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Random Subspace Neural Classifier for Meteor Recognition in the Night Sky

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***Abstract*—**This article describes the Random Subspace Neural Classifier (RSC) for the recognition of meteors in the night sky. We used images of meteors entering the atmosphere at night between 8:00 p.m.-5: 00 a.m. The objective of this project is to classify meteor and star images (with stars as the image background). The monitoring of the sky and the classification of meteors are made for future applications by scientists. The image database was collected from different websites. We worked with RGB-type images with dimensions of 220x220 pixels stored in the BitMap Protocol (BMP) format. Subsequent window scanning and processing were carried out for each image. The scan window where the characteristics were extracted had the size of 20x20 pixels with a scanning step size of 10 pixels. Brightness, contrast and contour orientation histograms were used as inputs for the RSC. The RSC worked with two classes and classified into: 1) with meteors and 2) without meteors. Different tests were carried out by varying the number of training cycles and the number of images for training and recognition. The percentage error for the neural classifier was calculated. The results show a good RSC classifier response with 89% correct recognition. The results of these experiments are presented and discussed.

***Keywords*—**Contour orientation histogram, meteors, night sky, RSC neural classifier, stars.

I. Introduction

At a certain time of the year, the start of a meteor shower is expected. This phenomenon has a certain name that is associated with the name of the constellations from which the meteor shower appears to originate, such as: - Quadrantids, Lyridids, Perseids, Draconids and Geminids [1]. The night sky with a meteorite is presented in Fig. 1.

Each meteor can be attributed to a magnitude of brightness compared to that of the stars, which by projecting their trajectory between the constellations they show well-defined areas of the sky called radiants. Astronomers have defined a logarithmic system for the magnitude of brightness of meteors, which can be compared with other stars or celestial bodies. Stars with magnitude +6 are the weakest, and planets and brighter stars are assigned a negative magnitude, for example, the star Sirius has a magnitude of -1.5 and planet Venus has a magnitude of -4. A meteor with a luminosity equal to or superior to that of the planet Venus is called a fireball. Table I shows the classification of meteors with respect to the magnitude of the brightness [2], [3].

Fig. 1 Meteorite in night sky

TABLE I
METEOROID CLASSIFICATION ACCORDING TO ITS BRIGHTNESS MAGNITUDE

Name	Magnitude of brightness (m)
Micrometeor	m < +6
Meteor	+6 < m < -4
Bolide	4 < m < 17
Superbolide	≥ -17

The number of meteors that can be observed in one hour, in a clear, cloudless sky and with the radiant located at the zenith, is defined as the ZHR (Zenithal Hourly Rate) [4]. A meteor is a luminous phenomenon produced by a meteoroid when it enters the atmosphere of a planet; the meteoroid is a small particle of a comet or an asteroid, with dimensions ranging from 100 μm to 50 m in diameter, orbiting around the Sun. Table II defines the lower and upper limits for the dimensions of meteoroids with respect to other types of space bodies; a meteoroid that does not completely disintegrate when passing through the atmosphere, eventually collides with the terrestrial surface becoming a meteorite, and, given its energy, can cause an impact crater [2]. Another classification for meteors considers dimensions of 100 μm to 10 m [5].

Currently meteor research is of great interest to science, as it helps to understand the origin of life and the solar system in a more meaningful way.

TABLE II
CLASSIFICATIONS OF METEORIC PHENOMENON ACCORDING TO METEOR DIAMETER (M, METERS)

Cosmic Dust (CD)	Meteoroid (M)	Comets and Asteroids
PC < 100 μm	M ≥ 100 μm up to 50 m ≥ M	50 m < CyA
PC < 100 μm	M ≥ 100 μm to 10 mM ≥ M	10 m < CyA

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Observing meteor showers or shooting stars is a beautiful and impressive phenomenon that is frequent throughout the year; in particular, on dark and cloudless nights, such phenomena can be observed without any instrument at up to 10 meteors per hour (Fig. 2) [6]; in seasons called Meteor showers, these phenomena can be observed up to 60 per hour [5].

The flow of material that annually reaches the surface of the earth is presented in [2]. An estimated 40,000 tons of space material enters the Earth's atmosphere each year, among which are meteoroids. These bodies are considered a space risk and can affect entire regions if they hit the Earth.

Fig. 2 The sky during the annual Perseids meteor shower in 2016 [6]

In 2005, NASA was assigned the task of identifying 90% of the near-Earth asteroids with characteristic dimensions of 140 m or more, because it considers these bodies [4], in addition to being of scientific interest in relation to many aspects of the universe (origin, etc.), to also be a risk, presenting potential for danger and disaster over large areas if they hit the Earth. It is estimated that this task will take at least another 30 years to consolidate the subject [4]. This is why having a better understanding of these space bodies will provide us with more information on their chemical and physical compositions, as well as their origin, calculation of their orbits, estimation of their trajectories and their regularity or periodicity patterns.

The scientists of NASA say and manifest the need to implement monitoring techniques using new technologies, such as artificial intelligence (AI) [4], [6]. The present work aims to provide AI elements for the recognition and classification of meteoroids using neural networks particularly using a RSC that is based on random threshold neural classifier (RTC).

Making use of computer vision based on neural networks for the study of meteors may become a powerful tool in the future for monitoring and reconstructing the trajectories of these bodies that enter the Earth's atmosphere, analyzing their possible collision points for their speedy recovery or otherwise, developing an early warning program that gives the population sufficient time to evacuate possible risk areas due to the fall of these meteors. Implementing computer vision for this recognition task will provide the advantage of being able to carry out remote monitoring, since it will only be necessary to process images obtained by cameras in strategic places and at low costs. In addition, including neural networks will increase the degree of effectiveness since, when properly trained, they could be used to perform recognition in real time and an alert message would only be provided when a celestial body is detected to enter the atmosphere. With some methods and algorithms, one could even predict possible impact trajectories for these meteorites before their fall.

II. Random Threshold Classifier and Random Subspace Classifier

In recent years we have developed several neural classifiers to resolve different tasks [7]-[15].

The RTC is based on the perceptron model, allowing a high processing speed for training and image recognition [7]. The structure of the RTC classifier consists of three main layers of neurons: the neural network input that corresponds to the image characteristics, the nonmodifiable neural blocks and a final layer of class neurons (Fig. 3).

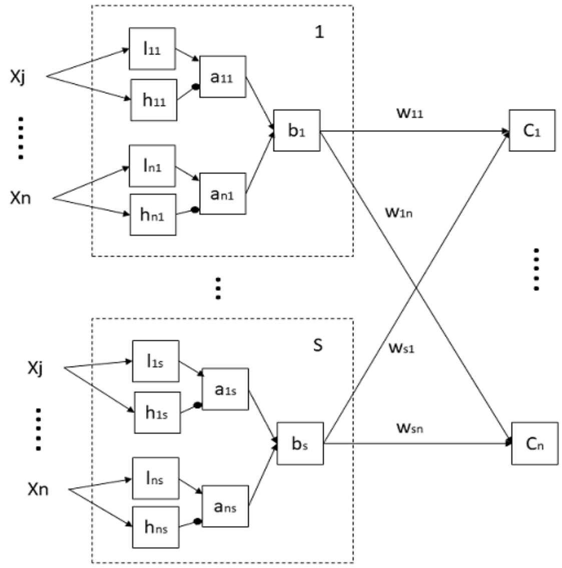

Fig. 3 RSC structure

The input characteristics are obtained from the image and can be calculated using different algorithms, for example, the brightness, contrast, color, and contour histograms. It should be noted that the characteristics extracted from the image depend on what you want to classify. Once the characteristics (X_1, X_2… X_n) of each image have been extracted, they are input to all of the nonmodifiable neural blocks which are structured in the form of several layers of neurons with specific functions. The first layer consists of two neurons: one for excitation and one for inhibition, h_{ij} and l_{ij}, respectively, where i represents the characteristic number and j represents the neuronal group number [7]. These neurons will have an activation threshold, which is chosen randomly, respecting the condition that a threshold of l is less than the threshold of h ($l < h$). These neurons l and h, are connected to the next layer of neurons a_{ij}. If the value of any input characteristic exceeds the threshold value l and is less than h, the neuron a is activated giving their output a value of 1, otherwise the value will be 0. This means that the characteristics of the image must lie between the thresholds of excitation and inhibition neurons, giving the neurons output a value of 1 if this criterion is met or a value of 0 in any other case. Subsequently, the a_{ij} neurons are connected to a layer of b_j neurons, which will correspond to the output of the neural group and whose activation will be possible, if and only if, all a_{ij} neurons have a value equal to 1 [7]. The neural vertical layer b_j, can represent the operation of an AND logic gate, which only provides output values when all its input values are 1's and will in any other case have output values of 0's.

Finally, the output of these blocks (the neurons b_j) provides us with a binary vector $B = (b_1, b_2, b_3\ldots, b_S)$. The number of 1's in this vector B will be much lower than the number of 0's ($N(1) << N(0)$). These values will enter the last stage of the classifier, which corresponds to the recognition layer c_n, and whose number of neurons will correspond to the number of classes that are being classified. The connections between the b_j and c_n layers have trainable weights, whose values will be modified by the b_j neural layer, according to the Hebbian training principle. Hebbian rule establishes that the weight values must be decreased for the connections to the incorrect response (incorrect output neuron) and the weight values should be increased to the connections with the correct answer (correct output neuron). Therefore, the entire RTC classifier recognition procedure involves supervised training [7]. A diagram representing the structure of the RTC classifier is shown in Fig. 3.

III. Image Database

For this project, a series of images obtained from the internet was selected, with the characteristics of having two classes that can be classified by our neural network. These classes are the night sky with background stars as the first class, and a meteor trail in the same image as the second class. Fig. 4 shows some images that were used in this project.

Our database contained a total of nine images with a size of 220 x 220 pixels, in color and stored in BMP format. From these images the characteristics were extracted. The processing consists of marking each image to differentiate the classes that the neural network is required to differentiate. First, the color was removed from the images, leaving the images in a grayscale format. Subsequently, the edge of the meteor trail was selected with a one-pixel line to delimit it from the background of the image. Finally, the areas that were delimited from the meteor were filled with white, with which a new marked image base was obtained. Fig. 5 shows a comparison between an original image and a marked image used in our classifier.

IV. Experiments

To perform the experiments, we developed software in the C language using the Borland 6 platform and the RSC classifier. The stages for RSC are the follows [7]:

Fig. 4 Meteors and night sky as background

Fig. 5 Marked image

I) Generation of masks (Mask Generation), which consists of preparing the process for the training and recognition of the image base. At this stage, the system randomly selects the images for training and recognition. Then, the l_{ij} and h_{ij} thresholds for the groups of nonmodifiable neurons are selected.

II) Coding (Open Image; Coding). In this stage the following characteristics are obtained: 1) the input characteristics, 2) the responses of the a_{ij} neurons that depend on the thresholds l_{ij} and h_{ij} respectively and 3) the binary vector for the b_j neuronal groups. In this procedure, a 20 x 20 pixels window is generated, which scans the entire image with a step size of 10 pixels. For every window (green color), the vector of the input characteristics with brightness, contrast and contour histograms is calculated. Once the image is completely scanned, this process repeats until the image base is complete. By using 220 x 220 pixel images and a window of 20 x 20 pixels with a 10-pixel step for scanning, a total of 484 samples per image were obtained (Fig. 6).

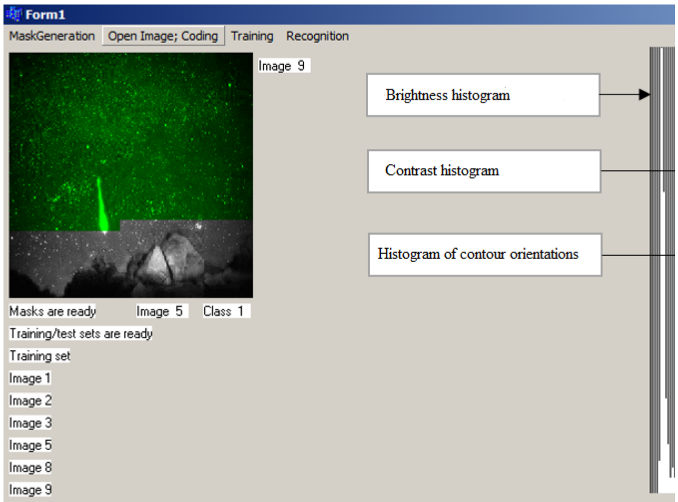

Fig. 6 Image coding (Open Image; Coding)

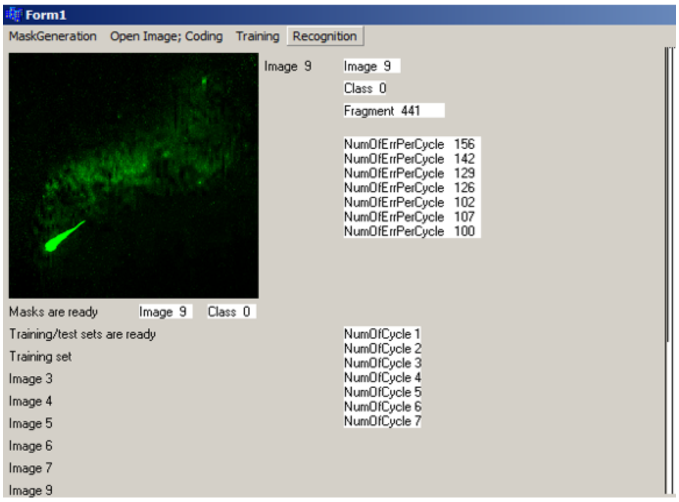

Fig. 7 Neural network training

III) Training denotes the training of the RTC neural network. At this stage the weights of the connection between the b_j neuron layer and the c_n layer are modified. If the recognized class matched with the correct class, the weight w_{ij} did not change; if the classes were different, then the weights w_{ij} were increased for the correct class and decreased for the wrong class. The training process was stopped, when at least one of the two criteria was met: 1) the number of cycles set at the beginning of the program or 2) the number of errors equal to zero.

IV) Recognition of classes (Recognition). At this stage a new group of images is presented that were randomly selected at the start. The RSC classifier defines the classes and calculates the errors. The error rate for all test images provides the percentage of effectiveness of the classifier (Fig. 7).

The tests were carried out as follows: 1) with seven cycles of training, four images are used for training and five for recognition, then five images are used for training and four images for recognition; subsequently, six images for training and three images for recognition are used; the process is carried out successively until one arrives at eight images for training and one image for recognition; 2) the same procedure is performed with 20 training cycles. Table III shows the procedure with a varying number of training and test images.

TABLE III
TESTS WITH RSC

Experiment No.	Number of training cycles	Number of images for training	Number of images for recognition
1	7	4	5
2	7	5	4
3	7	6	3
4	7	7	2
5	7	8	1
6	20	4	5
7	20	5	4
8	20	6	3
9	20	7	2
10	20	8	1

V. RESULTS

We obtained the following results. Having 220 x 220 pixel images and feature extraction windows of 20 x 20 pixels with a scanning step of 10 pixels, we obtained a total number of (220/10) x (220/10) = 22 x 22 = 484 samples per image. With these data the system calculates the error percentage for our neuronal classifier, which is given in Table IV.

TABLE IV
RESULTS FOR THE RSC CLASSIFIER TESTS

Experiment No.	Error number	Sample number	Error (%)
1	183	2420	7.56
2	116	1936	5.99
3	73	1452	5.03
4	57	968	5.89
5	22	484	4.55
6	195	2420	8.06
7	147	1936	7.6
8	69	1452	4.75
9	46	968	4.75
10	31	484	6.41

Fig. 8 Error number (%)

Fig. 8 shows a graph for both experiments, and the percentage error against the number of tests performed with different numbers of training images is shown. For the first test with seven training cycles, four images are used for training and five for recognition; then, five images for training and four images for recognition are used; then, six images for training and three images for recognition are used; the process is carried out successively until reaching eight images for training and one image for recognition; the second test is carried out with the same methodology except that 20 training cycles are used instead of seven.

VI. Conclusion

The results show 89% correct recognition for the RSC classifier. This is a good result and the parameters of the RSC classifier are adjusted. To improve the results, we need to use more images. The use of neural networks to classify meteors can be considered a necessary tool for monitoring their luminous phenomenon.

The RSC neural classifier has a good response for the recognition of images with meteors and the night sky. The test results also show that the RSC neural classifier can work with a different base of images, as long as they are processed correctly, before their characteristics are entered into the neural network.

The use of neural networks to classify images with meteors is an area of research that could have a great impact on the monitoring of celestial bodies in the future, leading to the realization of possible early warning tools, as well as the reconstruction of trajectories for the possible recovery of meteors in case of impact in uninhabited areas. However, more work needs to be done in this type of project to optimize the classifier so that it can carry out work in real time with the help of cameras located in strategic areas for monitoring the sky both during the day and night.

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