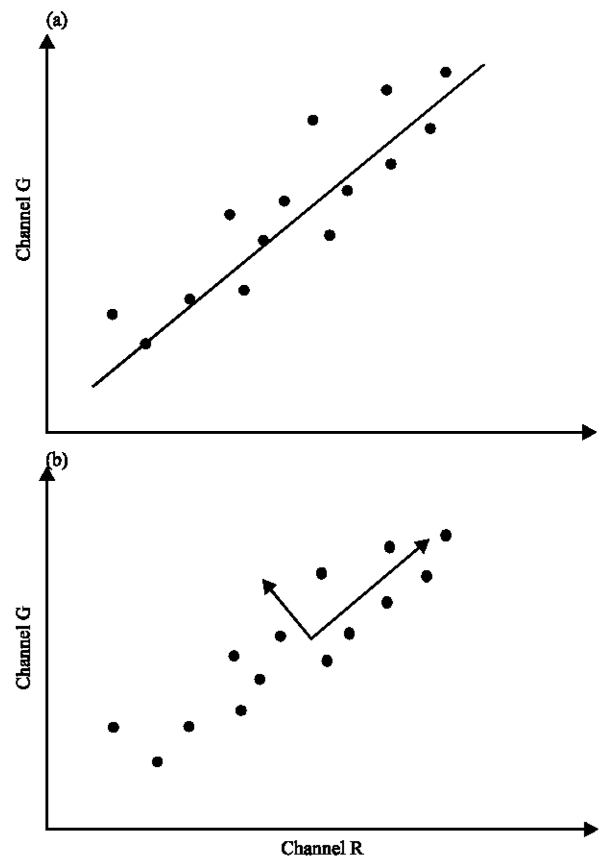


Fig. 3: The hotelling transform operation

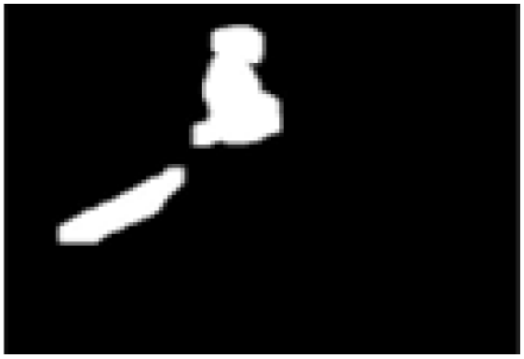


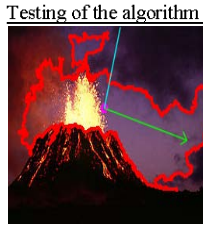
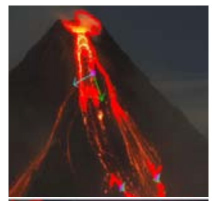
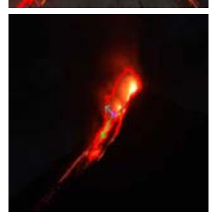
Fig. 4: Image captured and processed, focused only on our region of interest (flow of lava)

through which it is possible determine the amount of existing flow and trajectory of the same ones to apply simple mathematical operations based on angles and regions of the processed images as shown in Fig. 4. Knowing the position of the camera we could add a database that shows the direction of flows in function to the cardinal points, thus, activating alerts in the populations that will be affected

RESUTLS AND DISCUSSION

Experimental results: To evaluate the algorithm, we used photographs and videos of real volcanic eruptions obtained from existing digital databases (Smithsonian Institution, 2016) were used to evaluate the algorithm with this we could determine the effectiveness of the algorithm with different types of volcanoes and different types of rashes as you can verify in Table 1. Although, the algorithm is very effective for to identify the lava flows and the direction of the same is not as sufficiently sophisticated to detect these phenomena as a whole due to the nature of the algorithm which is based on the transformation of hotelling that eliminates redundant information. To the perform tests with different images and videos of eruptions volcanic (50 tests) is obtained excellent results being the algorithm reliable and obtaining percentages of detection superior to the 50% in all them tests, this process is verified to the submit the images to an algorithm to detect color with which is obtained the area of them flows and is compared by a rule of three simple with the area obtained by our algorithm.

Table 1: Presentation of results obtained to the evaluate the algorithm with different eruptions volcanic and types of volcanoes

Testing of the algorithm	Detection of flows and address (%)	Type of cone volcanic and eruption
	Flow 57 Address 78	Boiler Eruption Strombolian
	Flow 66 Address 85	Stratovolcano Eruption Hawaiian
	Flow 89 Address 95	Cone of ash Eruption Vulcanian
	Flow 96 Address 90	Stratovolcano Eruption Vulcanian
	Flow 95 Address 98	Dome of lava Eruption Peleana

Systems embedded: The systems of vision artificial through systems embedded presented many advantages at the time of make applications in environments hostile, it is thanks to the benefits of them same is makes possible the monitoring of volcanoes active. For the analysis of images is employed them libraries of Open CV that are completely free and also by their features due to the conditions environmental to which will be subject the project in case of an eruption is you endowed of a panel solar for the feeding of the Raspberry Pi 3.

The use of systems embedded of vision artificial, provides large advantages for the acquisition of images thanks to its compatibility and capacity of process, for this prototype is employed the Raspberry Pi 3 due to their features as: incorporate connectivity Wi-Fi, a processor of 64 bits with four nuclei (ARM Cortex-A53), besides operate on the platform free linux which is a great advantage for develop the project by the speed of process, power computing, compatibility, cost, low consumption energy, etc. (Kolsch and Butner, 2009).

Fig. 5: Execution of the code in images of volcanoes in eruption for the determination of paths

The reliability of the algorithm is of a 80% when evaluated with images of erupting volcanoes due to the nature of the images and the form of the flows in that instant when evaluating it in videos it reliability increases to a 90%, since, the trajectories are updated according as the flow is displaces giving the address in time real as is observes in the Fig. 5 and thanks to the features of processing of the raspberry allows to have an efficiency computational when the code is executed.

CONCLUSION

The results of the experiment with this algorithm show that the greater problem is have a system invariant to them changes of light that is the greater challenge to beat in the systems of vision artificial exposed to them conditions half environmental by such reason is important work in the space of color HSV, since, so is can modify easily them parameters of nuance, saturation and brightness of an image without affect the features of the image original, also for best results and focus us only in the areas of our interest can resort to tools as transformations morphological that is responsible of change the form and structure of the objects, also us allows separate the objects ones of others, get components primary, decompose forms complex, etc., allowing us to implement a robust system designed to the monitoring self-employed of volcanoes. But this always meant a higher computational cost besides a greater time of process by which is of vital importance debugging the code for best results and thus get a monitoring that is perform in time real that is the objective of the project.

The algorithm allows to determine the direction of flows from an erupting volcano in real-time with a reliability of 90%, this value is due to the noise present in the images because of the volcanic phenomenon, this percentage can be improved through the implementation of other algorithms to focus better on the areas of interest or with the use of a thermal imaging camera that would eliminate the low visibility generated by volcanic ash.

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