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Texture retrieval using mixtures of generalized Gaussian distribution and Cauchy–Schwarz divergence in wavelet domain

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This paper presents a novel similarity measure in a texture retrieval framework based on statistical modeling in wavelet domain. In this context, we use the recently proposed finite mixture of generalized Gaussian distribution (MoGG) thanks to its ability to model accurately a wide range of wavelet sub-bands histograms. This model has already been relied on the approximation of Kullback–Leibler divergence (KLD) which hinders significantly the retrieval process. To overcome this drawback, we introduce the Cauchy–Schwarz divergence (CSD) between two MoGG distributions as a similarity measure. Hence, an analytic closed-form expression of this measure is developed in the case of fixed shape parameter. Otherwise, when the shape parameter is variable, two approximations are derived using the well-known stochastic integration with Monte-Carlo simulations and numerical integration with Simpson's rule. Experiments conducted on a well known dataset show good performance of the CSD in terms of retrieval rates and the computational time improvement compared to the KLD.

1. Introduction

Content-based image retrieval (CBIR) is a fast advancing research area, which uses visual contents to retrieve images from large databases according to users requests. The term content-based image retrieval, as defined in [1], refers to an automatic process for images retrieval from a database. This process is based on a set of features that qualify similar images to the characteristics of a given query image. Thus, a typical architecture of a CBIR system consists in two major tasks as shown in Fig. 1. First, features extraction (FE) step consists on a set of features considered as a signature, and generated to fit accurately the content of each image in the database. The second task concerns the similarity measurement (SM). It is performed by computing a distance between the query image and each image in the database using their signatures, in order to retrieve the top N of closest images. No less important is the similarity measurement method adopted by the CBIR system as it requires a lot of precision and a short time response.

Image content may include shape, color and/or texture. Basic texture analysis techniques include Markovian analysis [2], Gabor filtering [3,4] and also autoregressive models [5] which consider texture as the outcome of a deterministic dynamic system subject to state and

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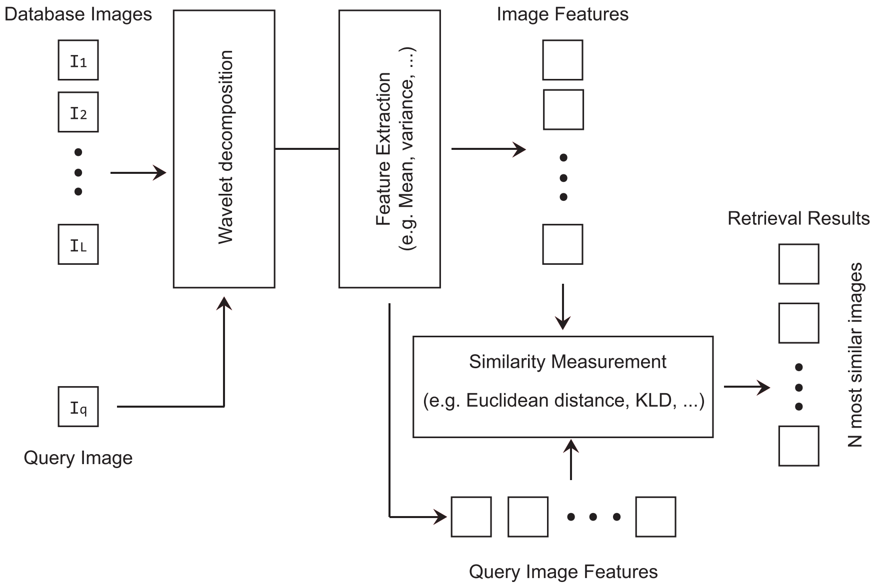

Fig. 1. Typical architecture for a content-based image retrieval system with two major steps : Feature extraction (FE) and similarity measurement (SM).

observation noise. Most of recent approaches used different types of wavelet-based signatures to discriminate between textures. Indeed, the discrete wavelet transform (DWT) is considered as a very powerful tool for texture representation [6,7]. In particular, statistical models of wavelet coefficients have been emerged as an efficient way to discriminate between texture classes [8–10]. Statistical-based approaches provide a natural way to formulate retrieval problem. This class of approaches casts this problem into a problem of similarity measurement between statistical models and provides a common ground for many existing similarity functions by simply modifying the underlying assumptions. It has been proven that the statistical-based modeling fits perfectly into this type of systems since a textured image can be regarded as a realization of a stochastic process. Specifically, parametric distributions have been successfully used to represent texture images in the wavelet domain. Among the earliest investigated models, we find the generalized Gaussian density model (GGD) combined with weighted Euclidean distance as a similarity measure in [11] and with the Kullback–Leibler Divergence (KLD) by Do et al. in [12]. The Student *t*-distribution [13] has been explored to characterize the marginal probability distribution of wavelet sub-band coefficients of textured images as well as Gamma and Weibull distributions to model complex coefficients magnitudes [14–16]. Recently, E. de Ves et al. [17] proposed a new approach to model magnitudes and angles of wavelet frame coefficients.

The joint modeling of multivalued wavelet images has also been considered in many works. For instance, powerful statistical algorithms have been proposed such as multivariate generalized Gaussian distribution (MGGD) [18] which is a particular case of elliptical distributions [19,20]. Based on Gaussian copula and student-*t* copula for modeling the dependence structure, in conjunction with Weibull and Gamma densities as parametric margin models, Kwitt et al. [21] characterized the complex coefficient magnitudes where significant enhancements in the context of texture retrieval have been achieved. Another Copula based multivariate modeling was proposed by Sakji-Nsibi et al. [22] for multicomponent image indexing using Gaussian Copula in conjunction with the GGD and Gamma densities. A larger study of coupla based models was recently done by Lasmar et al. [23]. Among the challenges encountered with those multivariate models is the difficulty to develop a closed-form expression for the similarity measurement. Boubchir et al. [24] introduced recently, the multivariate Bessel K-Forms density (MBKF) to characterize joint statistics in wavelet domain and for which one can develop a closed solution for KLD between MBKF densities. Kwitt et al. [21] proposed a Copula-based statistical model of complex wavelet coefficient magnitudes for color texture image retrieval but they did not found any closed-form expression for the KLD between two multivariate Gaussian copula distributions. Hence, a pragmatic Monte-Carlo (MC) approach have been chosen. Lasmar et al. [23] developed a closed-form expression of KLD between multivariate Gaussian copula distributions with GGD and Weibull marginals. Various multivariate models have also been proposed in the literature. For instance, Verdoolaege et al. [25] characterize wavelet coefficient sub-bands with a bivariate GGD model. Although, they were unable to find an analytic expression for the KLD between two MGGDs in general, i.e. for dimension greater than two, they developed a closed-form expression for a bivariate GGD. Another similarity measurement has been used for MGGD model by Verdoolaege et al. [18] where they successfully derived a closed-form expression for the geodesic distance (GD) between MGGDs in the case of a fixed MGGD shape parameter and have proposed a suitable approximation to the geodesics on the manifold of MGGDs with varying shape parameters. However, all these approaches are based on single