

HYBRID CLASSIFICATION ANN, DWT AND FRACTAL ANALYSIS FOR DIRECTIONAL TEXTURES

CLASSIFICATION HYBRIDE RNA, TOD ET ANALYSE FRACTALE POUR TEXTURES DIRECTIONNELLES

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ABSTRACT

In this paper, we present a hybrid directional classification of anisotropic textures. Our proposed method based to yield a robust attributes vector to classify the different anisotropic textures. A robust fractal analysis is put forward by hybridization of the statistical fractal with Discrete Wavelets Transform (DWT). Beside, to enhance the quality of texture, a preprocessing stage using histogram equalization is carried out. Then for a given direction from 0° to 360° by a step of 10°, we applied the DWT using Daubechies wavelets (db5) to the corresponding direction where the approximate image is inputted to Differential Box-Counting Method (DBCM) in order to yield a robust Fractal Dimension (FD) estimated in wavelets domain. We formed the vector attributes to each texture that correspond to the inputs of our Artificial Neurons Network (ANN) classifier. The originality of our work, reside in the use of the Daubechies Wavelets (db5), in particular the use of approximate image with the fractal analysis, by, estimating the directional FD and using the directional classification based on ANN classifier. To validate our algorithm, we used two classes of the Brodatz textures database. Performance classification was assessed by ROC analysis and confusion matrix. We report a successful separation of the two classes, after different training. Area under-curve (AUC) values for training, validation and testing are 1, 0.96 and 1 and classification rates are 94.1%, 85.7%, 85.7% respectively, with the classification rate for all data is 91.7% and a fail classification is 8.3%.

KEYWORDS: Discrete Wavelets Transform (DWT), Fractal Analysis, Differential Box-Counting Method (DBCM), Directional Fractal Dimension (FD), Histogram Equalization (HE).

1 INTRODUCTION

Texture analysis and classification remain as one of the biggest challenges for the field of computer vision and pattern recognition. It have a wide variety of applications such as medical, biological, satellite... Various methods are presented; like filtering methods, mathematical morphology, and fractal analysis; which may be classified under two classes, structural analysis and statistical analysis. In structural analysis, the image is described in terms of textural elements and their spatial relations. And in statistical analysis, the texture is quantified on the basis of the local spatial distribution of the gray-value parameters such as the co-occurrence matrices and the Haralick parameters [1-5]. The anisotropy (opposite of isotropic) is the property of being dependent on the direction.

Something anisotropic may present different characteristics according to its orientation.

The discrete wavelet transform (DWT) is a tool who has been widely applied in signal and image processing field, such as classification, futures extraction, face recognition, compression and biomedical engineering.

A fractal is a geometrical object characterized by two fundamental properties: Self-similarity and Hausdorff Besicovich dimension. A self-similar object is exactly or approximately similar to a part of itself and that can be continued in parts, each of which is (at least approximately) a reduced-scale copy of the whole. Furthermore, a fractal generally shows irregular shapes that cannot simply be described by Euclidian dimension, but, fractal dimension (FD) has to be introduced to extend the concept of

dimension to these objects. However, unlike topological dimensions the FD can take non-integer values, meaning that the way a fractal set fills its space is qualitatively and quantitatively different from how an ordinary geometrical set does. The fractal dimension (FD) describe how an object occupies space and related to the complexity of its structure ; it gives a numerical measure of the degree of irregularity [4]. The fractal analysis have a wide varieties of applications in texture analysis [6,7] and signals and images processing [8-11].

Several algorithms estimating fractal dimension have been described (box-counting BC, differential box-counting DBC, morphological, variance, power spectrum...) [12]. They are all based on measuring an image characteristic, chosen heuristically, as a function of a scale parameter. In the main, these two quantities are linearly regressed on a log-log scale, and the fractal dimension is obtained from the resulting slope. All these algorithms estimate the fractal dimension in the spatial domain (except the power spectrum) and without preprocessing. In an image, there is often a high correlation between neighboring pixels, which generates a redundancy in the information. To decorrelate these ones; as we know, that the energy of an image (information) is concentrated at low frequencies, we have proposed the use of preprocessing to the texture before estimating the fractal dimension using histogram equalization to enhance the quality of the image and using the discrete wavelets transformation (DWT).

Neural network has been exploited in very wide variety of applications. Classification or pattern recognition is one of the most application areas of neural network. An artificial neural network (ANN) is a general mathematical computing paradigm that models the operation of biological neural system. In 1943, McCulloch, a neurobiologist, and Pitts, a statistician, published her first model of the neuron biologic, the development of the modern digital computer or the electronic brain. At approximately the same time, Frank Rosenblatt led to the first generation of neuron network, known as the perceptron. An artificial neural network (ANN) is made up of many neurons, which are correlated together in accordance with explicit network architecture. The learning can be supervised or unsupervised depending on both the structure of the network, the inputs and outputs and how are interconnected. The ANN have different structures based on type of its input-output and its application. The most comment used of ANN is the Multilayer Perceptron (MLP), which is a feed forward neurons network trained in supervised learning [14-15].

The aim of this study is to combine the fractal geometry with the wavelets analysis that have the great success in signal and image processing, to the directional texture classification using ANN classifier. The influence of preprocessing stage is also quantified using the histogram equalization (HE) then the rotation of the texture from 0° to 360° by a step of 10° to enhance the quality of image in order to get the directional robust features (directional FD) using the differential box-counting method (DBCM) in the wavelets domain. The results demonstrate the feasibility

and usefulness of the proposed approche yielding a robust rate of classification.

Section 2 of this paper details the basis of fractal analysis and highlighting the calculus of FD parameter, especially the differential box counting method (DBCM). Section 3 presents the overall methodology that fruitfully combines preprocessing, discrete wavelets transform DWT, ANN classifier and our proposed algorithm in order to robustify the estimation of directional FD analysis. Section 4 exhibits the experimental results and discussion using the Brodatz database texture. Whereas section 5 is dedicated to conclusion and perspective work.

2 FRACTAL ANALYSIS

Mandelbrot is the first used the fractal concept [3]. A fractal is a geometrical set of points whose Hausdorff-Besicovitch dimension also known as fractal dimension exceeds its topological dimension. The fractal word is a term who comes from the Latin "fractus" means splitting up, irregular. It characterizes all the irregular geometrical forms. It is an object consisted of several sub-objects. The global characteristic of the object is similar to the local characteristic of each sub-object.

We say that an object is auto-similar if it is the union of the copies of itself in various scales. In the case of exact auto-similarity, the fractal object is a mathematical object which arises from an iterative process and which presents a character of auto-similarity [4-5, 9].

2.1 Fractal Dimension (FD)

The fractal dimension can be defined as the exponent of the number of self-similar pieces, N , with magnification factor, $1/\epsilon$, into which a figure may be broken. The equation for FD is as follows [10] :

$$FD = \frac{\log(\text{number of self similar pieces})}{\log(\text{magnification factor})} = \frac{\log(N)}{\log(1/\epsilon)} \quad (1)$$

Where N is the number of elements of the box size, ϵ , required to form a cover of the object.

The FD is a non-integer value in contrast to objects that lie strictly in Euclidean space. A fractal curve has a fractal dimension between a straight line and a plane ($1 < FD < 2$), while a fractal surface has a dimension between a plane and three-dimensional space ($2 < FD < 3$). The fractal dimension characterize an object with a dimensionality greater than its topographical dimension [10].

2.2 Differential Box Counting Method (DBCM)

Differential box-counting method (DBCM) is an adaptation of the box-counting method (BC). Chaudhuri and Sarkar

(1995) propose to solve some of limitations of the BC method proposed it. It has the advantage to work on grey-scale images and thus the binarization step is avoided. The signal is partitioned into boxes of various size ϵ and $N(\epsilon)$ is computed like the difference between the minimum and the maximum grey levels in the (i, j) th box. This step repeated for all boxes and the dimension of the boxes calculated as [12, 13]:

$$Dim_B F = \lim_{\epsilon \rightarrow 0} \left[\frac{\log(N(\epsilon))}{-\log(\epsilon)} \right] \quad (2)$$

Moreover, afterward the estimation of the fractal dimension by the use of the linear regression in a log-log plan. The dimension of the box is nothing else than the fractal dimension FD which given by the following relationship:

$$FD = \lim_{\epsilon \rightarrow 0} \frac{\log(N)}{\log(1/\epsilon)} \quad (3)$$

The result of the calculation presented in a bi-logarithmic plan, and the slope of the right gives a dimension of the surface box dim_B , which represent the FD.

3 METHODOLOGY

3.1 Database used

We have used two classes of the publicly available Brodatz database that are presented in Fig. 1. For each class there are three texture images, two with size (512x512) pixels, and the third one with (1024x1024) pixels.

For each image, we have subdivided into 16 sub-images (see Fig. 2); for the two ones images, they become of size (128x128) pixels, and for the third one of size (256x256) pixels. Therefore, for each class we get 48 images. We take a set of 70% of images for training, 15% for validation and 15% for testing.

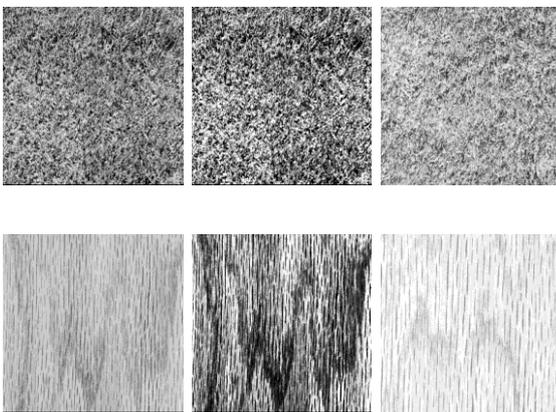


Figure 01: Brodatz Texture database used (two classes)

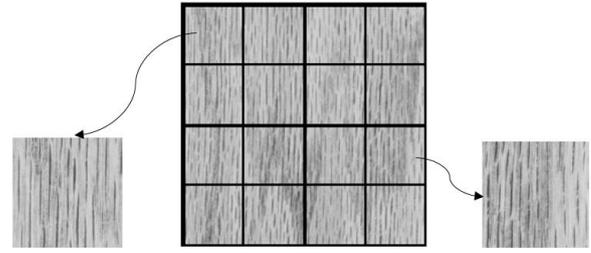


Figure 02: Example of texture from class 2, subdivided into 16 sub-images, and example of two sub-images

3.2 Preprocessing

The histogram of an image provides the frequency distribution of gray levels in that image. The histogram equalization (HE) is usually used for contrast enhancement, it is a method for adjusting the contrast of a digital image using the histogram for enhancing and improving the visibility of significant features and the quality of the image. The enhancement used to reduce image noise and increase the contrast to form a preprocessing step for subsequent automated analysis. The histogram equalization (HE) consists in applying a transformation of each pixel of the image, and thus to obtain a new image from an independent operation of each pixels. This transformation constructed from the cumulative histogram of the original image. The performance of the enhancement measured in terms of the mean and standard deviation where the mean stands for the average brightness of the image, whereas the standard deviation describes the average contrast of the image.

3.3 Discrete Wavelets Transform (DWT)

The discrete wavelet transform (DWT) defined as a decomposition of the original signal filtered by a low-pass filter and a high-pass filter, with down sampling by a factor of two. The 1-D multi-resolution wavelet decomposition can be easily extended to 2-D by introducing separable 2-D scaling and wavelet functions as the tensor products of their 1-D complements. The 2-D wavelet analysis operation produces one smooth part, which represents the coarse approximation of data, and three detailed parts, which represent the information of the horizontal, vertical and diagonal directions of the data [16-17].

The energy or information of the image is situated in the low frequency (in the approximate image), so in the high frequency (the details : Horizontal, Vertical and Diagonal) we get the details of information (the edges of image).

3.4 The ANN classifier

A neural network is a parallel-distributed information processing structure consisting of processing elements (neurons) interconnected via unidirectional connections (see Fig. 3). The artificial neural networks (ANN) are a tool

for multivariate analysis; derive their power to their parallel structure. They can be used for accurate classification of input data into categories. Learning can be divided into two categories, supervised learning and unsupervised learning [15].

Multilayer Perceptron (MLP) is a feedforward ANN with one or more hidden layers, trained with supervised learning requires a set of examples for which the desired network response is known. The MLP is widely used in pattern recognition and classification and it can solve the problems that are not linearly separable.

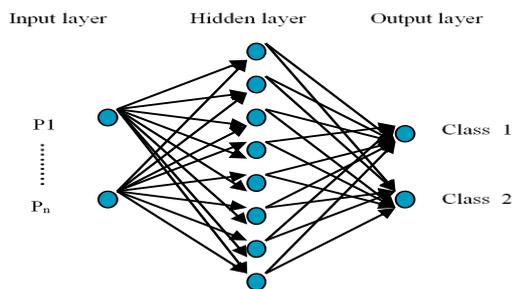


Figure 03: The MLP Neural Network Architecture

3.5 The proposed texture classification algorithm

Our proposed approach resumed in the “Algorithm”; the hybrid classification of ANN using DWT with the fractal analysis. We have applied the histogram equalization as preprocessing stage, then we have rotate the texture with different angles from 0° to 360° with step angle of 10° . For each rotated texture, we have applied the DWT in the first resolution with Daubechies wavelets db5. Since the information of the image is in the low frequency, we have used the approximate image and applied the DBCM to estimate the value of the directional FD with the boxes size from 5 to 30 with a step of 5 pixels.

For each texture image, we get the attributes vector of 37 elements (37 directions: $(FD(\theta))$) which become the number of input neurons for our ANN classifier; we have used the pattern recognition neural network (PMC) (feed-forward networks that can be trained to classify inputs according to target classes). The parameters of the ANN classifier are: ten neurons in the hidden layer, Training function (trainscg) scaled conjugate gradient back-propagation and performance function (cross-entropy), and two neurons in the output layer correspond to the class one or class two.

Algorithm: Estimation of directional FD with DWT

Input X = sub-image Brodatz texture.

Output directional FD value.

For each texture do

1. Apply a preprocessing method using histogram equalization (HE).
2. Rotate the texture preprocessed from $0^\circ:10^\circ:360^\circ$
3. For each rotated texture
 - Apply the DWT (db5) to the preprocessed and rotated texture.
 - Apply the DBCM using (3) to the approximate image texture.

End

End

4 RESULTS AND DISCUSSION

We have used pattern recognition neural network (MLP). The network fed with different combinations of features in each run to investigate the predictive significance of each feature. Hence, the number of features defines the number of input neurons, the number of hidden neurons optimized using ten neurons, and two neurons in the output layer correspond to the class one or class two. The network then trained using scaled conjugate gradient back-propagation (trainscg) and performance function using cross-entropy, validated with confusion matrix and ROC curves.

The features are composed by the $(FD(\theta))$ for each sub-image, corresponding to FD value for each direction. Fig. 4. shows an example of Brodatz texture sub-image preprocessed using histogram equalization (HE) and rotated with angles 30° and 120° . After this step, we applied the DWT using db5 wavelets, then we estimate the fractal dimension (FD) using the differential box counting method (DBCM) of the approximate image for each direction to get the features which become the input of our ANN classifier (Fig. 5.).

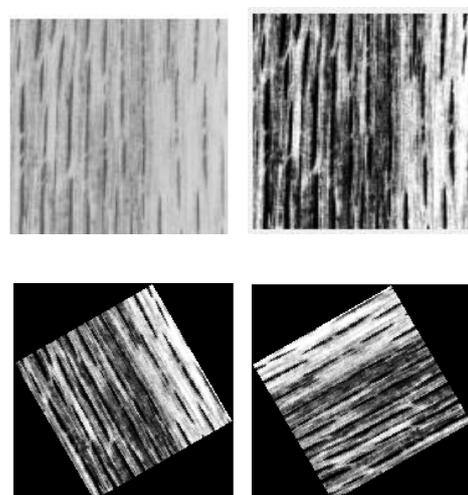


Figure 04: Example of Brodatz texture sub-image preprocessed and rotated with angles 30° and 120°

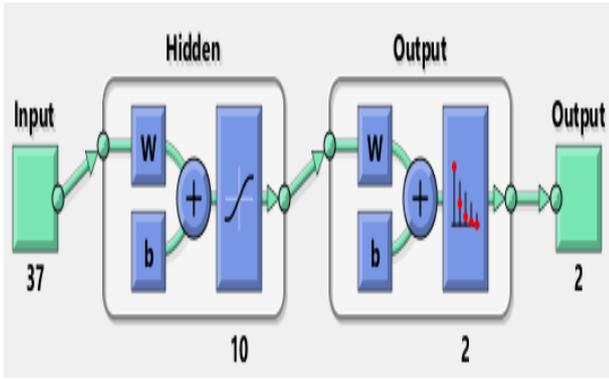


Figure 05: Neural network architecture



Figure 06 : Confusion Matrix

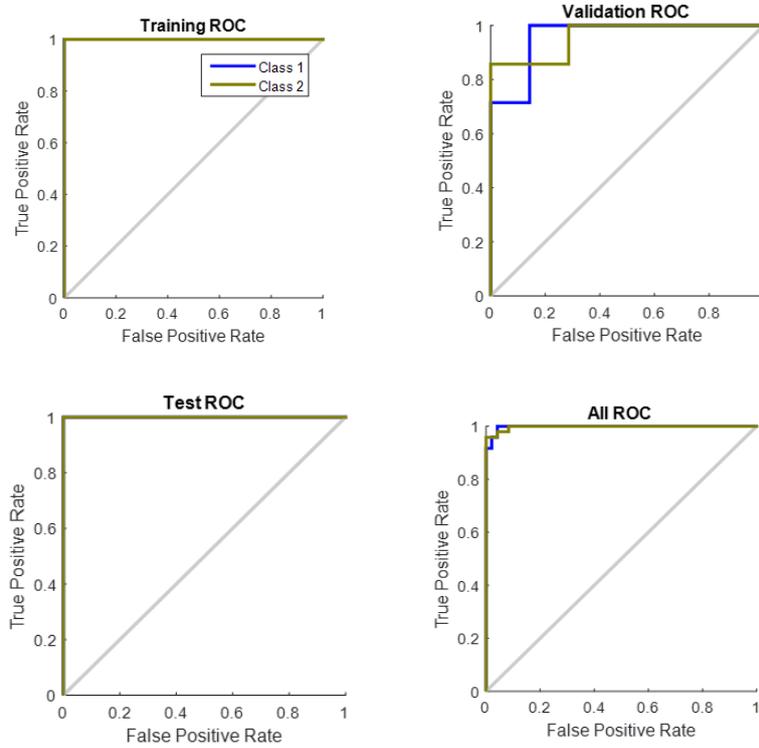


Figure 07: ROC curves for training, validation and testing

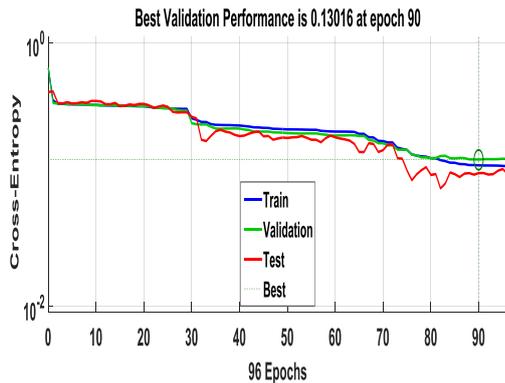


Figure 08: Variation of performance function for training, validation and testing

We have used the directional fractal analysis in the wavelets domain to classify the Brodatz anisotropic texture using ANN classifier (pattern recognition neural network). We have chosen two classes of Brodatz which are anisotropic textures (grass for class one and wood grain for class two).

We have applied the histogram equalization (HE) as preprocessing to enhance and adjusting the contrast of the texture. The enhancement of the contrast is assured by the augmentation of the standard deviation. Figure 4 present an example of texture enhanced using histogram equalization.

Then we have rotated the texture with the different angles from 0° to 360° with a step of 10° . For example, we present, in Fig. 4 the sub-image 12, preprocessed and rotated in 30° and in 120° . After this, we have applied the DWT with a Daubechies wavelets chosen (db5) in the first resolution and implemented the DBCM method to the approximate image with boxes size for 5:5:30 pixels to estimate the value of the directional FD. We have obtained various results of FD, according to the angles of rotation $FD(\theta)$ (37 different values of FD for each direction), which represent the attributes vector (features) of the texture image (the number of input neurons to the ANN classifier).

After several training of our network, we get the results of our ANN classifier for directional texture classification using a hybridization of wavelets with the fractal analysis. The performance classification was assessed by ROC curves and confusion matrix. We report a successful separation of the two classes.

The receiver operating characteristics (ROC) analyses were done to compare the performance of these features to distinguish the different classes. The plot of the ROC curves is given in Fig. 7. A ROC curve was generated by using a sliding threshold on the selected features and computing the sensitivity and specificity for each threshold. The true positive fraction (TPF) or sensitivity is the proposition of the abnormal cases correctly identified by the feature. The false positive fraction (FPF) is the portion of the normal cases incorrectly identified by the classifier as abnormal.

Performance classification was assessed by ROC analysis and confusion matrix. We report a successful separation of the two classes, after different training. Area under-curve (AUC) values for training, validation and testing are 1, 0.96 and 1 and classification rates are 94.1%, 85.7%, 85.7% and the fail classification of 5.9%, 14.3 and 14.3% respectively. Hence, the classification rate for all data is 91.7% and a fail classification is 8.3%.

The best performance of our ANN classifier is obtained at the 90 epoch of training the network which equal to 0.13016 (see Fig. 8).

5 CONCLUSION

In this paper, we have presented a new method; the directional texture classification using a hybridization of wavelets transform and fractal analysis to estimate the efficient directional FD in the wavelets domain using the ANN classifier for classifying two classes of anisotropic Brodatz texture.

We have used the directional fractal analysis based on differential box counting method (DBCM) after a preprocessing by histogram equalisation (HE) and rotation from 0° to 360° with a step of 10° , then transformation of the image texture using DWT and using the approximate image in the fractal analysis.

We have chosen two classes of Brodatz textures (grass and wood grain) for training, validation and testing our algorithm. 48 sub-images for each class, and for each sub-image 37 FD values (features) corresponding to 37 directions of rotation corresponding the number of inputs neurons (input layer of the classifier).

The approach has demonstrated a successful separation of the two patterns (classes) as demonstrated by both matrix confusion and ROC curves with a classification rate for all data of 91.7% and a fail classification of 8.3%.

The results exhibited in this paper open new door to estimating the directional FD, which rather focuses on image transforms instead of complex transformations of differential box counting method (DBCM).

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