# SHAPE-TEXTURE FEATURES FOR THE VHSR SATELLITE IMAGES CLASSIFICATION USING THE MLP NEURAL NET

## Habib Mahi, and Mounia Kaouadji

Earth Observation Division, Centre of Space Techniques, Arzew, Algeria; {mahihabib / kaouadjimounia}(at)yahoo.fr

# ABSTRACT

With the emergence of commercial satellites with on-board sensors characterized by Very High Spatial Resolution (VHSR), identification and localization of topographic features are becoming conceivable. The VHSR sensors provide images with significant amount of geometrical details that yield new kinds of information, such as shape information. On the other hand, the classification of this heterogeneous information set requires also the establishment of new techniques different from those used for low and medium spatial resolution data classification. To this end, the Multi-layer Perceptron (MLP) neural network has been investigated to classify this heterogeneous set of information using a combination of different features extracted from objects, namely Quaternion Zernike moments as shape descriptor and Haralick's features as textural descriptor. The proposed approach was tested using a sub-scene of Quickbird image datasets of Algiers (northern Algeria). The results indicate a mean accuracy value of 79.99% using only the shape feature information, 74.89% by applying the textural features information and 86.23% by combination of shape descriptor and texture descriptor. The results of the proposed method with MLP classifier are also compared with those results obtained by k-NN and SVM classifiers, a fact which confirms the effective-ness of the suggested approach.

# INTRODUCTION

With the advent of very high spatial resolution satellites (VHSR), the spatial details within the image scene have increased considerably. Indeed, VHSR sensors provide images with significant amount of geometrical details and consequently facilitate the recognition of urban man-made structures, such as buildings, houses or roads. However, we observe that the traditional pixel-based classification techniques do not perform well when applied to VHRS images due to large withinclass spectral variations and between-class spectral confusions that characterize urban man-made features.

So, we will be interested in the object-based image analysis. It consists essentially of two main steps: segmentation, which partitions the image in homogeneous regions or objects; and classification of the objects obtained in the segmentation step. In this work, Multilayer Perceptron (MLP) was originally designed for classification. Both segmentation and classification are guided by criteria based on the image object features (spectral, textural, spatial...).

The best-known features are shape descriptor and textural descriptor. The former is very popular since its emergence in the 60's (1). These include geometric (2), Legendre (2) and Zernike moments (3). Comparative studies (4,5,6) show that Zernike moment descriptor outperforms the other moment descriptors in terms of invariance, computation complexity, compact representation and robustness to noise and distortions. However, in colour image case, most studies use the conventional formulation of Zernike moments by transforming the colour image to greyscale (loss of information) or by calculating them for each component of the image (loss of the notion of dependency 03 between the colour components). To overcome these drawbacks, the use of Quaternion Zernike moments as object shape invariant descriptor can achieve a good discrimination between object shapes. By performing the classification on the obtained Quaternion Zernike feature vectors instead of the original objects consequently, a good discrimination between object with the same shapes and different colours can be discriminated. The second descriptor is concerned with texture analysis. Many approaches have been developed; however, three major categories are commonly

used, namely structural, spectral and statistical methods. The Grey Level Co-occurrence Matrix (GLCM) is one of the most well-known and widely used texture features by the remote sensing community.

### **METHODS**

In this section, we briefly describe the Haralick's texture feature, the theory of quaternion, the Quaternion Zernike Moments and finally the MLP neural net used for classification.

### **Texture features**

In image classification, texture is a powerful source of information and is used to identify, characterize and compare objects in an image. Texture features have been widely studied in remote sensing image classification (7,8). There are many different methods to extract model texture from the image. In this study, we have used Grey Level Co-occurrence Matrix (GLCM) texture measures as texture features. Proposed by Haralick et al. (9), the GLCM is an illustration of how frequently different combination of grey levels concur in an image. For a grey level image *I* of  $N_x \times N_y$  dimension with  $N_G$  grey levels, the element  $P(i, j, d, \theta)$  of the co-occurrence matrix of grey levels *P* with a displacement vector  $d = (d_x, d_y)$  and a direction  $\theta$  is given by:

$$P(i, j) = Card\{(x, y) : I(x, y) = i, I(x + d_x, y + d_y) = j\}$$
(1)

Where *Card* is the cardinal function, I(x, y) is the grey level of Image I at coordinates (x, y) and  $i, j \in \{1, 2, ..., N_G\}$ .

In this paper, we use mean, standard deviation and entropy of four measures from the Grey Level Co-occurrence Matrices: Homogeneity, Dissimilarity, Angular Second Moment and Entropy. Let us recall their definitions:

Homogeneity = 
$$\sum_{i,j=1}^{N_{G}} \frac{P(i,j)}{1 + (i-j)^{2}}$$
 (2)

Dissimilarity = 
$$\sum_{i,j=1}^{N_{G}} P(i,j) |i-j|$$
(3)

Angular Second Moment = 
$$\sum_{i,j=1}^{N_G} P(i,j)^2$$
 (4)

$$Entropy = \sum_{i,j=1}^{N_{G}} P(i,j) \log[P(i,j)]$$
(5)

#### Shape features

#### Quaternion algebra

The quaternions, introduced first by the mathematician Hamilton in 1843, are the generalization of complex numbers. They refer to a system of hypercomplex numbers (denoted H) defined in four-dimensional complex number (10) with one real part and three imaginary parts as follows:

$$q = a_0 + a_1 i + a_2 j + a_3 k \tag{6}$$

where  $a_0, a_1, a_2, a_3 \in \mathbb{R}$  and  $i, j, k \in \mathbb{C}$  obeying the following rules:

$$\begin{cases} i^2 = j^2 = k^2 = ijk = -1\\ ij = -ji = k, jk = -kj = i, ki = -ik = j \end{cases}$$
(7)

It easily follows from the above equation that the quaternion multiplication is distributive but noncommutative. The conjugate and modulus (i.e. the Square Root of the quaternion dot product) of a quaternion *q* are defined by:

$$\overline{q} = a_{\circ} - a_{1}i - a_{2}j - a_{3}k \tag{8}$$

$$|q| = \sqrt{q\overline{q}} = \sqrt{a_o^2 + a_1^2 + a_2^2 + a_3^2}$$
(9)

The quaternion, with zero as real part ( $a_o = 0$ ) is called a pure quaternion. The unit quaternion has a unit length |q| = 1.

#### Quaternion Zernike moments

Moments were firstly introduced in image processing by Teague (3) in 1934. They have been subsequently extensively used in a wide range of two- and three-dimensional pattern recognition and computer vision applications (3,10). They have been also considered superior in terms of their robustness to image noise and distortions, expression efficiency, fast computation, and ability to provide faithful image representation (11). In addition, they are invariant against linear transformations and especially against object boundary deformation.

The conventional Zernike moments are constructed using a set of complex polynomials, also named the Zernike polynomials. The latter form a complete orthogonal basis set defined on the unit disk  $(x^2 + y^2) \le 1$ . In the case of a digital image with current pixel P(x,y), the two-dimensional complex Zernike moments are defined as:

$$Z_{nm} = \frac{n+1}{\pi} \sum_{x,y} P(x,y) V_{nm}^{*}(x,y)$$
(10)

*n* and *m* are generally called order and repetition, respectively. The order *n* is a nonnegative integer, and the repetition *m* is an integer subject to the conditions: n - |m| even,  $0 \le |m| \le n$ .  $V_{nm}(x, y)$  are the Zernike polynomials defined in polar coordinates as:

$$V_{nm}(x, y) = V_{nm}(\rho, \theta) = R_{nm}(\rho) \exp(jm\theta)$$
(11)

where  $\rho$  is the length of vector from origin (*x*,*y*) pixel,  $\theta$  is the angle between vector  $\rho$  and *X* axis in counter clockwise direction and  $R_{nm}(\rho)$  is the real-valued radial polynomial of  $\rho$  given as follows:

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}} \frac{(-1)^{s}(n-s)! \rho^{n-2s}}{s! \left(\frac{n+|m|}{2}-s\right)! \left(\frac{n-|m|}{2}-s\right)!}$$
(12)

Now and for colour images using RGB space for example, P(x,y) is expressed as a vector given by:

$$P(x,y) = \begin{bmatrix} P_{R}(x,y) \\ P_{G}(x,y) \\ P_{B}(x,y) \end{bmatrix}$$
(13)

where  $P_R(x, y), P_G(x, y), P_B(x, y)$  are respectively the red, green and blue components of the pixel P(x, y). So, it can be represented by encoding three components as a pure quaternion as follows:

$$P(x,y) = P_{R}(x,y)i + P_{G}(x,y)j + P_{B}(x,y)k$$
(14)

Using this new formulation, Eq. (10) becomes:

$$Z_{nm}^{Q} = \alpha \sum_{x=1}^{N} \sum_{y=1}^{M} P(x, y) R_{nm}(\rho) \exp(-\mu m \rho)$$
(15)

where 
$$\alpha = \frac{n+1}{\pi(N-1)(M-1)}$$
 and the unit quaternion  $\mu = (i+j+k)/\sqrt{3}$ .

Using this last formulation of Quaternion Zernike moments, a feature vector is constructed for each segment. In this study, we have used Quaternion Zernike moments up to 20<sup>th</sup> order which has given rise to 119 moments in total. Table 1 depicts the first 5 order of the moments with their repetitions.

| Order | QZMs   | No. of Moments | Accumulative No. |  |  |
|-------|--|----------------|------------------|--|--|
| 2     | $\left Z_{20}^{Q}\right , \left Z_{22}^{Q}\right $                                     | 2              | 2                |  |  |
| 3     | $ Z_{31}^{Q} ,  Z_{33}^{Q} $   | 2              | 4                |  |  |
| 4     | $\left Z_{40}^{Q}\right , \left Z_{42}^{Q}\right , \left Z_{44}^{Q}\right $            | 3              | 7                |  |  |
| 5     | $\left Z_{51}^{Q}\right , \left Z_{53}^{Q}\right , \left Z_{55}^{Q}\right $            | 3              | 10               |  |  |
|       |  |                |                  |  |  |
| 20    | $\left  Z_{200}^{Q} \right , \left  Z_{202}^{Q} \right ,, \left  Z_{2020}^{Q} \right $ | 11             | 119              |  |  |

#### Table 1: List of Quaternion Zernike Moments up to order 20.

### Supervised classification using MLP

Neural Networks refer to an information processing technique based on the biological nervous systems principle. The most popular neural network model is the Multilayer Perceptron, which is an extension of the single layer perceptron proposed by Rosenblatt (12). This type of neural network is known as a supervised network because it requires a desired output for learning. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

In the MLP structure, the neurons are grouped into layers. The first and last layers are called input and output layers. The remaining layers are called hidden layers. It is worth noting that the number of neurons in input and output layers is equal to the number of characteristics presented to the input and to the number of classes respectively. The architecture of a Multilayer Perceptron with a single hidden layer is shown in Figure 1.



Figure 1: Multilayer Perceptron with a single hidden layer.

When  $x_i$  is presented to MLP, the output value from the *j*th hidden neuron is computed as:

$$\mathbf{y}_{ij}^{\prime} = f\left(\sum_{i=1}^{n} \mathbf{w}_{ij} \mathbf{x}_{ii}\right)$$
(16)

where *f* represents the transfer function and  $w_{ij}$  is the connection weight from the *i*th input neuron to the *j*th hidden neuron. Then, the final output value from the output neuron is computed as

$$\mathbf{y}^{out} = f\left(\sum_{j=1}^{k} w_j \mathbf{y}_{ij}^{\prime}\right)$$
(17)

where k is the number of hidden neurons and  $w_j$  is the connection weight from the *j*th hidden neuron to the output neuron.

MLP is trained using supervised learning technique called back-propagation learning algorithm. This latter is the generalization of the Windrow-Hoff rule (13) (also known as Delta rule) to multiple layer networks and nonlinear differentiable transfer functions. Recall that the Delta rule serves to minimize the squared error between the network outputs and the desired ones. Then, this error is back-propagate to the neural network and used to adjust weights. This process is known as training stage.

## EXPERIMENTAL RESULTS AND DISCUSSION

The sub-scene of a Quickbird image dataset of Algiers (northern Algeria), acquired on August 23 2003, is used in this study. The dataset consists of three pan-sharpened multispectral images with a spatial resolution of 0.61 m obtained by applying a fusion technique to the panchromatic channel and the three bands (red, green and blue) of the multispectral image. The adopted technique is based on the Gram-Schmidt procedure implemented in the ENVI software package. Figure 2 shows the sub-scene of size 1600×1400 pixels.



Figure 2: Sub-scene of a Quickbird Image used in the Experiment.

The first step in the object-based classification is segmentation. Generally speaking, image segmentation refers to the partition of an image into a set of homogeneous segments that cover it. The Mean-Shift segmentation method (14,15) is used in this study. It is worth noting that the performance of the segmentation method has a great effect on the shape descriptor and the classification result. For the Mean-Shift (16), we have four parameters: the spatial bandwidth  $h^s$ , the range bandwidth  $h^r$ , the merging threshold *s*, and the stopping threshold  $\varepsilon$  (this parameter is kept fixed to 0.0005). In order to determine the optimal values of the Mean-Shift parameters which give the best segmented image, several combinations of the three parameters  $h^s$ ,  $h^r$  and *s* are done as follows: Tests from 1 to 5:  $h^r = 3, s = 5, h^s$  has been gradually increased from 3 to 7 at the interval of 1. Tests from 6 to 12:  $h^s = 7$  (best segmentation result in the previous test set),  $h^r = 3, s = 4$  (best seg-

mentation result in the second test set),  $h^r$  has been gradually increased from 4 to 17 at the interval of 1. In this way, twenty six segmentation results are obtained. Quantitative assessments of these results were done to select the optimal values of the parameters  $h^s$ ,  $h^r$  and s. The quantitative assessment allows quantifying the quality of segmentation result. To this end, we use Borsotti criterion (17), which is given by:

$$Q = \frac{\sqrt{R}}{10,000 \times N \times M} \sum_{i=1}^{R} \left( \frac{\mathbf{e}_{i}^{2}}{1 + \log A_{i}} + \left( \frac{\Psi(A_{i})}{A_{i}} \right)^{2} \right)$$
(18)

where  $N \times M$  is the size of the segmented images *s*, *R* is the number of segments of *s*, *A<sub>i</sub>* is the area of the *i*th segment, *e<sub>i</sub>* is the colour error of the segment *i* and  $\Psi(A_i)$  the number of segments with the same area. A small value of *Q* means a good segmentation quality. The value of Borsotti criterion computed for each of the segmentation results corresponding to the combinations of the three parameters shows that the smaller value is equal to  $4.62 \cdot 10^4$ . This value corresponds to the parameter values  $h^s = 7$ ,  $h^r = 17$  and s = 4. Figure 3 presents the best segmentation result corresponding to these values.



Figure 3: The best segmentation results according to Borsotti Criterion.

After segmentation stage, texture and shape features are extracted from each segment (i.e., buildings). The set of interest objects is composed of 190 objects representing eight classes (Figure 4).



Figure 4: Mask on the selected map features for based-object classification.

Regarding texture features, the co-occurrence matrices are calculated with four directions (0°, 45°, 90° and 135°) and six analysis window size (from  $3\times3$  to  $13\times13$  at interval of 2). The value of displacement vector is kept fixed to 1 and the quantification parameter to 16. Finally, each object is

characterized by a feature vector consisting of 288 components. Note that only the green band has been used in the texture features calculation. Regarding the shape features, the quaternion Zernike moments up to order 20 are computed also for each object. Table 2 summarizes the number of components according to each feature.

| Table 2: Number of com | ponents for each feature. |
|------------------------|---------------------------|
|------------------------|---------------------------|

| characteristics | number of components |  |  |  |
|-----------------|----------------------|--|--|--|
| Texture         | 288                  |  |  |  |
| QZM             | 119                  |  |  |  |
| Total           | 407                  |  |  |  |

Finally, these vectors are used as inputs to the MLP classifier. In order to have an optimal architecture of the neural network MLP, several experiments are performed on each of the descriptors independently, then with combination between them. The training set is formed by only one object from each class. At the end of this study, we have the following parameters:

| Number of hidden layers               | : 1                                   |
|---------------------------------------|---------------------------------------|
| Number of neurons in the hidden layer | : From 5 to 50 in steps of 5          |
| Transfer Function                     | : Sigmoid                             |
| Maximal number of epochs              | : 5000                                |
| Performance function                  | : Normalized Mean Square Error (NMSE) |
| Error tolerance                       | : 0.001                               |
| Training function                     | : Back-propagation                    |
| Number of output classes              | :8                                    |

The overall classification accuracy is obtained by comparing the classified objects and the ground truth reference objects. The overall accuracy is defined as:

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of object classes}} \times 100$$
(19)

Table 3 and Figure 5 show the result of classification accuracy according to the number of neurons in the hidden layer. As shown in the table, the combination of texture and shape features gives the best result with accuracy of 86.23%. This accuracy is 6% higher than the ones obtained by the characteristics of shape at it alone, 11% when using texture features. Figure 6 provides a visual illustration to best classifications obtained for each experiment. Table 4 presents the confusion matrix of object-based classification based on QZM and texture features.

Table 3: Overall Accuracies obtained by the MLP classifier in function on the number of neurons in the hidden Layer.

| Number of<br>neurons<br>Features | 5     | 10    | 15    | 20    | 25    | 30    | 35    | 40    | 45    | 50    |
|----------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| QZM+Texture                      | 50.44 | 73.01 | 71.27 | 76.08 | 70.77 | 75.64 | 77.86 | 74.74 | 78.64 | 86.23 |
| QZM                              | 49.32 | 70.74 | 75.78 | 74.27 | 72.11 | 72.41 | 70.42 | 74.00 | 76.13 | 79.99 |
| Texture                          | 46.24 | 63.70 | 69.64 | 68.72 | 68.68 | 73.20 | 70.92 | 66.59 | 63.46 | 74.89 |



Figure 5: Evaluation of features descriptors.



Figure 6: Object-Based Classification by MLP: (a) With QZM + Texture, (b) With QZM.

On the basis of these results, we can see that the combination of QZM and texture features has important contribution in the object-based classification.

To assess the performance of the proposed classifier, a comparative evaluation against two very popular supervised algorithms in the remote sensing field, namely Supervised Vector Machines (SVMs) (18,19) and k-Nearest Neighbour (k-NN) (20) is performed. The same test set is used. As shown in Table 5, MLP provides the highest accuracy compared with the accuracies obtained with SVMs and k-NN. This leads us to the conclusion that MLP is to be preferred for best classification accuracies, but is also sensitive to the choice of its parameters.

|          |                              | Classification |                                 |                                 |                                |             |             |                                 |                               |       |
|----------|------------------------------|----------------|---------------------------------|---------------------------------|--------------------------------|-------------|-------------|---------------------------------|-------------------------------|-------|
|          | Overall Accuracy = 86.23%    | Buildings 1    | Buildings 2 with<br>grey roof 1 | Buildings 2 with<br>grey roof 2 | Buildings 2 with<br>white roof | Buildings 3 | Buildings 4 | Buildings 5 with<br>yellow roof | Buildings 5 with<br>blue roof | Total |
|          | Buildings 1                  | 100            | 0.00                            | 0.00                            | 0.00                           | 0.00        | 0.00        | 0.00                            | 0.00                          | 100   |
| cts      | Buildings 2 with grey roof 1 | 0.97           | 61.17                           | 1.94                            | 2.91                           | 29.13       | 3.88        | 0.00                            | 0.00                          | 100   |
| bje      | Buildings 2 with grey roof 2 | 0.00           | 0.00                            | 83.33                           | 0.00                           | 0.00        | 16.67       | 0.00                            | 0.00                          | 100   |
| o<br>e   | Buildings 2 with white roof  | 7.14           | 0.00                            | 0.00                            | 92.86                          | 0.00        | 0.00        | 0.00                            | 0.00                          | 100   |
| Referenc | Buildings 3                  | 0.00           | 0.00                            | 0.00                            | 0.00                           | 100         | 0.00        | 0.00                            | 0.00                          | 100   |
|          | Buildings 4                  | 0.00           | 0.00                            | 0.00                            | 0.00                           | 0.00        | 100         | 0.00                            | 0.00                          | 100   |
|          | Buildings 5 with yellow roof | 0.00           | 0.00                            | 0.00                            | 0.00                           | 0.00        | 35.00       | 65.00                           | 0.00                          | 100   |
|          | Buildings 5 with blue roof   | 0.00           | 0.00                            | 0.00                            | 0.00                           | 0.00        | 12.50       | 0.00                            | 87.50                         | 100   |

Table 4: Confusion matrix of object-based classification based on QZM and texture features.

Table 5: Accuracy of different supervised classification algorithms.

| Classifier<br>Features | MLP   | SVM   | k-NN  |  |
|------------------------|-------|-------|-------|--|
| QZM+Texture            | 86.23 | 81.74 | 31.60 |  |
| QZM                    | 79.99 | 81.62 | 31.60 |  |
| Texture                | 74.89 | 72.78 | 68.54 |  |

## CONCLUSIONS

In this paper, a new approach for VHSR satellite images classification has been proposed. First, image objects extraction is performed using the Mean-Shift segmentation algorithm. Then, the Quaternion Zernike moments and the texture features are computed for each object. Finally, the MLP-based classification using the feature vector as input of the original objects is carried out to assign a class label to each of the objects. The preliminary experimental results clearly demonstrated the efficiency of the proposed approach. Also, the results show that both classifiers namely MLP neural network and SVM give better efficiency than the k-NN classifier.

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