# Texture Classification using a Linear Configuration Model based Descriptor

Yimo Guo
guoyimo@ee.oulu.fi
Guoying Zhao
gyzhao@ee.oulu.fi
Matti Pietikäinen
mkp@ee.oulu.fi

Machine Vision Group
University of Oulu
OULU, Finland

Texture classification can be concluded as the problem of classifying images according to textural cues, that is, categorizing a texture image obtained under certain illumination and viewpoint condition as belonging to one of the pre-learned texture classes. Therefore, it would mainly pass through two steps: image representation or description and classification. In this paper, we focus on the feature extraction part that aims to extract effective patterns to distinguish different textures. Among various feature extraction methods, local features have performed well in real-world applications, such as LBP[4], SIFT [2] and Histogram of Oriented Gradients (HOG) [1]. Representative methods also include grey level difference or co-occurrence statistics [10], and methods based on multi-channel filtering or wavelet decomposition [3, 5, 7]. To learn representative structural configuration from texture images, Varma *et al.* proposed texton methods based on the filter response space and local image patch space [8, 9].

We show in this paper the descriptor MiC that encodes image microscopic configuration by a linear configuration model. The final local configuration pattern (LCP) feature integrates both the microscopic features represented by optimal model parameters and local features represented by pattern occurrences. To be specific, microscopic features capture image microscopic configuration which embodies image configuration and pixel-wise interaction relationships by a linear model. The optimal model parameters are estimated by an efficient least squares estimator. To achieve rotation invariance, which is a desired property for texture features, Fourier transform is applied to the estimated parameter vectors. Finally, the transformed vectors are concatenated with local pattern occurrences to construct LCPs. As this framework is unsupervised, it could avoid the generalization problem suffered by other statistical learning methods.

To model the image configuration with respect to each pattern, we estimate optimal weights, associating with intensities of neighboring pixels, to linearly reconstruct the central pixel intensity. This can be expressed by:

$$E(a_0,...,a_{P-1}) = |g_c - \sum_{i=0}^{P-1} a_i g_i|. \tag{1}$$

In this formula, $g_c$ and $g_i$ denote intensity values of the center pixel and neighboring pixels of a particular pattern type respectively, $a_i$ $(i = 0,...,P-1)$ are weighting parameters associated with $g_i$, and $E(a_0,...,a_{P-1})$ is the reconstruction error regarding model parameters $a_i$ $(i = 0,...,P-1)$. To minimize the reconstruction error for each pattern, optimal parameters are determined by the least squares estimation [6].

Given an image $I$, suppose the occurrence of a particular pattern type $L$ is $N_L$, which means there are $N_L$ pixels in $I$ with the pattern type $L$. We denote the intensities of these $N_L$ pixels as $c_{L,i}$ $(i = 0,...,N_L-1)$, and organize them into a vector:

$$C_L = (c_{L,0}; c_{L,1}; ...; c_{L,N_L-1}). \tag{2}$$

The intensities of their neighboring pixels $v_{i;0},...,v_{i;P-1}$ $(i = 0,...,N_L-1)$ can thus be organized as:

$$V_L = \begin{pmatrix} v_{0;0} & v_{0;1} \cdots & v_{0;P-1} \\ v_{1;0} & v_{1;1} \cdots & v_{1;P-1} \\ & . & \\ & . & \\ & . & \\ v_{N_L-1;0} & v_{N_L-1;1} \cdots & v_{N_L-1;P-1} \end{pmatrix}. \tag{3}$$

In order to minimize the reconstruction error in Equation 1, the unknown parameters $a_i$ $(i = 0,...,P-1)$ are constructed as a column vector:

$$A_L = (a_0; a_1; ...; a_{P-1}). \tag{4}$$

In this way, the problem to be solved becomes a least-squares problem $C_L = V_L A_L$. When the system is over-determined, optimal parameter vector $A_L$ is determined by:

$$A_L = (V_L^T V_L)^{-1} V_L^T C_L. \tag{5}$$

Otherwise, when $N_L \leq P$, the pattern $L$ rarely occurs, so it would be considered as a non-reliable pattern to serve as a feature. In this case, each entry of the parameter vector will be set to zero. In the area of texture analysis, rotation invariant analysis is a widely studied problem, which aims at providing with texture features that are invariant to rotation angle of the input image. To produce rotation invariant features, we apply 1D Fourier transform to the estimated parameter vector $A_L$. The transformed vector can be expressed by:

$$H_L(k) = \sum_{i=0}^{P-1} A_L(i) \cdot e^{-j2\pi ki/P}, \tag{6}$$

where $H_L(k)$ is the $k$th element of $H_L$ and $A_L(i)$ is the $i$th element of $A_L$. Although image rotation would lead to cyclic translations of $A_L$, Fourier transform is invariant to this kind of translations so that $H_L$ could achieve rotation invariant property. The magnitude part of vector $H_L$ is taken as the MiC feature, which is defined by:

$$|H_L| = [|H_L(0)|; |H_L(1)|; ...; |H_L(P-1)|]. \tag{7}$$

Considering that $|H_L|$ encodes the image configuration and pixel-wise interaction relationship of each specific pattern, it together with pattern occurrences of local binary patterns would construct a complementary feature for both the discrimination of microscopic configuration and local structures. In this way, the final feature is:

$$LCP = [[|H_0|; O_0]; [|H_1|; O_1]; ...; [|H_{q-1}|; O_{q-1}]], \tag{8}$$

where $|H_i|$ is calculated by Equation 7 with respect to the $i$th pattern of interest, $O_i$ is the occurrence of the $i$th local pattern of interest (i.e., the LBP), and $q$ is the total number of patterns of interest. Moreover, multi-scale analysis can be achieved by combining LCPs with different radii and neighboring samples.

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