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Rotation invariant texture characterization using a curvelet based descriptor

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ABSTRACT

This paper introduces a highly discriminative, precise and simple descriptor of natural textures, based on the curvelet transform. The proposed descriptor is calculated from the statistical pattern of the curvelet coefficients. The image is mapped to the curvelet space, where a statistical parametric model approaches the data distribution for each of the sub-bands. Once these parameters are estimated, they are subband-energy sorted out, achieving thereby the invariance to planar rotations. Finally, the Kullback–Leibler divergence between the statistical parameters is used to estimate a distance between images. We demonstrated the effectiveness of the proposed descriptor for classification and retrieval tasks.

1. Introduction

Features with highly discriminant texture characteristics are a fundamental concern in the artificial vision domain, particularly for the problem of classification and/or retrieval. Typical applications include microscopical or satellite images (Randle and Engler, 2000). Formally, the feature extraction process is thought of as a mapping of an image collection to a characteristic space, which provides a representation where similar images are close and different images are far. Images projected onto this space are characterized by features which capture particular image properties, typically statistical data attributes. In the particular case of textures, the most popular characteristic spaces are currently the discrete cosine, wavelets and Gabor transforms (Randen and Husy, 1999; Petrou and Sevilla, 2006). Unfortunately, these spaces are sub-optimal for this problem because textures are naturally entailed with geometrical, scale and directional properties which are poorly described with these transforms (Do and Vetterli, 2003). Texture is usually classified using either statistical methods, primitive-based methods or multichannel filtering methods. Most of the first and second order statistical models, for instance gray level co-occurrence matrices or Markov random fields, have shown acceptable results only for microtextures (Haralick et al., 1973; Cohen et al., 1991). Primitive-based methods may capture only regular patterns since they follow specific matching rules (Hong et al., 1980). Multichannel filtering methods decompose a texture input image into image features using a bank of filters (Randen and Husy, 1999). Multiresolution analysis is a natural characteristic of spatial-frequency methods, case in which correlation through the different scales allows a much more complete texture analysis. Spatial-frequency analysis such as Gabor filters (Arivazhagan et al., 2006) and Wavelet transform (Chang and Kuo, 1993; Arivazhagan and Ganesan, 2003) provide good multiresolution analytical tools for texture classification, and achieve a high accuracy rate. Gabor filters are well localized in space and frequency, but they are computationally expensive for the low frequency components. In addition, Gabor filter banks are not orthogonal, whereby a significant texture feature correlation is inevitable (Unser, 1995). On the other hand, the success of any comparison between images depends on the metrics one selects for the specific problem. The usual metrics is either Euclidian or an estimation of the statistical dependence such as the Kullback–Leibler divergence (KLD) (Kullback, 1987). In these terms, the problem of texture characterization consists in constructing a feature with high discriminative power that takes into account the statistical image contents.

Some of the features, already used in this problem, are apt to capture information of the energy coefficient distribution and include the total energy, the mean and the variance (Randen and Husy, 1999). However, these features result insufficient to capture the statistical properties of natural images (Van De Wouwer et al., 1999). The problem of texture characterization with curvelets was already addressed by Dettori and Semler (2007), who studied the performance of several features, namely: the energy, entropy, mean and standard deviation of the curvelet subbands. Results showed significant improvement when comparing with wavelets, but this characterization did not take into account the particular statistical patterns of the curvelet coefficients (Alecu et al., 2006). Sumana et al. (2008) also proposed the curvelet subband mean and variance as features and the Euclidian distance as similarity measurement. Results showed again improvement, when comparing with Gabor features. Nevertheless, texture curvelet subbands

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are not described by simple Gaussians so that mean and variance result insufficient to describe the observed distribution (Alecu et al., 2006).

In this paper we present a new global descriptor, invariant to rotation changes. The curvelet space is used to capture information about edges, which are in fact one of the most discriminating features (Field, 1993). These features are the moments of a generalized Gaussian density (GGD), a good approximation to the marginal curvelet subband distribution (Alecu et al., 2006), whilst the Kullback–Leibler divergence estimates differences between curvelet coefficient distributions. The main contribution of this paper is the design of a highly discriminative, precise and simple descriptor of natural textures, provided with a rotation invariance mechanism and based on the use of GGD moments fitted to the curvelet coefficients whose distance is estimated with the KL divergence.

2. Materials and methods

Two input images are curvelet-represented and their frequency subbands are statistically characterized, using the moments of a GGD. Invariance to planar rotation is obtained via the circular shifting process (Li et al., 2008), based on the subband energies. Finally, the Kullback–Leibler divergence computes a distance estimation between the two representations. This strategy will be further explained hereafter:

2.1. The curvelet transform

The curvelet transform is a multiscale decomposition, developed to naturally represent objects in 2D, improving the wavelet limitations for representing geometrical information (Candes et al., 2006). Curvelets are redundant bases which optimally represent 2D curves. Besides the usual information about scale and location, already available from a wavelet, each of these frame elements is able to capture orientation information.

A curvelet can be thought of as a radial and angular window in the frequency domain, defined in a polar coordinate system, upon which the different scales are represented as different rings with different level of frequential detail from the inner (low frequencies) to the outer (high frequencies) rings. This representation is constructed as the product of two windows: the angular and the radial dyadic frequential coronas. The angular window provides a directional analysis and the radial dyadic window is a bandpass filter, used to analyze image details at different scales (see Fig. 1). Frequency cuts in both windows are selected, following the parabolic anisotropic scaling law $width \approx length^2$ (see Fig. 1). The motivation behind this selection is to efficiently approximate a smooth discontinuity curve by "laying on" basis elements with elongated supports along the curve (Candes et al., 2006). Curvelet bases were designed to fully cover the frequency domain, in contrast to other directional multiscale representations such the Gabor transform, case in which some information is always lost. Thanks to the anisotropic scale, curvelets adapt much better to scaled curves than Gabor transform, improving the representation at different scales and noise robustness (Candes and Guo, 2002). All these statements have been experimentally demonstrated by comparing wavelets, curvelets and Gabor in retrieval tasks (Sumana et al., 2008). The Fig. 1 shows a curvelet multiscale decomposition example.

2.2. Statistical characterization

Psychophysical research has demonstrated that two homogeneous textures are not discriminable if their marginal subband distributions are alike (Field, 1993), i.e., the frequency subband distributions have a highly descriptive capacity, at least for the texture problem. This discriminative power was also experimentally verified for wavelet and Gabor representations (Randen and Husy, 1999). In the curvelet case, each subband contains information about the degree of occurrence of similar curves within the image, that is to say, edge energy levels with similar direction and size. Recent evidence has demonstrated that the marginal distribution of curvelet subbands has a discriminant power (Alecu et al., 2006). Our fundamental hypothesis is that the curvelet distribution information may also provide enough discriminant power to texture patterns. As observed in Fig. 2, the curvelet subband coefficient distributions are characterized by sharper peaks at zero and heavy tails. In this case, usual Gaussian distribution assumptions proposed in the literature are not satisfied (Dettori and Semler, 2007; Sumana et al., 2008). In contrast, a generalized Gaussian density distribution fully characterizes the subband curvelet distribution. As observed in Fig. 2(c) and (e), the GGD (green) provides a better adjustment to the marginal density than the Gaussian distribution (red). This observation was quantitatively confirmed by comparing the Kullback–Leibler divergence between the empirical distribution (ED) and the fitted GGD, and the ED and the fitted Gaussian distribution. For the example in Fig. 2(a), the KLD value for ED-GGD comparison was 0.061 and 0.071 for ED-Gaussian. We extended this analysis to the complete set of subband curvelets for a set of 20 randomly selected textures in our database, resulting in a KLD value of 0.096 ± 0.05 (mean ± std) for the ED-GGD and 0.10 ± 0.05 for the ED-Gaussian case. This analysis shows that GGD provides a better adjustment to the curvelet subband distribution than the usual Gaussian characterization.

In general, the curvelet coefficient distribution in natural images is characterized by a sharper peak centered at zero with symmetrical smooth tails. This shape is associated to the sparse property of this transformation, i.e., relatively few large coefficients capture most of the information. This leptokurtic pattern has been previously observed in curvelets (Alecu et al., 2006; Boubchir and Fadili, 2005) as well as in wavelets (Do and Vetterli, 2002). This work proposes a texture characterization via the marginal distribution of the subband curvelet coefficients, specifically using the parameters of a generalized Gaussian density. Recent experimentation in natural images (Alecu et al., 2006) shows that the generalized Gaussian density provides a good adjustment to the marginal density of the curvelet coefficient, within each subband. The GGD reads as $p(x;\alpha,\beta) = \frac{\beta}{2\alpha\Gamma(1/\beta)} e^{-(|x|/\alpha)^{\beta}}$, where $\Gamma(z) = \int_0^\infty e^{-t} t^{z-1} dt, z > 0$ is the Gamma function, α is the variance and β is related to the decreasing rate of the GGD. The parameters α and β are estimated from the subband data using maximum likelihood, as detailed in (Do and Vetterli, 2002). These parameters (α, β) are herein used as descriptor of the probability density function of the energy levels inside each curvelet subband.

2.3. Rotation invariance

Previous texture characterizations have failed when the image is rotated, basically because similar textures with different orientations have very different statistical subband moments. Some works (Li et al., 2008; Islam et al., 2009) have tried to overcome this limitation by using the curvelet rotation shifting property, that establishes that the curvelet subbands of a rotated image are a shifted version of the original subbands. These approaches have independently performed a circular shifting on each scale level, assuming that the energy of the dominant orientation usually spreads between two neighboring subbands. Nevertheless, our experiments on the Brodatz database (Brodatz, 1999) rapidly drive us to the conclusion that this statement was true only for some patterns. Indeed, orientation information is not homogenously distributed between the different scale levels and its calculation is not therefore