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Gaussian Markov random field based improved texture descriptor for image segmentation

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ABSTRACT

This paper proposes a novel robust texture descriptor based on Gaussian Markov random fields (GMRFs). A spatially localized parameter estimation technique using local linear regression is performed and the distributions of local parameter estimates are constructed to formulate the texture features. The inconsistencies arising in localized parameter estimation are addressed by applying generalized inverse, regularization and an estimation window size selection criterion. The texture descriptors are named as local parameter histograms (LPHs) and are used in texture segmentation with the k-means clustering algorithm. The segmentation results on general texture datasets demonstrate that LPH descriptors significantly improve the performance of classical GMRF features and achieve better results compared to the state-of-the-art texture descriptors based on local feature distributions. Impressive natural image segmentation results are also achieved and comparisons to the other standard natural image segmentation algorithms are also presented. LPH descriptors produce promising texture features that integrate both statistical and structural information about a texture. The region boundary localization can be further improved by integrating colour information and using advanced segmentation algorithms.

1. Introduction

Texture plays a vital role in human perception of visual objects and scenic regions, together with other visual cues such as colour, brightness and form [1]. As a result, much research in recent years has been carried out in texture feature extraction [2–6]. Segmentation of textured images has its own significance in image segmentation domain with wide spread applications in many fields including medical image processing, remote sensing, document processing, defect detection and object recognition [1]. Feature-based texture segmentation basically consists of two successive processes; texture feature extraction and a routine of feature clustering [7]. The texture feature extraction mainly aims at formulating effective discriminative texture descriptors and has been intensively studied [2–4,6].

In statistical model based texture feature extraction, texture is assumed as a realization of a random process which is governed by the model parameters. Texture features obtained from these methods, especially Markov random fields (MRF), have proved to offer a powerful framework for image analysis [8–10]. Gaussian Markov random field (GMRF) is an important subclass of MRF whose joint distribution is a multivariate Gaussian distribution [9]. A local conditional probability distribution of GMRF encapsulates spatial dependencies between a pixel and its neighbours [11]. Model parameters of the conditional distribution offer a satisfactory feature set, which successfully enables to discriminate many different textures [12]. GMRF is widely popular because it avoids the difficulties in parameter estimation and therefore makes the process analytically and computationally efficient [9,13,14]. Using a Gaussian model is a valid assumption because most of the real textures like wood, wool, water, etc. obey the Gaussian notion [14]. GMRF based features produce good results for homogeneous, fine, stochastic textures, but poorly perform when characterizing more structured and macro textures [10,15].

In this paper our contribution is to propose a method based on GMRFs which can easily capture both statistical and structural properties of a texture. It can overcome the problem of parameter smoothing occurred in traditional GMRF parameter estimation. Our method suggests simple alterations to the existing GMRF feature extraction technique and achieves significantly better results. We perform parameter estimation using least squares estimation similar to the traditional GMRF parameter estimation, however we fit localized linear models at each pixel based on local linear regression. The issues arising in the local parameter estimation process are drawn into special attention and are addressed by using the generalized inverse [16], setting constraints on estimation window size and applying regularization.

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The localized process of parameter estimation results in spatial variations in the parameter estimates which are repetitive with the periodic texture patterns. We propose the distributions of these local parameters as a successful discriminative texture descriptor and designate as local parameter histograms (LPHs).

LPH descriptors capture both pixel dependencies and spatial distributions in a texture and therefore give a significant discriminative performance over classical GMRF features. In this study, we perform general and natural texture image segmentation using the novel LPH descriptors and demonstrate convincing segmentation results with a simple segmentation method such as k-means clustering algorithm. Segmentation experiments on large datasets are carried out. The LPH descriptors are also compared against the state-of-the-art structural and spectral texture feature extraction methods based on local feature distributions. The results on natural image segmentation could be further improved by integrating colour information and using advanced segmentation algorithms for better boundary localization. Therefore, for texture segmentation where more discriminative features are required rather than exact modelling of texture, LPH features are a better choice over the classical GMRF features.

The remainder of this paper is organized as follows. In Section 2 we provide the background which lead to the novel texture descriptors. Section 3 presents the theoretical foundation of GMRFs and in Section 4 we discuss local linear regression and its adaptation to GMRF parameter estimation. In Section 5 we address the issues arising in localized estimation with small sample sizes. Section 6 describes the construction of local parameter histograms. Section 7 illustrates the experimental results on texture segmentation and finally, we conclude this work in Section 8.

2. Background

Model parameters of conditional GMRF model offer descriptive features for texture analysis and have been directly used as texture features. In feature-based segmentation adaptive GMRF features are acquired by sliding window estimation. These GMRF features have been used in many studies focusing on texture segmentation [14, 17–21] and are referred to as the classical GMRF features. The parameter estimation is performed either by least squares estimation (LSE) or maximum likelihood estimation (MLE) and both methods lead to the same solutions [11,18,22].

Techniques have been proposed to enhance the discriminative power of classical GMRF features. Most of these methods specially focus on improving the parameter estimation process of GMRFs [11, 23–25]. Hierarchical formulations of GMRF model and mixture of Gaussian model have also been proposed to derive improved GMRF features [26–31].

During the estimation process, the estimation window size not only should be large enough to capture a homogeneous texture region but also should be small enough to achieve accurate boundary localization at the texture boundaries [11,12]. Many studies have been performed to address the boundary localization problem by proposing better adaptive segmentation algorithms and model-based segmentation approaches [7,12,18].

However, another issue of using larger estimation windows, other than the boundary localization problem, is that the large sample size for the estimation process, sampled from the large estimation window leads to over smoothed parameter estimates. This causes loss of structural information. Especially when the texture is deterministic and structured [10,15]. This parameter smoothing effect mainly occurs due to the Gaussian and linear neighbour dependency assumptions forced on the model. Comparative studies have shown that the GMRF features inherit a reduced discriminative ability in large scale empirical evaluations including many deterministic textures [10,32–34].

To find a solution to this smoothing problem, which has not been addressed before, we investigate the performance of locally estimated GMRF features based on local linear regression. Local regression also referred to as the kernel regression is a non-parametric method that depends on data itself rather than highly relying on a specific pre-selected model [35]. This framework gives a rich mechanism for computing point-wise estimates with minimal assumptions about the global model. For local regression the underlying model may remain totally unspecified. However, the local linear regression fits many localized linear models to describe any signal [35]. Here, we use the local linear regression to simplify the estimation process over the local regression and to maintain the direct link to the GMRF parameter estimation. Local estimates of GMRF model parameters obtained by local linear regression can integrate both statistical and structural texture information while minimizing the effects of parameter smoothing. The method proposed here reduces the large dependence of GMRF features on Gaussian constraints but inherits the computational simplicity of GMRF parameter estimation.

The concept of local linear regression has been used as an effective tool for image de-noising, interpolation and other image processing tasks [36–39]. However, it has not been used previously in formulating improved GMRF texture features.

Furthermore, recent studies on texture and object recognition have demonstrated that image representation based on distributions of local features is surprisingly effective [34,40]. Distributions of local features such as local binary patterns, spectral histograms and non-parametric MRF methods have demonstrated impressive results in texture classification and segmentation [2,6,32,34, 40–42]. Following this in the present study, we investigate the performance of distributions of local parameter estimates. The localized parameter estimation captures the spatial dependencies in the texture and the histogram construction captures their structural spatial variations.

Another concern in classical GMRF features is that the analysis of spatial interactions is limited to a relatively small neighbourhood, i.e. the usage of small neighbourhood sizes or low model orders [2]. During the parameter estimation, model order should be approximately equal to the pattern size. Such a model order preserves the Markovianity [24]. But the pattern size is usually unknown. Also if the model order is freely increased to follow the pattern size, the number of interaction parameters in the model increases quadratically. Such an increase in the model parameters leads to a computationally more expensive estimation process. These difficulties have been observed before and many studies in the literature have been directed to choose manually fixed small neighbourhood sizes [14, 17,18,23,43]. As a result, the adequacy of these features to characterize textures of various pattern scales is rarely checked [2,41]. However, the dependence of proposed localized parameter estimation method on selected neighbourhood size is small. In fact small neighbourhood sizes are generally more favourable for constructing local feature distributions. This is because it enables ease of fitting localized models onto small regions and achieves spatial variations of estimates which more closely resemble the spatial structure of the texture.

Therefore, in this study we explore the relevance and performance of distributions of local parameters estimates of GMRFs as an improved GMRF based texture descriptor.

3. Gaussian Markov random field model

The local conditional probability distribution of GMRF model encapsulates spatial dependencies between a pixel and its neighbours. This probability distribution associates any pixel with its neighbours in a Gaussian function [11]. Let $\Omega = \{s = (i,j) | 1 \leq i \leq H, 1 \leq j \leq W\}$ represent the set of grid points on a $H \times W$ regular lattice corresponding to an image region. The image region on Ω is preprocessed to have zero mean. The intensity value of the pixel at the location s is given by y_s and N denotes the set of relative positions