Interest of the Combination of Classifiers for Volumetric Textures Classification

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Abstract- Nowadays, classification is applied in various fields such as pattern and writing recognition, prints checking, faces identification, medical images analysis, 2D textures characterization and volumetric textures characterization. Indeed, the three-dimensional field is considered among one of the most important fields in image processing because of the great quantity of information that can be extracted. In this work, we try to improve the performances of classification for volumetric textures images by proposing a multiple classifier systems (MCS) based method combining three Euclidean classifiers: simple Euclidean classifier (ES), normal Euclidean classifier (EN) and balanced Euclidean classifier (EB). Thereafter, we compared the performance of the proposed method to the Euclidean methods (ES, EN and EB). The hybrid presented approach has proven to be more efficient in classification and mostly robust against Gaussian noise.

Keywords - volumetric images textures, combination of classifiers, Multiple to Classify System: MCS

I. INTRODUCTION

The analysis of the textured images is an important field and many researchers worked on this axis. The field of image processing can be divided into three axis: segmentation, synthesis and classification. The literature summarizes the extraction in various types: statistics, parametric and frequential. All these methods were mainly developed and tested on two-dimensional texture. Recently, some of these methods were studied to analyze volumetric texture. In fact, the three-dimensional field is very rich in information what makes the classification very complex and highlights the concept of combination of the classifiers [5]. Indeed, several classifiers can deliver different answers for the distribution of the image and the class to which it corresponds. This is due mainly to the specific error of the classifier. This error rises from the model of decision of the classifier and the used database. The behavior of each classifier is given by providing different basic information for the textured images. The various results of the classifiers are then combined in order to improve classification.

Our article is organized as follows: section II describes the volumetric texture classification using the co-occurrence matrix (GLM3D). Section III presents the freely accessed database of volumetric textures used in this paper. Also, the aspect of combining classifiers is raised in this section. Moreover, the following section, section IV, gives the significance of classifiers as well as the definitions of the various types of studied Euclidean classifiers as well as the system of combined classifiers (MCS). Section V demonstrates the superiority of the hybrid proposed method of classification against the methods containing single classifiers as well as the robustness of this method against Gaussian noise. Finally, section VI concludes this work by resuming the performed works.

II. DESCRIPTION OF CO-OCCURRENCE MATRICES FOR VOLUMETRIC DATA

In this section, we present the 3D matrix of co-occurrence or the space method depending on gray levels. In fact, it makes it possible to determine the frequency of appearance of a formed "distance" for voxel separated by a certain distance D in a particular direction.

A co-occurrence matrix for volumetric data is an n x n matrix, where n represents the number of gray-levels within an image. For reasons of speed computing, the number of gray levels can be reduced if one chooses to bin them. Thus, the size of the co-occurrence matrix is decreased. This matrix acts as an accumulator so that M[i, j] counts the number of pixel pairs having the intensities i and j. However, this matrix is defined by specifying a displacement d = (dx, dy, dz), where dx and dy are the same as described for 2D co-occurrence matrices, and dz represents the number of pixels moved along the z-axis of the three-dimensional image. We take the matrices while resulting and measuring the space dependence of the values of gray-level by computing the devices of following texture of Haralick[3].

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TABLE I
HARALICK FEATURES

<table>
<thead>
<tr>
<th>Feature</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inertia</td>
<td>$\sum_{k}^{M} \sum_{l}^{N} (k - l)^2 \ p(k, l)$</td>
</tr>
<tr>
<td>Total Energie</td>
<td>$\sum_{k}^{M} \sum_{l}^{N} p^2(k, l)$</td>
</tr>
<tr>
<td>Entropy</td>
<td>$\sum_{k}^{M} \sum_{l}^{N} p(k, l) \ \log \ p(k, l)$</td>
</tr>
<tr>
<td>Local Homogeneity</td>
<td>$\sum_{k}^{M} \sum_{l}^{N} \frac{1}{1 + (k - l)^2} \ p(k, l)$</td>
</tr>
<tr>
<td>Maximum Probability</td>
<td>$\max p(k, l)$</td>
</tr>
<tr>
<td>Cluster Shade</td>
<td>$\sum_{k}^{M} \sum_{l}^{N} (k - M_x + j - M_y)^3 \ p(k, l)$</td>
</tr>
<tr>
<td>Cluster Prominence</td>
<td>$\sum_{k}^{M} \sum_{l}^{N} (k - M_x + j - M_y)^4 \ p(k, l)$</td>
</tr>
</tbody>
</table>

With:  
- $M_y = \sum_{k}^{M} \sum_{l}^{N} lp(k, l)$  (1)  
- $M_x = \sum_{k}^{M} \sum_{l}^{N} kp(k, l)$  (2)

III. VOLUMETRIC TEXTURE DATABASE

The notion of textures classification is one moreover problem for volumetric textures. Those are with the fact that there did not exist a common reference index able to evaluate differently the methods of volumetric classifications. A database is now available in free access\(^1\) and it is possible to evaluate volumetric texture.

The database is organized as follows: each volumetric texture is assigned according to the method of synthesis i.e. one divides in four files. In each file of texture, to synthesize the type, images are assigned according to the deformation applied: nothing, Gaussian noise. The files of the deformation contain examples of the various classes of volumetric textures.

Currently, this database contains 95 classes. 30 are different from these classes which were established with the method of interpolation, 25 with the geometrical method of form. Each class is composed of 50 examples. Each volumetric image corresponds to a totality of 64 images of BMP of 64 x 64 gray level pixels stored in a specific directory. Figure 1 presents an example of 3D texture of this database.

\(^1\)http://www.rfai.li.univ-tours.fr/fr/ressources/3Dsynthetic_images_database.html
III. CONCEPT OF DATA COMBINATION

The aspect of combining data coming from several sources is a primitive idea. However, it is necessary to distinguish between the combination term and fusion on the one hand and between this last and the fusion term from data on the other hand.

In fact, the fusion of data is to combine various relative information’s problem. In another aspect, it was suggested using the combination of information in a direction much broader than the fusion of information. The latter describe any process which implies an operation carried out on at least two information sources. The combination is not defined like a term opposed to fusion [5, 12 and 22]. It is simply more general, it is often used to describe processes and methods generally.

There exist various levels of combinations: data fusion, characteristics fusion and decision fusion. In this work, we are interested in combining the answers of the classifiers. Hence the term combination of classifiers or multi-classifiers system (Multiple to Classify System: MCS) used in the remainder of the article.

The principal aim of combining classifiers is to increase classification performances. Within this framework, many research identified the various strategies of combination of classifiers. As much, the criterion about execution of the classifiers confirms various types of combination: sequential, parallel etc. In the sequential combination several classifiers are carried out and the obtained results are used to modify the execution of other classifiers.

The order of execution of the classifiers is important and if it is changed, the result can be different [8]. On the other hand, with parallel combination, the obtained results don’t affect the execution of the other classifiers. Consequently, the order of execution of the classifiers does not have any influence.

IV. COMBINED CLASSIFICATION ALGORITHM

1. Euclidean Classifiers

In this case, we proceed to the simplest algorithm. For each texture of reference, one measures the distance between the characteristic vector to classify and each characteristic vector from the texture of reference. We repeat this operation for each texture of reference. The vector to be classified will be assigned with the texture for which this distance is minimal [8].

Another classifier can be studied in this part: We keep in memory the three weakest distances and make a vector out of them. Then we compute the standard of this vector. This operation is repeated for each texture of reference. The vector to be classified will be assigned with the texture for which this standard is minimal.

The difference between classifiers comes from the definition of “distance”. The two first ones will be called simple Euclidean classifier (ES) and normal Euclidean classifier (EN). They simply use the Euclidean distance. The third is called balanced Euclidean classifier (EB), balances the Euclidean distance by the variance of the feature vectors associated with the texture of considered reference. With this classifier, for a texture of reference K and feature vectors, the distance $d_{k,l}$ between the vector characteristic 1 of the texture of reference K and the vector test is given by:

$$d_{k,l} = \sqrt{\sum_{i=1}^{d} (x_i - y_{1,l})^2} \quad (3)$$

The index $i$ is the component count of the vectors, $K$ is the index of the texture of reference, and $l = 1..., N$ the index of the vector characteristic of texture K, if one has N vectors characteristic.

2. Combination of classifiers

There are two: methods of combination: that of the vote with simple majority and that of the balanced sum. The first method consists on choosing the most suggested class by the classifiers. Each classifier gives a different result from the others. For the combination by balanced sum, each various classifiers give in result a value corresponding to the class of exit. The concept of weighting is used to appear this concept of importance.

3. Multiple Classifier System: MCS

The main aim of our work is to conceive and carry out a multiple classifier system (MCS) for volumetric textures classification. The capital idea
is to combine the three Euclidian classifiers previously described (EN, ES and EB). The combination consists in making the final decision by applying functions of combination to the results of classification given by each classifier [14].

V. EXPERIMENTAL RESULTS

In this section, we apply the classification methods already presented on the database of volumetric texture. We consider a totality of 30 different volumetric textures from the dimension (64x64x64) and extracted from the site quoted previously. For such a goal, 5 volumetric images (64x64x64) are selected for each class of texture. The various methods for extracting the attributes of texture for the 150 images are then evaluated by the Euclidean classifiers. The same work is made for the database containing noised volumetric textures.

1. Efficiency of the Multiple Classifier Systems (MCS) based classification

We compared the different methods of classification for the volumetric textures previously described. The first method of classification (GLCM 3D) is based on the Simple Euclidean Classifier (ES).

The (ES) classifier, described in the preceding section, is the basic classifier that leads to a percentage of classification of 54.66%. The second method of classification (GLCM 3D) is based on the concept of the normal Euclidean classifier (EN) and it leads to a percentage of classification of 42.33%. The third method of classification is based on the concept of the Balanced Euclidean classifier (EB) and permits a percentage of classification equal to 57.33%. The fourth method of classification (GLCM 3D) is based on the concept of the Multiple Classifier Systems (MCS) and guaranteed a percentage of classification equal to 77.66%.

Figure 3 compares the four methods of classification. It is noticed that the method of classification combining classifier (MCS) has a percentage of classification better than the other methods of classifications (ES or EN or EB). This is due to the fact that MCS uses a combination of different exiting classifiers. Consequently, this fusion has to improve only the percentage of classification.
In this section, we classify the database that contains the same volumetric textures, except when they are spread with a Gaussian noise =5db. We employ the same principle of classification, GLCM 3D, with the different methods of classifications previously described with the two databases (without noise and with noise equal to 5db). Table III contains the percentages of classification for each type of classifications and each database.

It is noticed that the percentage of classification decreases while passing from the database without noise towards the noised database. For the method of classification containing simple Euclidean classifier (ES), the rate of classification decreased by 15% (from 50.66% to 40.33%) while passing from the database without noise towards the noised database. As well as for the classification based on normal Euclidean classifier (EN), the rate of classification decreased by 10% (from 40.33% to 29.66%) while passing from the database without noise towards the noised database. In the same way, the method of classification based on balanced Euclidean classifier (EB), decrease by 12% the rate of classification (from 57.33% to 45%) while passing from the database without noise towards the noised database. In the same way, the method of classification based on balanced Euclidean classifier (EB), decrease by 12% the rate of classification (from 57.33% to 45%) while passing from the database without noise towards the noised database. However, the method of classification based on multiple classifier systems (MCS) decreased only by 2% in the rate of classification (from 77.66% to 75.33%) for the same database.

Figure 4 proves that the classification based on multiple classifier systems (MCS) is less sensitive to the noise than the other methods. This underlines the robustness of the proposed hybrid approach for the classification of the volumetric texture.

VI. CONCLUSION

In this work, we discussed the interest of the combination of classifier for improving volumetric textures classification. Multiple classifier systems (MCS) give a better percentage of classification exceeding 77% against a percentage less than 58% for the other studied classifiers. This underlines the efficiency of the combination of many classifiers. Furthermore, this study is devoted to treat the influence of the noise on the classification. Within this framework, the robustness of the MCSs based method against Gaussian noise was proven. The rate of classification decreases by at least 10% for the single classifier methods. However, the MCSs based method records a fall less than 2%.

VII. REFERENCES


