Comparison of supervised classification methods of Maximum Likelihood image, Minimum Distance, Parallelepiped and Neural network in images of Unmanned Air Vehicle (UAV) in Viçosa-MG

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Abstract: *The aim of this work was testing the classification techniques in digital air images of spatial high resolution obtained by Unmanned Air Vehicle (UAV). The images recover an area of the Federal University of Viçosa, campus Viçosa-MG. From the orthophoto generated, the classification test was made, by using four classifiers: Parallelepiped, Average Minimum Distance, Maximum Likelihood and Artificial Neural Networks. The classification that best delimited the different features present in the image was the classification by Artificial Neural Networks. In order to prove statistically the classification efficiency, the validation was carried out through Kappa index and visual analysis.*

1. Introduction

Nowadays, there are many methods for digital images treatment of remote sensing which allow to carry out tasks of manipulation, analysis and images comprehension. In the images processing of remote sensing, the target nature is determined based on the fact that different materials are characterized by interacting in different ways in each band of electromagnetic spectrum (JENSEN, 2009).

The use of Air Vehicles Unmanned (AVUs) is the study field that has grew fast in the technologies of remote sensing, by offering an option of low cost that allows to measure and monitor aspects of the environment with the possibility of the images acquisition (HONKAVAARA, et al., 2013). Air images with spatial and time high resolution contribute for obtainment of field information, characterization of the problem and even thematic maps generation of elevated detail. Lian e Chen (2011) worked with guided classification to object in satellite images of spatial high resolution and concluded that the precision of classification is directly related to spatial resolution.

According to Queiroz et al. (2004), the information contained in the images can be extracted through the classification process. There are various classification methods which search through sundry approaches identify with accuracy the information that each image pixel, by classifying it in category. The methods of image classification can present different levels of accuracy, depending on the approach used by the method and the specification of its parameters.

Thereby, the aim of this study was evaluating and comparing the performance of four classifiers: Parallelepiped (PPD), Minimum Distance Average (MDA), Maximum Likelihood (ML) and Artificial Neural Network (ANN) to determine the use and cover map with the classes: Forest, Water, Urbanization, Agriculture, Exposed Soil, in UAV images, in Viçosa, in order to verify which method offers best results through the validation by the Kappa Index.

2. Images classification

The methods of classification can be divided in classifiers per pixel or per regions and can take into account one or more bands of images. The classifiers per pixels use the spectral of each pixel isolated to find homogenous regions, defined as classes. Classifiers per regions are based on information of a group of neighboring pixels (INPE, 2014). In accordance with Santos (2003), the method of ADM assigns each unknown pixel to class whose average is next to it. Each pixel inside and out of the areas of training is evaluated and marked to class which it is more likely to belong to (Figure 1–A). The method PPD defines square areas, by using units of standard deviation or minimum and maximum reflectance values into each training area, according to Figure 1-B.

However, the MAXVER method, according is the most used in remote sensing within the statistical approach (JENSEN, 2005). This method suits ellipses, so that the location, shape and ellipse size reflect the average variance and covariance of two variables. The distribution of reflectance values is described by a probability function that evaluates the possibility of a given pixel belongs to a category and classifies the pixel to a category which it is more likely to associate, (SANTOS, 2013) as shown in the Figure 1c.

(A) (B) (C)

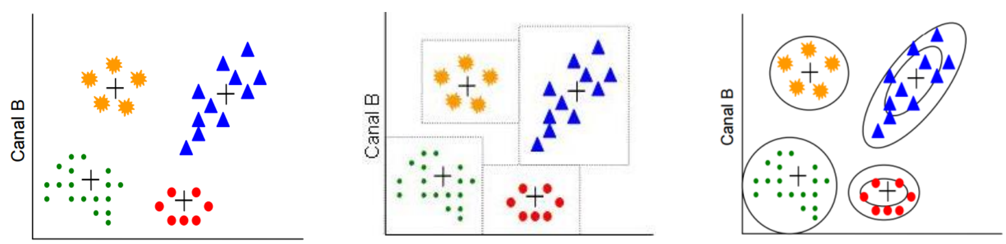


Figure 1: A - Rating method scheme supervised of Minimum Distance to the Average, B - Scheme of classification method supervised of parallelepiped and C - Scheme of classification method supervised of Maximum Likelihood.
Source: Santos (2013).

The RNA networks are also used in images processing. In Queiroz et al.'s (2004) opinion, as RNA are algorithms whose operation is based on structure of the human brain because it acquires and keeps knowledge through the learning process, which happens through neurons connections, what is also known as synapses. According to Abdalla and Sá Volotão (2013), there are neural networks of simple layer which consist of a group of neurons arranged in a single layer only and multilayer networks, formed by numerous hidden layers or the combination of several networks of simple layers.

To Belinda et al (2013), in a neural network the input layer X_i is one in which patterns are presented to the network. The intermediate layers (also called occult or hidden) which can be more than one, are responsible for most of the processing. At this stage the input data is multiplied by the weight W_{ji} and it is also added polarization $\theta_j$to adjust the residual error. An activation or transference function f calculates output Y_j of the neuron, by using a predefined logic. The output of the transfer function goes to other neurons or environment through the output layer. The operation of a typical neuron in a network is shown in Figure 2, can be written mathematically by equation 1 and 2:

$$I_j = W_{ji}X_i + \theta_j \tag{1}$$

$$Y_i = f\left(I_j\right) = f\left(W_{ji}X_i + \theta_j\right) \tag{2}$$

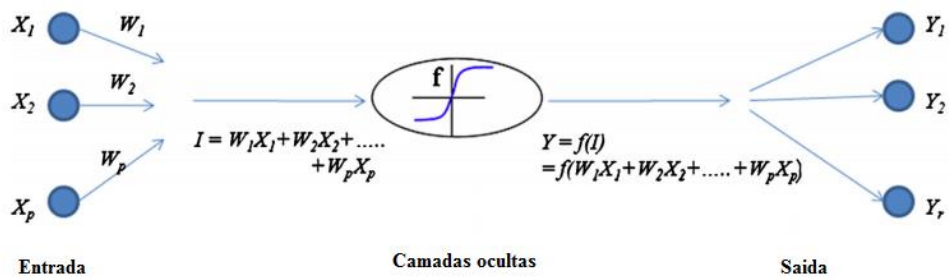


Figure 2: Architecture of a RNA with two hidden layers.
Source: Mazhar et al (2013).

The neurons number of the first layer corresponds to the dimensionality of input attributes vector. The output layer will have as many neurons as there are classes to be separated. The biggest problem is in the definition of hidden layers number, and the neurons number that composes them. In practical this problem has been generally solved by attempt and error, or by previous experience in domain of a given situation (GALO, 2000).

3. Classification rating

The classification rating can be determined by the *Kappa* index method, calculated based on an error matrix and by using as measuring of agreement between the map and the reference adopted for the estimative of the accuracy, in this case, the orthophoto. The equation 3 calculates the *Kappa* coefficient (COHEN, 1960):

$$K = \frac{N\Sigma X_{ii} - \Sigma(X_{i+} \times X_{+i})}{N^2 - \Sigma(X_{i+} \times X_{+i})} \quad (3)$$

Considering that:

K = *Kappa* coefficient of agreement;

N= Number of observations (sample points);

X_{ii} = Observation in the line i and column i;

X_{i+}= Total marginal of the line i;

X_{+i}= Total marginal of the column i;

The results of the *Kappa* index calculated for each test of classification can be understood according to Mangabeira et al. (2003) (Table 1).

Kappa index (%)	Estimative quality
80 a 100	Excellent
60 a 80	Very good
40 a 60	Good
20 a 40	Reasonable
0 a 20	Bad
<0	Very bad

Table 1: Table for *Kappa index interpretation* .
Source : Mangabeira et al. (2003).

4. Experiments and Results

The study area is part of the Federal University of Viçosa (UFV), Viçosa campus, Minas Gerais. The UFV landscape has classes variety of use and soil occupation such as: forest remnants; experimental fields of agriculture and bare soil; buildings and patio area with different characteristics; water bodies such as rivers and lakes, among others. Due to these characteristics classes of forest, agriculture, bare soil, urbanization and water were chosen for the experiment.

In this study the equipment UAV Echar 20A manufactured by XMobots (2015) was used, coupled with Sony ILCE camera - 7R, 36.4 MP full-frame CMOS sensor Exmor®. The photos processing was carried out in PhotoScan Professional Edition 1.0.2 of Agisoft software. Points Control and validation were collected by using the Global Navigation Satellite System (GNSS), Javad TRIUMPH 1 receptor with application of the method Real Time Kinematic (RTK) for georeferencing to the Brazilian Geodetic System.

It also used the Geographic Information System (GIS) IDRISI version 17 - *Jungle*, developed by Clark University. The software was chosen because of various processing tools and analysis of digital images.

5. Methodology

In order to facilitate the methodology comprehension applied, a flow diagram of the activities performed is presented in the Figure 3.

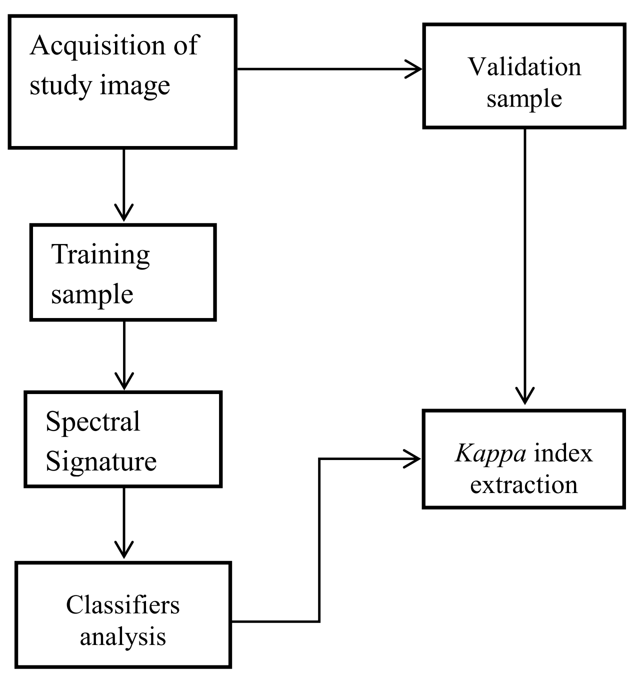


Figure 3: Flow diagram of the methodology proposed.

The UAV images were obtained on 10/08/2015 at 11:41. Possessing the UAV and control points, it was generated orthophoto with spatial resolution of 0.5 cm. In order to minimize the computational effort of the classifiers, the orthophoto was cut within the limits of the study area.

Then the class samples of Forest, Water, Urbanization, Agriculture and exposed soil were collected, divided into two groups: training and validation. On average, there were 61,995 training pixels and 12,810 validation pixels for each class. It is important to highlight that the sample size of each class was a control factor in the experiment enabling that the classifiers analysis were independent of the sample size of each class.

The spectral signatures of classes were extracted with the training samples and then the classifiers analysis PPD MDM MAXVER and RNA were performed. Possessing the four maps generated by using classifiers along with the validation sample it was extracted Kappa index of each classifier tested thus to carry out the analysis. Qualitative analysis was also conducted, based on the visual analysis, where the results of the classified images with the original image were compared, aiming to verify if the identification of classes was consistent with reality.

6. Results

It was observed that the four classifiers rated, RNA and MAXVER demonstrated the best performance, with Kappa index of 93% and 87%, respectively, according to the Figure 4. The Figure 5 illustrates the classifiers maps used.

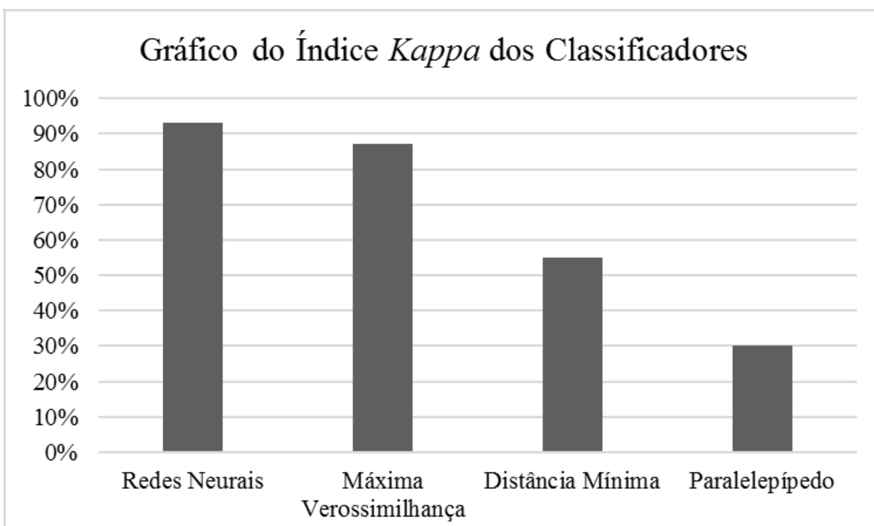


Figure 4: Graphic of Kappa index of the dos classifiers tested.

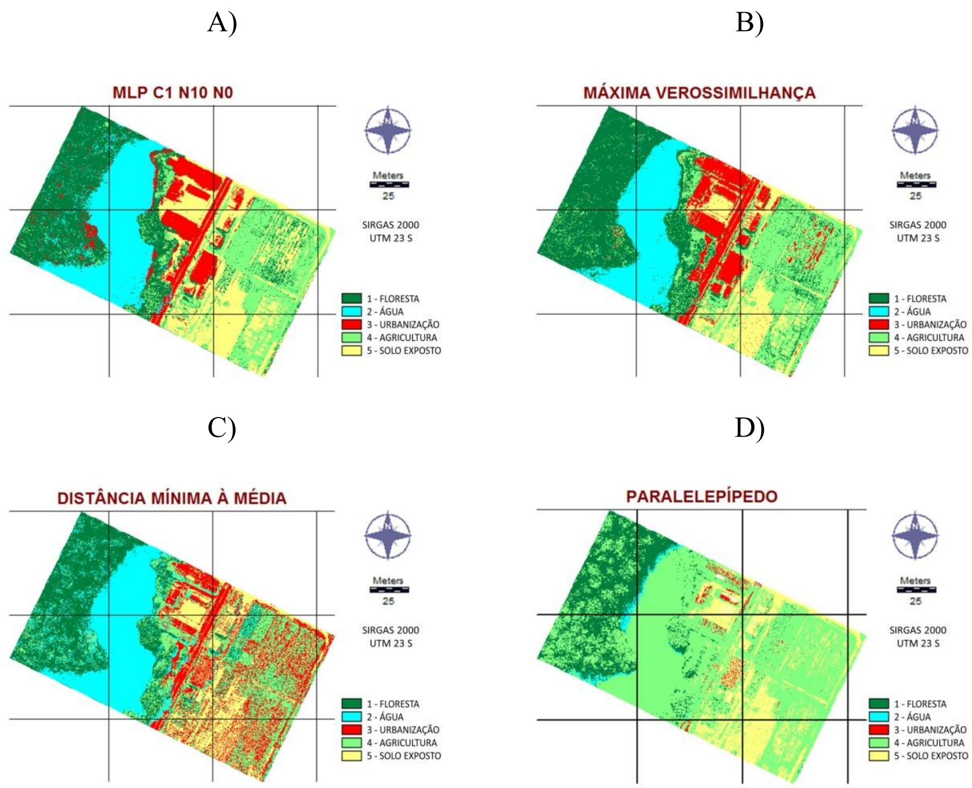


Figure 5: Map with best classification.

It can be observed that the parallelepiped method had the worst result (Figure 5d), since it is more appropriate for images that have classes with well-defined shapes, different from the image used, obtained by UAV, which has a low definition of class boundaries. In accordance with Crósta (1992) one of the problems is that an image that contains thousands of pixels most likely fell out of the decision limits of classes, no matter classes to define. Nevertheless, the method result of the minimum distance is due to the fact that interest classes were worked in the image that was better suited to the method algorithm, with good spectral similarity, which facilitated the classification.

Evaluating visually the images generated by the classifiers, it is observed that the method of neural networks and maximum likelihood were more compatible with reality, by distinguishing better the targets. To obtain the image classified as RNA, the parameters were changed, and by trial and error, an acceptable result was obtained.

The settings used for test in an attempt to obtain the network that best classifies the image are shown in Table 2.

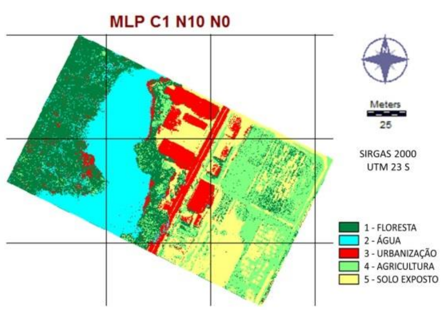
Table 2. Setting used for the tests performance.

HIDDEN LAYERS	NODES 1	NODES 2	RMS TRAINING	RMS TESTING	*KAPPA*
1	10	0	0,2	0,2	89%
1	12	0	0,3	0,3	66%
1	14	0	0,2	0,2	91%
2	10	6	0,1	0,1	93%
2	12	8	0,1	0,1	93%
2	14	10	0,1	0,1	93%

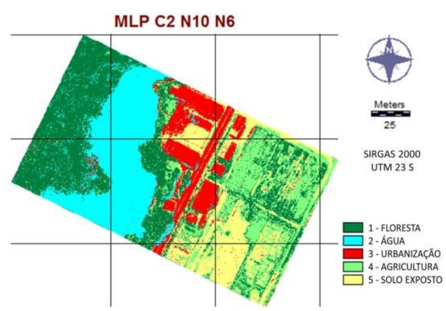
In accord with Table 2, it is stated that with a layer and increasing the knots number, the *Kappa* has random behavior. The neural network had best performance with two layers and independent when the second layer is inserted.

In the tested carried out, it was observed that, increasing the number of second layer, the network did not product significant results in the image and its *Kappa* index stayed constant. Figure 6 illustrates the maps obtained by Artificial Neural Network method.

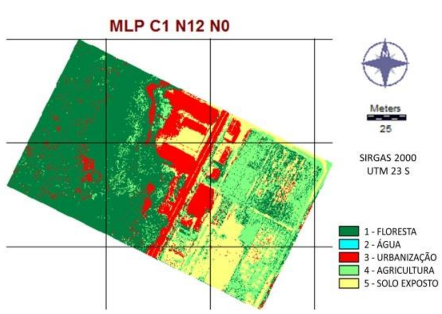
A)



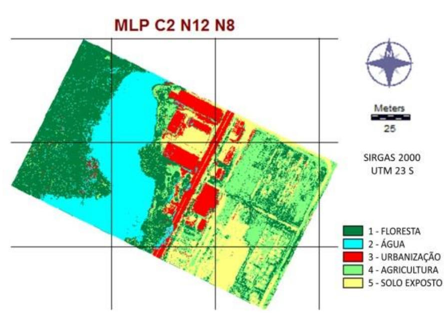
D)



B)



E)



C) F)

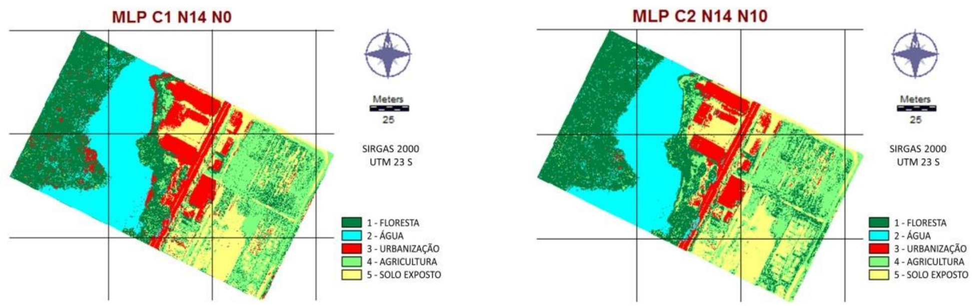


Figura 6: Mapas das classificações por Redes Neurais Artificiais.

7. Conclusion

Higher spatial resolutionimages can improve the classification, due to better identification of objects on the soil. Thus, after the work accomplishment, it was found that the use of UAV images was efficient to define targets of interest, avoiding the scan, based on photo-interpretation. It is also to note that these analyses can be made extremely quickly and dynamically, by enabling the monitoring of physical, environmental and urban social evolution, for example.

The choice of the best results in this work was based on the results of the Kappa index and visual analysis of the results generated thereby it was concluded that the use of the classification method by neural networks was more efficient than other tested methods, however the definition of the parameters and their training were long, requiring tests with modified parameters, in order to reach an acceptable result. In this context, the data generated by this research, can bring an effective contribution, once they can be considered as an alternative to systematization in the detection of classes in the image, not limited to traditional techniques.

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