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# PARAMETRIC GAUSSIANIZATION PROCEDURE OF WAVELET COEFFICIENTS FOR TEXTURE RETRIEVAL

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## ABSTRACT

In this paper, we deal with the problem of feature extraction in content-based image retrieval (CBIR) using statistical approach. A Gaussianization procedure based on parametric density assumptions of steerable pyramid coefficients is proposed. The extraction method of features including the Gaussianization step allows us to limit the order of the statistical model used to characterize the image textures. The performances of the proposed method are analyzed on a database of texture images and compared with the performances of other texture features proposed in previous works.

***Index Terms*—** Image texture analysis, Information retrieval, Steerable pyramid, Generalized Gaussian distribution, Gaussianization procedure

## 1. INTRODUCTION

To improve the management of large digital image databases, it is necessary to develop effective and precise methods to describe the visual information. These methods could be used in machine vision or in image processing applications using segmentation or classification systems. A content-based image retrieval (CBIR) system is a suitable example of these systems dealing with visual information to automatically retrieve relevant images similar to a given query image. Derived features are computed, namely visual features (VF), from the query image and a suitable similarity measure (SM) finalizes the definition of the CBIR system. For all these systems using visual content, VF or image signatures are composed of low-level image attributes such as color, texture, shape or layout.

For the last few years, numerous works have been dedicated to one of the most important visual cue: the texture. The texture has been subject of intense study because this visual component is application-dependant. The texture can be the result of physical surface properties or reflectance effects showing particular spatial characteristics such as roughness or oriented strands.

When dealing with statistical texture modeling, many authors proposed to make use conventionally of multiorientation and multiscale filter-banks such as real or complex wavelets [1], [2], [3], [4]. This decomposition captures the directionality, the structuredness, and coarseness of a texture. The problem which follows is to select a whole set of statistical features from the coefficients obtained with the filter-banks. Previous works in [2], [5], [6] proposed to model the texture with first and second-order statistics. Wouwer *et al.* [7], Do and Vetterli [8] employed generalized Gaussian density (GGD) functions as parametric model. Other authors in [9], [10], [11] applied a sub-Gaussian model for joint and marginal statistics. In their work, Tzagkarakis *et al.* [9], following the sub-Gaussian density model, propose a Gaussianization process and argue the interest of this step to increase the performances in CBIR framework. In a second article [10], the same authors note the high computational complexity of the Gaussianization process: spanned by the sub-Gaussian model. In [12] Portilla and Simoncelli developed a statistical model for texture images using a steerable pyramid representation. They use the output of filter banks to define four statistical constraints as texture features: marginal statistics, coefficient correlation, magnitude correlation and cross-scale phase statistics. These features can be used for texture retrieval or synthesis but the selection of the second order statistics used is not justified.

In this paper, we focus on the enhancement of the quality of the VF used for CBIR system. We propose to implement a parametric Gaussianization step in the procedure of VF extraction based on GGD model. This aims at using only the second order statistics to characterize the image textures. The quality of obtained VF will be evaluated taking into account the characterization criteria used in CBIR system: *recall* and *precision.*

The paper is organized as follows. The next section provides the proposed features extraction method for CBIR system. The analytical Gaussianization procedure (GP) is discussed followed by a description of the proposed texture features. In section 3, experimental results are given to evaluate the retrieval performance.

## 2. PARAMETRIC TEXTURE RETRIEVAL BASED ON WAVELET SUBBAND COEFFICIENTS

The system diagram for our feature extraction method is shown in Fig.1. It is based on steerable pyramid representation [4], [12], which consists to recursively decompose an image into a set of oriented and scaled subbands, followed by three main stages. First, we approximate the marginal density of wavelet subband coefficients, in various scales, by generalized gaussian density. The use of the family of GGD, as an accurate tool for modeling the heavy-tailed behavior of steerable pyramid coefficients has been justified by Do and Vetterli in [8]. Second, we apply a GP of the wavelet coefficients using the estimating model parameters using Maximum Likelihood estimator. This procedure will be examined in section 2.1. Finally, we estimate the second order statistics of the Gaussianized wavelet coefficients as a set of features (signatures). Thus, this step allows us to take into the account the interdependencies between wavelet coefficients at different orientations subbands and scales. The second order statistics constituting the feature vector are described in section 2.2.

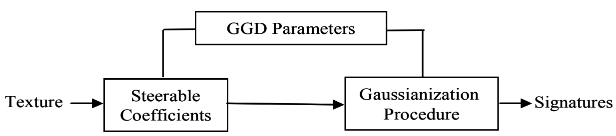


Fig.1. System diagram of the analysis method

In the following section, the principle of the used GP is described.

### 2.1 Gaussianization procedure

Let $X$ be a random variable with probability density function $f(.)$ and cumulative density function (CDF) noted $F(.)$. Consider the CDF function $\Phi(.)$ of normal distribution $N(0,1)$. It is know that the random variable $Y$ given in (1) have a normal distribution

$$Y = \Phi^{-1}[F(X)] \quad (1)$$

In the particular case of GGD [8], the probability density function $f(.)$ is defined with two parameters $\alpha$ and $\beta$ as follows

$$f_{\alpha,\beta}(x) = \frac{\beta}{2\alpha\Gamma(1/\beta)} e^{-(|x|/\alpha)^{\beta}} \quad (2)$$

where $\Gamma(.)$ is the *Gamma function* defined for $z > 0$ by the following equation:

$$\Gamma(z) = \int_0^{\infty} e^{-t} t^{z-1} dt \quad (3)$$

Using equation (2), we show that the cumulative density function of GGD has the following closed expression:

$$F_{\alpha,\beta}(x) = \frac{1}{2}\left[1 + \gamma\left(\left(\frac{x}{\alpha}\right)^{\beta}, \frac{1}{\beta}\right)\right] \quad (4)$$

where $\gamma(.,.)$ is the *incomplete Gamma function* [13], which is defined as

$$\gamma(y,z) = \frac{1}{\Gamma(z)} \int_0^{y} e^{-t} t^{y-1} dt \quad (5)$$

As a result, the Gaussianization procedure was carried out by employing (4) and (5) in (1). An illustration of Gaussianization is given in section 3.

### 2.2 Feature extraction and similarity measure

For a given texture image $I$ decomposed in $Nsc$ scales and $Nor$ orientations, we denote by $x_k^l$, the coefficients corresponding to the subband at $l$ th scale and $k$ th orientation. For all $x_k^l$ we write $y_k^l = \mathrm{Re}(x_k^l)$ and $z_k^l = \mathrm{Im}(x_k^l)$ to refer to the real and imaginary parts of $x_k^l$, respectively. After the GP of each subband coefficients the feature extraction is carried out using only the following second order statistics:

- $A_{i,j}^l$ : autocorrelation samples of the real part of coefficients at each subband

$$A_{i,j}^l(n,m) = \overline{y_k^l(i,j)\, y_k^l(|i+n|_N, |j+m|_M)} \quad (6)$$

where $|a+b|_N$ indicates the sum of $a$ and $b$ modulo $N$, $\overline{y}$ denotes the estimated mean of $y$, and $(M,N)$ represents the size of $x_k^l$.

- cross-correlation of each real part subband with other orientations at the same scale

$$\rho_{k,j}^l = \overline{y_k^l(m,n)\, y_j^l(m,n)} \quad (7)$$

- cross-correlation of the real part of coefficients with the real part of coefficients at all subbands at the next scale

$$\rho_{k,j}^{l,l+1} = \overline{y_k^l(n,m)\, y_i^{l+1}(n,m)} \quad (8)$$

- cross-correlation of the real part of coefficients with the imaginary part of coefficients at all subbands at the next scale

$$\tilde{\rho}_{k,j}^{l,l+1} = \overline{y_k^l(n,m)\, z_i^{l+1}(n,m)} \quad (9)$$

All these statistics will be concatenated to obtain a feature vector $f(I)$. We note that if we use a support of the autocorrelation of length $Na$, the number of the extracted features to characterize an image is given by

$$N_f = Nsc.Nor.\frac{(Na^2 + 5Nor + 2)}{2} - 2.Nor^2 \quad (10)$$

In order to determine similarity between two images in the database, we use the $L^2$ Euclidean distance between the feature vectors, preceded by a homogenization step to bring back all values between 0 and 1. Explicitly, given a features vector $[\, f_1^j, \cdots, f_i^j, \cdots f_{N_f}^j \,]$ of the image $I^j$, its components are homogenized as follows:

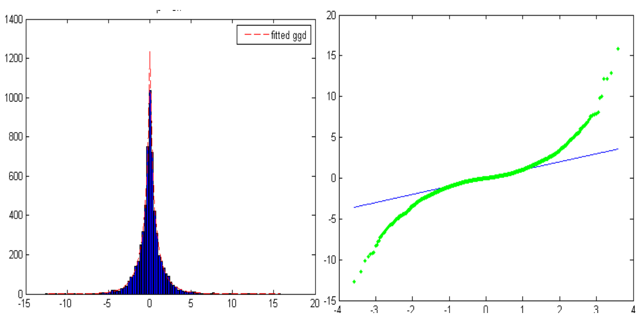
$$Hom(f_i^j) = \frac{f_i^j - \min(f_i^k)_{1\le k\le K}}{\max(f_i^k)_{1\le k\le K} - \min(f_i^k)_{1\le k\le K}} \quad (11)$$

where $K$ is the size of the database.

## 3. EXPERIMENTAL RESULTS

In this section, two kinds of experiment results are provided. In the first one, the GP is studied. The second gives an evaluation of the proposed VF in the framework of texture retrieval.

*GP experiments*: As illustration of the Gaussianization procedure, we generate sample observation from generalized Gaussian (GG) population having the following parameters: $(\alpha, \beta) = (0.5, 0.7)$. The histogram of observations is shown in Fig.2-a. The plot in figure 2-b shows the normal q-q plot of the generated samples to get some idea on the straggling about the line. After the Gaussianization procedure, the corresponding histogram and normal q-q plot of transformed observation are shown in Fig.3. From these figures, we observe that the most q-q plot points adhere to the target straight line. Thus, the distribution of transformed observations weakly deviates from $N(0,1)$.




(a) (b)

Fig. 2. Histogram and q-q plot of GG observations

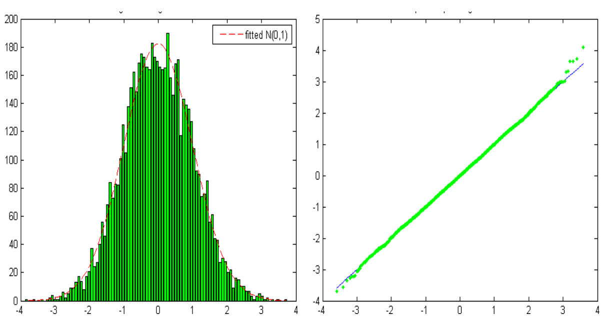



Fig.3. Histogram and Normal q-q plot of the transformed observations

*CIBR evaluation:*

The proposed retrieval scheme is applied on a set of texture images obtained from the MIT Vision Texture (VisTex) database [14]. From each of these texture images of size 512x512 pixels, 16 subimages of 128x128 pixels are created. A test database of 640 texture images is thus obtained. In the retrieval stage a query image is any one of these images in the database. The relevant images for each query are the other 15 images obtained from the same original 512x512 image.

To evaluate the performances of the proposed method we used a conventional criterion from the information retrieval framework, the *recall* and the *precision:*

$$recall = \frac{number\ of\ relevant\ retrieved\ images}{number\ of\ relevant\ images}$$

$$precision = \frac{number\ of\ relevant\ retrieved\ images}{number\ of\ retrieved\ images}$$

First we show the impact of the GP by comparing the performance of retrieving between the features obtained after GP and the same features without GP. The recall-precision curves presented in Fig.4 shows the improvement obtained by the GP step.

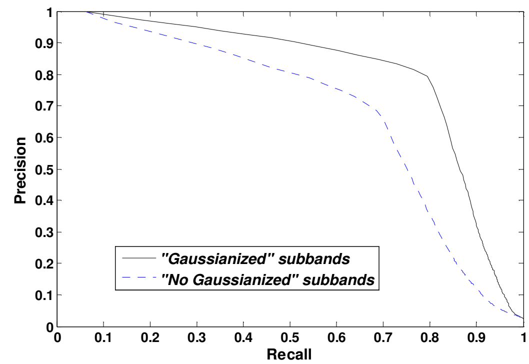



Fig. 4. Recall-Precision curves showing the impact of the GP with $Nsc = 2$ and $Nor = 3$.

Second, we compare the performances of our method with those obtained by the following methods:

- The wavelet-based texture retrieval method of Do-Vetterli which uses a GGD model with the Kullback-Leibler Distance (GGD+KLD) [8]
- The Portilla-Simoncelli method which uses a parametric model based on joint statistics of steerable pyramid coefficients [12].

In this study, the method of Do-Vetterli is tested using Daubechies' filters with 4 decompositions levels. However, the two others method are tested using 2 scales and 3 orientations. Table 1 provides a comparison of average retrieval accuracy of the three methods. From this table we observe that the proposed method has about 6% improved retrieval rate than Do-Vetterli method. The good performances of the proposed method are also revealed using the recall-precision criterion as shown in Fig.5.

| | GGD+KLD | Proposed method | Portilla-Simoncelli |
|---|---|---|---|
| Average retrieval rate (%) | 73.2617 | **79.4238** | 76.1035 |
| Number of parameters | 24 | 180 | 277 |

Table 1: Average retrieval rates (%) comparison

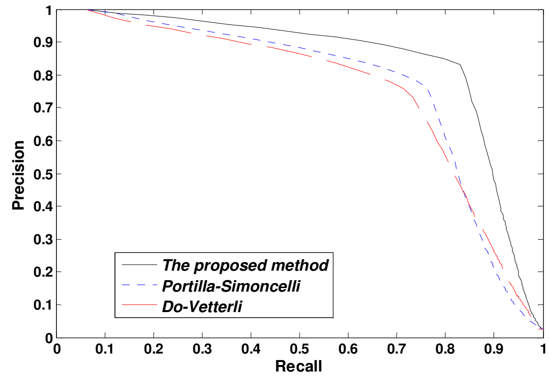



Fig. 5: Recall-Precision curves comparison.

Furthermore, we also observe that the proposed method converge faster than the two others. From Fig.6, we show for example we retrieve 91.86% of the relevant images on considering $Nor = 6$ and a query of size equal to 40 images.

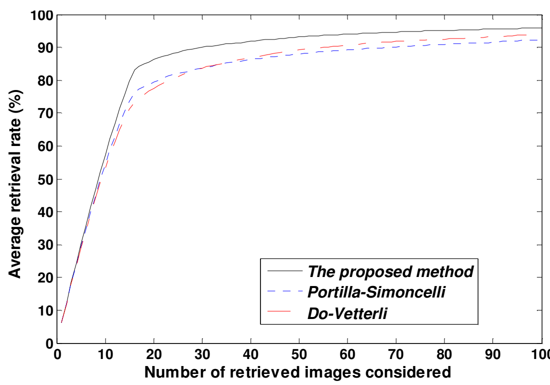



Fig. 6: convergence methods comparison.

We note that the average success retrieval of the proposed method can be improved by increasing the number of orientations. Indeed, we can reach 82.9883% of success retrieval while using 6 orientations and 2 scales of decomposition. The average success retrieval rates of the proposed method using two scales and number of orientation from 3 to 6 are represented in table 2.

| Number of orientations | 3 | 4 | 5 | 6 |
|---|---|---|---|---|
| Average retrieval rate (%) | 79.4238 | 81.0547 | 82.7734 | **82.9883** |
| Number of parameters | 180 | 252 | 330 | 414 |

Table 2: Average success retrieval rates of the proposed method according to the number of orientations

## 4. CONCLUSION

In this paper, the feature extraction problem in CBIR system is considered. We have proposed a texture retrieval method based on Gaussianization of steerable pyramid coefficients. It takes advantages of the steerable pyramid decomposition and uses a simple Euclidean distance requiring few computational time. The Gaussianization procedure is justified by the fact that it results in a normalized transformation domain where statistics can be limited to the second order. The proposed method was tested on 640 texture images from the VisTex collection with promising results. An extension of the proposed work is to evaluate the extracted features for a task of texture synthesis.

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