Machine learning using neural networks for recognizing impact craters in other planets with Mars satellite images.

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The classification of geoforms, especially meteorite impacts in planetary sciences, has been a fundamental task toward space exploration and the processing of satellite images in other rocky bodies of the solar system. In this study, we seek to implement a supervised machine learning algorithm (neural networks) to classify meteorite impacts on planetary surfaces. This, taking into account different characteristics of image analysis (shape, grey level, contours, brightness) of each pixel that makes up the panchromatic image obtained from the Mars Odyssey mission. The images database were obtained from the NASA web page and occupy an approximate memory of 3.5 to 5 GB, which indicates that pre-processing was necessary to divide and remove the noise of the images. The algorithm had a classification accuracy of 89.5%

Key words: Impact meteorites, Machine learning, Neural networks, Supervised classification, Planetary sciences.

I. INTRODUCTION

An Impact Crater (IC) is commonly a circular depression in the surface of a rocky body formed as the result of the hypervelocity impact of an asteroid. IC typically have raised rims and floors that are lower in elevation than the surrounding terrain [1] and are classified in a range from small, simple, bowl-shaped depressions to large, complex, multi-ringed impact basins.

These geoforms are the dominant geographic features on many rock planets and icy moons. Those planets have experienced active surface geological processes make visible IC. They can also be a result of erosion or tectonics transformation overtime, where such processes destroy most of the original crater topography [15]. Those are usually called impact structures. The cratering records of very old surfaces, such as Mercury, the Moon, and the southern highlands of Mars, record a period of intense early bombardment in the inner Solar System around 3.9 billion years ago. The cratering rate in the inner solar system fluctuates as a consequence of collisions in the asteroid belt. It creates a sequence of fragments that are often sent into the inner solar system[2] that has formed in a collision 160 million years ago. The asteroid belt is thought to be the source of the impact bodies have caused a large spike in the impact rate. It is important to notice that the rate of impact cratering in the outer Solar System could be different from the inner Solar System [3].

Craters counts are the only way for measuring remotely the relative ages of geologic formations on planets in geological scales. Besides, knowledge of crater morphologies enables studies of several outstanding issues in planetary geomorphology, such as the nature of degradational processes [4]. Data mining in remote sensing image databases is focused on clustering methods that work on the feature space and the multi-dimensional space, which is created by the different spectral bands of a panchromatic image. These techniques are useful for distinguishing spectral signatures of different land-use types, such as finding areas classified as "lakes", "cities" or "forests" [5]. The geometric structures or patterns can be extracted from the images using extraction techniques, segmentation, and image classification, must be identified and labelled according to a type which describes its importance. Examples of such patterns include corridor-like regions and regular-shaped polygons representing patterns of the mined data [5].

A. Machine learning techniques

Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNNs) can be thought of as a connected set of classifiers, each of which is designed to generate a specific decision and classify simple labels. Usually, ANN has an input layer which receives the input image; a set of hidden layers which serves as the classifier; and an output layer which gives the result of the classification. This method is a variation of the architecture of traditional neural networks in which a large number of layers share percentile weight, rather than each input having a single percentile. Moreover, CNNs use patches and impose convolutions within the architecture, which makes them robust against some image transformations, such as translations, rotations, and scaling [6]

Characteristic set for each class type is a representation of a particular class. In meteorology, is usually used for cloud classification, using six different criteria are brightness, texture, size, shape, organization and shadow effects [4],[13]. The brightness corresponds to the electromagnetic spectrum range feature. Textural features are those characteristics such as smoothness, fineness and coarseness or certain patterns associated with an image [8]. They describe the spatial distribution property in a specific region. The spectral and textural features are used features in machine cloud classification. Other labels such as size, shape and organization information attribute to the large scale or global spatial distribution [11].

Following , the segmentation of an image based on the histogram is a of the simplest techniques taking into account the memory that each image can occupy [12]. In this way, this segmentation process is used to select the levels of greys to group pixels in regions. In general, is possible to consider that an image has two phases: the background and the object. In the background, the level of grey occupies most of the image. Therefore, is a large peak in the histogram. The study object of the image it's another level of grey and it's another peak smaller in the histogram. The importance of this technique consists of choosing an optimum threshold point which divides the two peaks of the histogram. The thresholding takes any pixel whose value is on the side of the object and gives the value of one and the others zero.[[12]]

Among craters classification, works made by Honda Azuma [10]. A classification method is described in three main stages: pre-processing, creating a database of candidates and categorization of the candidates. The pre-processing is done by filtering and binarization of the database. Binarization uses a threshold determined statically to split the database. Then the Combinational Hough Transform and Genetic Algorithm extract candidates with circular objects inside. And the categorization with a Self-Organizing Mapping using Kohonen's self-organizing method. These methods conclude in a robust algorithmic for classifying highly noise lunar images. However, some problems were presented such as extremely noisy images which couldn't be classified by the algorithmics and sun direction and altitude. CNNs[4] are consequently gaining attention, due to their capability to discover relevant contextual features in image categorization problems autonomously. This, consist of a stack of learned convolution filters that extract hierarchical image features and are a popular form of deep learning networks. They are already outperforming other approaches in various domains such as digit recognition [5] and natural image categorization [7].

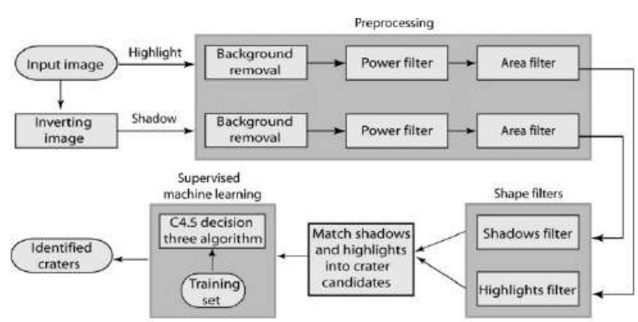

Figure 1: Neural network path for classification.

The independent or combined use of these algorithms allows generating powerful tools for object classification. In this particular case, the objects are the craters, and the set descriptors are the geomorphological characteristics of each from them. Some algorithms require training to function in a manner adequate before trying the set of interest. That is why in this work they use images of craters located throughout the earth's surface, which must be analyzed to extract their geoforms automatically and use such data as input to the classifier used. Artificial neural networks (ANN) are a paradigm of learning and automatic processing inspired by the way the nervous system of animals. It is a neuron interconnection system that collaborates each other to produce an exit stimulus. In the field of Automatic Learning is often referred to as neural networks or neural networks [12].

However, since the satellite sensor images usually contain many complex factors and mixed pixels, high classification accuracy is not easy to attain. Especially for a nonhomogeneous region, the grey values of its satellite sensor image vary greatly and thus, the direct statistic grey values fail to do the categorization task correctly. To handle complicated satellite sensor image classification problems accurately and efficiently, we first combine three types of features including original grey values, statistically structural measurements, and spectrum features as the inputs of a classification system [13].

Surfaces of rocky planets can record the history of them. The impacts of meteorites show up in almost all planets. Craters have many shapes and size and reveal the rheology of the planetary surfaces [10]. As mentioned in past sections, many methods for its characterization and clustering had been implemented. Most of the classification processes are done by statistical correlations, comparing pixel-by-pixel to find similarities and don't take into account complement information such as topography, shapes or form [14].

ANN reproduce the clustering of images simulating similar processes of the decision-making of human beings. In this method, input images are dispose as nodes that pass typically through more than three layers as mentioned before. Several authors suggest that training phase can be bypassed [8]. That method consists in elaborate a saliency maps with three saliency channels. The map is decomplexified by K clusters that contain main characteristics and then analysing each of them features. ANN is faster than traditional methods and suited for implementation on parallel machines [9]. This method has to pursue adaptability and stability, methods with good trade-off both characteristics are called Adaptative Resonance Theory (ART). ART Unsupervised methods with simpler mathematical structure and architecture were also presented and applied to satellite image clustering [9].

ANNs consist of a series of layers that are compound by neurons that pass information among them [4]. These layers are called convolutional layers and they receive inputs and return and output. They are compound by neurons that are filters learnt and extracted by convolutional processes. At the start, it is needed to set some filters for each layer and they represent image features. They are defined as matrix that is used to compare parts of the images to extract information. The main objective of using this method is to find patterns inside the data and make sense of it. In this work, the target pattern is the caters and it is expected that the layers could identify them.

II. METHODOLOGY

A. Overview

An overview of the methodology used in this project is presented in the figure 2. A database of 1000 IC was constructed. The main objective of this step is to have enough information to train the algorithm. Then, the CNN was design and constructed. Once it was constructed, the CNN was trained and used with the rest of the images.

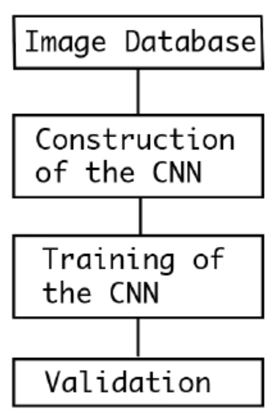

Figure 2: Methodology overview.

B. Database

The Mars Odyssey provides a set of thousands of satellite images from the Mars surface. As the database quality is highly important for the kind of algorithm used in the project, the highest resolution craters were taken to create the data set. For that reason, satellite images from the NASA website were taken and filtered to choose the best with IC. Therefore, images from the 30° N latitude from 000° to 360° longitude were used. Among those images, the images of 30°N longitude and 060° latitude and 30°N longitude and 210° latitude have a high density of IC as is shown in figure 3. Because of that, 1000 IC were chased mainly from those two images.

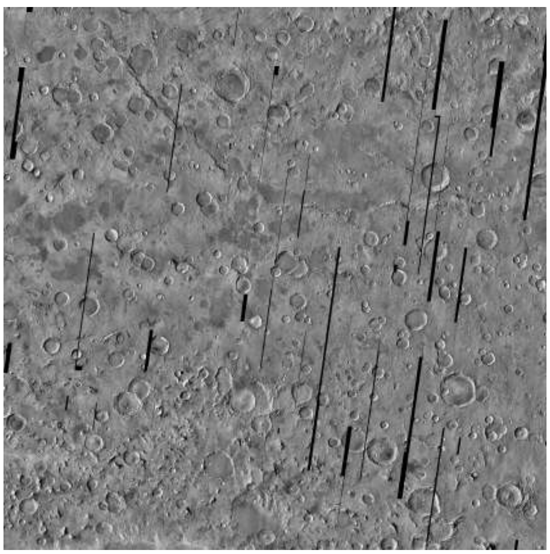

Figure 3: Mars image from 30°N060.

Also, a data set without images of craters were needed to be created. The objective of these images is to train the algorithm with no-craters images. Besides, it was needed that these images were highly similar to the surface of mars and to don't contain any crater. This data set aims to be similar to the real surface of Mars to achieve a better classification. For that reason, images from the surface of the desert of Atacama and Utah were used to create the data set.

A validation data set was created using images from the impact crater and the surface of the deserts. These images were used to get the results of the final code after the training of the algorithm. All the images from the data sets were renamed and reshape to 150x150 pixels because is part of algorithm parameters.

C. CNN Construction

The target of the CNN was to identify craters. So, four layers of neurons were considered enough to achieve reasonable results. Adding more layers could slow down the process and add unnecessary complexity to the classification

The CNN Constructed has 4 layers. The first layer, input layer, accepts images of 150x150 pixels and has 32 neurons. This layer will convolute the images and search for the best spatial features found in the image. Another three layers are created with 64 neurons: two hidden layers and the output layer. The hidden layers are not fully connected, they should be activated depending on the local spatial features. The activation will depend on a kernel of 3x3 set up arbitrary. In the end, the output layer is supposed to classify the image base on the connections created with the hidden layers. As the classification target were the craters the prediction is binary. It means that the algorithm can just identify craters and no-craters.

D. Training of the CNN

The method start with the training of the algorithm with the IC database and then it testes with validation database. The main objective of these different steps is evaluate the performance of the algorithm.

Mathematically, a neuron is described as in the equation 1, where x represents weight vector, b the bias and the activation function. During the training is expected that the algorithm could find optimal values for the parameters weight and bias [4]. These optimal values will be acquire by finding specifically features that shares the images of the data set.

$$\alpha = (wx + b)$$

In order to teach the network hierarchical features, neurons will be organized in a set of stacked layers that transform outputs of the previous layer and feed it to the next layer. Due to this process, it is expected that the first layer of the network will perform low-level reasoning and in the last-layers higher-level tasks.

Majori (2017) reported some improvements of the CNN such as: elimination of discontinuities, improve accuracy and lower execution time. Figure 1 exemplify how convolutional process of Majori function, a similar one is expected to be created in this work. In the example, a image of 80X80 is used as input. Two convolutional layers of 4x4 and 3x3 were set and at the end a deconvolutional layer is set in order to increase the resolution of the output. This output is a predicted map of 16x16. For this works, convolutional layers to be choose will be Euclidean distances, size, elongation and the angle of solar light. Those will be explained in detail in the following sections.

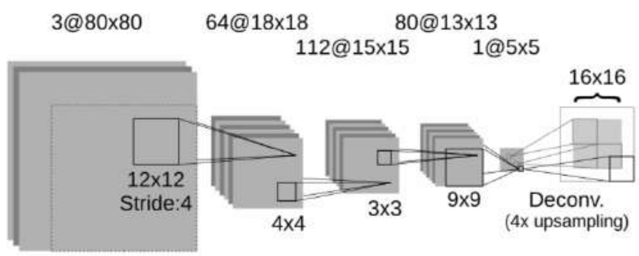

Figure 4: Network structure.

The algorithm trained itself by doing many loops of the training data set. First, it has to complete 20 loops with the dataset. This process is called an epoch. For this project, 5 epochs were defined. Every time that the algorithm began a new epoch all the values of the previous neurons were erased so each epoch sets new values for each neuron. In the end, the algorithm takes the best classification values of the epochs.

E. Validation

In this step, the evaluation of the performance of the algorithm is done. In the beginning, it performed with high classification values during this step. It was mainly because 50 epochs were established so it could find the best parameters. Despite the good results, the computing time during the training phase was too long. Because of it, the epochs were reduced and it was discovered that there was no need for more than 5 because it didn't change fundamentally the final results of the classification. By this way, the algorithm achieve values closer to the 90

III. PROCESS DESCRIPTION

Initially, a panchromatic image obtained by satellite is taken from any surface of a rocky body of the solar system. In general, these images come in various spectral bandwidths available to the user. However, for this study case we are only interested in using the images in the visible range, since the characteristics we seek to classify are clearly morphological. These panchromatic images have the particularity of having bright areas and areas of shadows due to the position of the sun with respect to the rocky body being observed. The training algorithm processes the characteristics in parallel with an inverted image to highlight the shaded areas. The main idea of the processing is to eliminate all the characteristics that do not represent morphologies such as craters especially. The bright and shaded areas combine with each other to mark regions that are potentially candidates for craters. Finally, a supervised training technique is used to differentiate between areas with craters and renewal zones.

This classification uses different filters by attributes that distinguish the craters of other geoforms, among these filters is the feed filter, area and shape respectively. These filters use a certain evaluation criteria to make a decision as to whether or not a specific feature is deleted or not modified. In this case, the attributes that are used for the classification are invariant before translations and rotations, which indicates that the filters eliminate all the characteristics that do not meet the requirements of the evaluated criterion regardless of the location and orientation of each characteristic. Also, the attributes of form are invariant before transformations of scale. Therefore, by passing the image through a single filter, it eliminates all the "false positives" of the process and reduces the computing time

A. Pre-processing

It is possible that shaded and bright areas are part of other types of morphologies (volcanic cones, orogeny, among others) can interfere with the classification of craters. For this reason the following filters are applied:

- Background noise elimination: In this filtering step, shapes such as mountains that are large enough in terms of pixels to be a crater are removed. In more technical terms, a medium filter is applied to the RAW image, obtaining a new image that did not contains the largest background characteristics, for this case the filter uses a circular window of 200 pixels wide. So the filtered image is subtracted from the RAW image, obtaining a first filter completed.

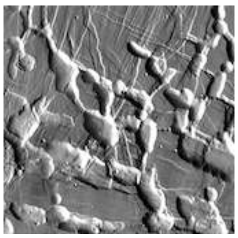

Figure 5: Sedimentary structures removed from the analysis.

- Power filter: In this filtering step, the characteristics that do not have enough contrast to be identified to the naked eye are eliminated and do not contribute to a classification with high accuracy. This filter is implemented in such a way that variables calculated as area A, the gray level h_a and the gray level of the set of dark near pixels h_b are used, which is still brighter than h_a. The power attribute is then defined as $P = A(h_a - h_b)$, where values of P ¡1000 eliminate the corresponding characteristics

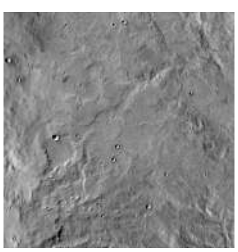

Figure 6: Examples of craters or features that are not apparent to an analyst's eye

- Area filter: This attribute is used as a criterion to evaluate the number of pixels occupied by a characteristic (bright and dark areas). In this step, all features that are too small to be considered as an impact crater or volcanic are removed. The characteristics are removed with A$\leq$ 30.

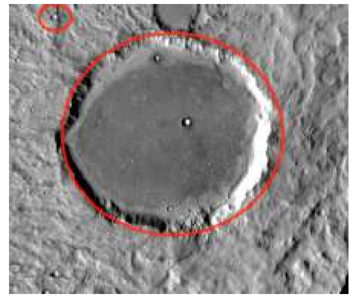

Figure 7: Craters with considerable size and shadows are taken

B. Shape-filters

After the elimination of noise in the form of mountains and small volumes, we proceed to eliminate the forms that are inconsistent with the forms corresponding to a crater. In this way, a filter with form attribute is used, whose is described as a vector that contains the Hu's seven moment invariants [2], these moments are vectors of recognition of patterns and orthogonal to each other and are invariant before translations, rotations and rescaling as mentioned above. The filter eliminates the characteristics that do not meet the criteria taking into account the minimum Euclidean distance between a shape attribute of a morphology and a set of shape attributes that are referenced. A feature with a Euclidean distance of less than 0.05 is preserved, passed through the filter and maintained for further processing.

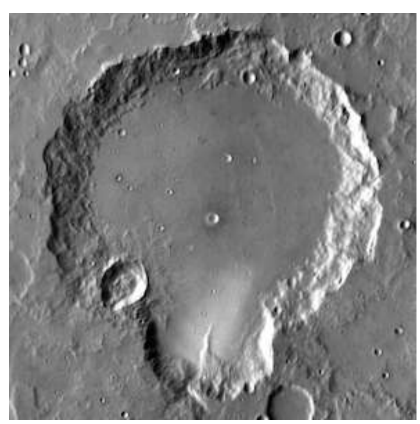

Figure 8: Crater with sedimentary and tectonic deformations are not taken into account because they do not obey the filter in a generalized way that is required.

C. Matching highlight and shadow regions

After applying the filters, two types of images are obtained: One that contains the bright areas of circular geoforms corresponding to possible craters and another image that contains the dark areas that complement the circumferences made by the impacts. In this way, it is necessary to match these images to obtain the complete crater, in this order of ideas, the images that do not match each other are not considered a crater and are discarded as possible candidates, but those that do match must comply with the following rules to be considered a potential crater candidate:

- Euclidean distance between high-light zones (H) and shadow zones (S) must be smaller than a threshold proportional to the regions size. This allow us removes pairs of H and S regions that are too far away from each other or did not match. We use $1.65\sqrt{A_H}$ as the threshold, where A_H is the area of H

- The H and S regions must coincide in their size, that is, the difference between these two zones cannot be greater than 4, since the half circumferences would not coincide together and geologically it would be meaningless

- The elongation of the combined H and S regions must be less than a threshold; Only pairs of images are processed with a combined round shape whose eccentricity is consistent. The elongation is quantified taking into account the first of the seven invariant moments of Hu. Combinations with elongation greater than 3 are rejected.

- The elongation of the combined H and S regions must be less than the unit elongations of each zone separately

- Depending on the angle of solar lighting, regions H and S must be aligned correctly to be consistent with the circular shape

D. Supervised classification

After having performed the filtering steps mentioned above, the first candidates for craters provided by the classification are obtained. However, it is necessary to polish this list of candidates with more rigorous criteria through a supervised classification. Initially, the shape and size of the possible craters are estimated by filling the space between regions H and S, closing the structure morphologically with an ellipse. Distinguish between craters and non-craters among candidates by training the algorithm with crater or non-crater tags assigned by hand by the user. The learning algorithm constructs a function or a classifier that works to label each candidate following the numerical rules of similarity between the candidates and the predetermined values thus generating a catalog of craters on a surface.

IV. RESULTS

Initially, the neural network was run on the 700 training images with IC on the surface of Mars. A number of iterations was established in order to obtain a good enough classifier with acceptable accuracy. The data set is modified in such a way that candidates for craters are labeled with the number 1 and non-craters as zero as shown below:

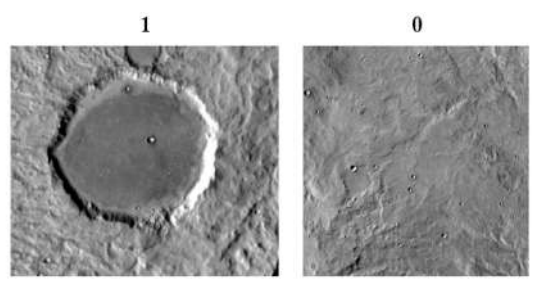

Figure 9: Labels for classification.

In this way, it was found that for each iteration performed by the network it was an increasing in the accuracy in the classification. However, from the 5th epoch or iterations, it begins to have a convergence at a stable accuracy value. Which indicates that it was not necessary to train the algorithm beyond this number.

In this way, a complete satellite image was used and the classification was carried out, going through the cleaning of the RAW image until the complete identification. Of 25 targets found by the algorithm, 22 were classified as craters greater than 30km without background noise and with the certainty of a circular shape. Showing that the

Epoch	Time (s)	Loss	Accuracy
1	31	0.9506	70.5
2	26	0.3904	92.4
3	27	0.1183	96.5
4	26	0.4138	89.9
5	27	0.0579	98.5
Average	**27.4**	**0.3862**	**89.5**

Table I: Results obtained from the training process

training allowed the network to learn in approximately 89.5 % the identification of an impact crater.

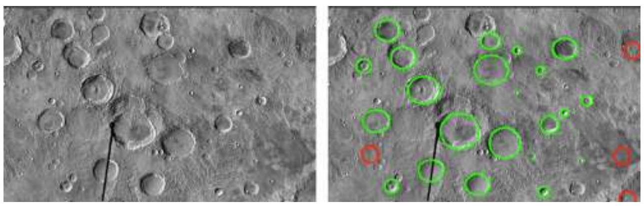

Figure 10: The image on the left is the input given to the algorithm and the image on the right are the craters in total classified after passing through the network

To ensure that the algorithm was not having failures or learning features different that the user wanted, the veracity of the algorithm was checked with the Fourier analysis in each image, which showed a maximum peak at the radial center of each crater. In this way, if the network classified it with an affirmative crater label, fft2 (python package) was carried out, to verify that it was not a set of damaged pixels of the sensor itself that gave the sensation of shadows on the Martian surface.

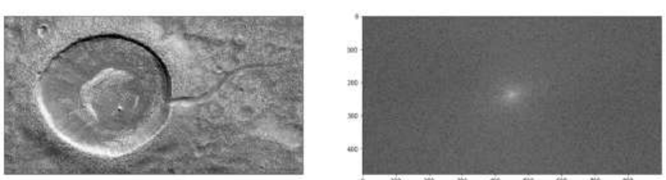

Figure 11: Fourier analysis of a common impact crater.

In this way, it is possible to make a python routine that manages to extract the RAW images, make them the orbital correction and then identify crater by crater so that it positively encloses the positive candidates as shown in Figure 9.

V. CONCLUSIONS

This machine learning code allows us to more easily classify geoforms such as impact and volcanic craters. The algorithm is constructed on supervised classification rules from a satellite image and with the help of different morphological filters it is possible to distinguish between craters or non-craters. All this information is translated by the arrangement of the pixels in the RAW image since these images are taken with a certain solar angle that allows the presence of shadows and bright areas, from which a geometric, dimensional and consistency analysis is performed, which allows us to identify a potential candidate. The neural network is trained with 1000 images of Martian craters so that the learning algorithm manages to identify the main characteristics of a crater and allows each candidate to be labelled individually. The algorithm has an accuracy of 89.5% being a binary classification and the processing took few memory resources.

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