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Rotation invariant texture descriptors based on Gaussian Markov random fields for classification[☆]

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ABSTRACT

Local Parameter Histograms (LPH) based on Gaussian–Markov random fields (GMRFs) have been successfully used in effective texture discrimination. LPH features represent the normalized histograms of locally estimated GMRF parameters via local linear regression. However, these features are not rotation invariant. In this paper two techniques to design rotation invariant LPH texture descriptors are discussed namely, Rotation Invariant LPH (RI-LPH) and the Isotropic LPH (I-LPH) descriptors. Extensive texture classification experiments using traditional GMRF features, LPH features, RI-LPH and I-LPH features are performed. Furthermore comparisons to the current state-of-the-art texture features are made. Classification results demonstrate that LPH, RI-LPH and I-LPH features achieve significantly better accuracies compared to the traditional GMRF features. RI-LPH descriptors give the highest classification rates and offer the best texture discriminative competency. RI-LPH and I-LPH features maintain higher accuracies in rotation invariant texture classification providing successful rotational invariance.

1. Introduction

Texture feature extraction mainly aims at formulating efficient discriminative texture descriptors [31,36]. Texture analysis has been extensively studied in recent years and a large number of texture feature extraction techniques have been developed [6–8,18,20,21,27,34,35,39,44]. These methods can be roughly grouped into four main categories, namely statistical, structural, spectral and model based feature extraction methods [42].

Model based methods use generative models to represent images, with the estimated model parameters as texture features. GMRF is a popular model based texture feature extraction scheme with an analytically and computationally efficient parameter estimation process [36]. The parameter estimation is achieved via Least Square Estimation (LSE). The model parameters of GMRF model, also known as traditional GMRF (TGMRF) descriptors, have been employed in successful texture classification and segmentation [5,23,24,40,41]. TGMRF features describe spatial pixel dependencies which is a primary characteristic associated with texture. However, these features ignore some important structural and statistical information about the texture and have performed poorly [15,22,29,31,32]. Therefore in recent work, we proposed Local Parameter Histogram (LPH) descriptor which is an improved texture descriptor demonstrating significant improvement in characterizing texture compared to the TGMRF descriptors [12].

LPH descriptors however, are not rotation invariant. Thus, in this paper our main contribution is to achieve rotation invariant texture features based on LPH descriptors. Rotation invariant texture features are primarily required when the considered texture instances are comprised of rotated versions of the original texture. These type of scenarios can be found in many applications, for example, in medical image texture, in natural image texture as well as in synthetically produced rotation variant texture database classification. We introduce two new rotation invariant texture descriptors known as Rotation Invariant LPH (RI-LPH) features and Isotropic LPH (I-LPH) features. RI-LPH descriptors are suitable for directional texture analysis while I-LPH descriptors are ideal for isotropic texture description. RI-LPH descriptors are constructed using a local circular neighbourhood shifting process and I-LPH features are based on Isotropic GMRFs (IGMRFs). Furthermore, this paper illustrates comparative generalized classification performance of TGMRF, LPH, RI-LPH and I-LPH

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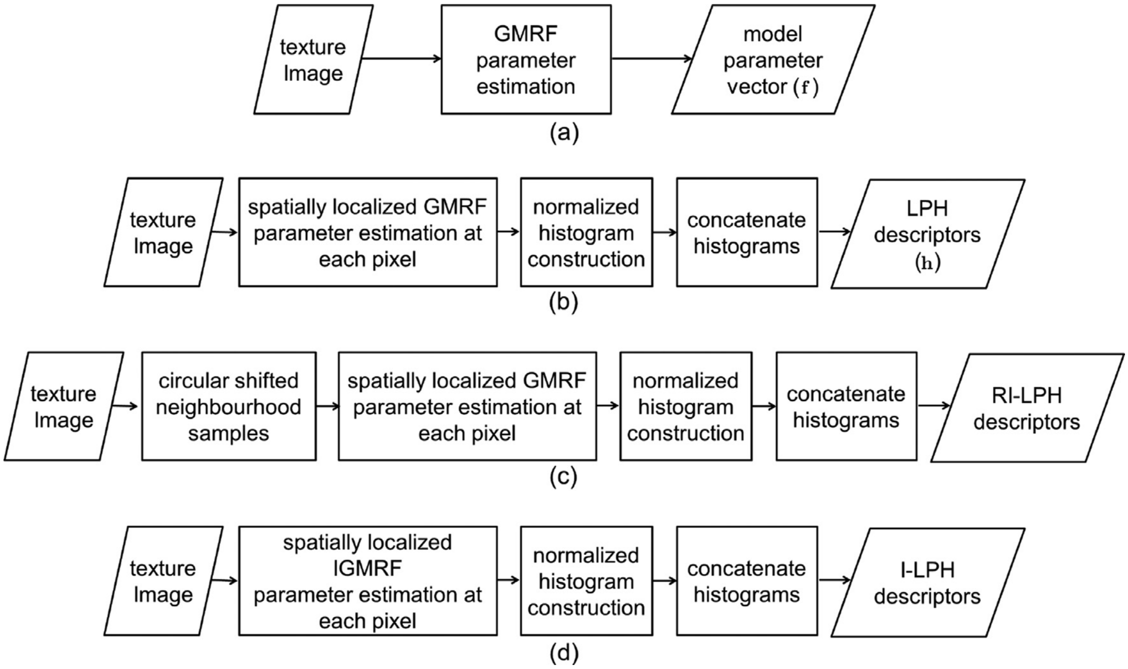

Fig. 1. Construction of (a) TGMRF descriptors, (b) LPH descriptors, (c) RI-LPH descriptors and (d) I-LPH descriptors.

descriptors and comparisons to the current state-of-the-art texture descriptors.

This paper is organized as follows. Sections 2 and 3 briefly explain the TGMRF features and LPH descriptors respectively. Section 4 introduces the rotation invariant texture descriptors and in Section 5 results and discussions are presented. Finally the conclusions are given in Section 6.

2. Traditional GMRF (TGMRF) descriptors

Let $\Omega = \{s = (i, j) | 1 \le i \le H, 1 \le j \le W\}$ represent the set of grid points on a regular lattice corresponding to an image region of size $H \times W$ which is pre-processed 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 of its neighbours. For simplicity only the square neighbourhoods of size $n \times n$ pixels are used here for N and n is a positive odd integer value. Then the local conditional probability density function of GMRF is given by,

$$p(y_s | y_{s+r}, r \in N) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{ -\frac{1}{2\sigma^2} \left(y_s - \sum_{r \in \tilde{N}} \alpha_r \bar{y}_{s+r} \right)^2 \right\} \quad (1)$$

where $\bar{y}_{s+r} = (y_{s+r} + y_{s-r})$. The pixels in symmetric positions about the pixel s are assumed to have identical parameters [3,31]. i.e. $\alpha_r = \alpha_{-r}$ with $r \in \tilde{N}$ where $\tilde{N}$ is the asymmetric neighbourhood [45]. α_r is the interaction coefficient which measures the influence on a pixel by a neighbour intensity value at the relative neighbour position r and the variance parameter σ indicates the roughness of the texture. The model parameters of conditional GMRF model are estimated using LSE. Overlapping $n \times n$ regions sampled from the image region Ω also known as the estimation window, are used to generate sample observations for LSE. In texture classification the Ω region will be same as the entire region of a texture image. The interaction parameters $\boldsymbol{\alpha} = col[\alpha_r | r \in \tilde{N}]$ and variance parameter σ are given by,

$$\boldsymbol{\alpha} = \left[\sum_{s \in \Omega} \bar{\boldsymbol{y}}_s \bar{\boldsymbol{y}}_s^T \right]^{-1} \left[\sum_{s \in \Omega} \bar{\boldsymbol{y}}_s y_s \right] \quad (2)$$

$$\sigma^2 = \frac{1}{|\Omega|} \sum_{s \in \Omega} \left(y_s - \boldsymbol{\alpha}^T \bar{\boldsymbol{y}}_s \right)^2 \quad (3)$$

where vector of neighbour values of y_s located at s is $\bar{\boldsymbol{y}}_s = col[\bar{y}_{s+r} | r \in \tilde{N}]$ and $|\Omega|$ is the number of observations used in the estimation process [12,24]. The vector of model parameters, $\mathbf{f} = [\boldsymbol{\alpha}^T, \sigma]^T$ is constant over the domain Ω and has been used to characterize the texture [5,23,24]. Fig. 1a illustrates the TGMRF feature extraction.

3. Local Parameter Histogram (LPH) descriptors

Parameter estimation stage of the TGMRF descriptors suffers from producing estimates that are biased and over-smoothed when the GMRF model do not capture the underlying data generating process [14]. This reduces the texture discriminative power of TGMRF features. To deal with this, in [12] we proposed LPH descriptors which produce more descriptive features. LPH feature extraction has two main stages: (*i*) local parameter estimation and (*ii*) histogram construction.

The local parameter estimation stage is similar to the TGMRF parameter estimation, however it is spatially localized to a smaller area Ω_s ($\Omega_s \subset \Omega$) and is carried out at each pixel. In [12] the spatially localized estimation window, Ω_s is proposed as a square window of size $w \times w$ with w selected as $w = 2n - 1$, where n is the neighbourhood size defined in Section 2. The small estimation window Ω_s leads to a small sample size and therefore, the local estimation process may become inconsistent. Tikhonov regularization is applied to find approximate solutions to ill-conditioned problem [2,12]. Therefore, the local parameter estimates are obtained by minimizing the regularized sum of square local errors and are given by,

$$\boldsymbol{\alpha_s} = \left[\sum_{s \in \Omega_s} \bar{\boldsymbol{y}}_s \bar{\boldsymbol{y}}_s^T + c^2 \boldsymbol{I} \right]^{-1} \left[\sum_{s \in \Omega_s} \bar{\boldsymbol{y}}_s y_s \right] \quad (4)$$

$$\sigma_s^2 = \frac{1}{|\Omega_s|} \sum_{s \in \Omega_s} \left(y_s - \boldsymbol{\alpha_s}^T \bar{\boldsymbol{y}}_s \right)^2 \quad (5)$$

where c is a constant and is called the regularization parameter and $\boldsymbol{I}$ is the identity matrix. By addition of the term $c^2 I$ in Eq. (4) the