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Feature extraction on local jet space for texture classification

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HIGHLIGHTS

- Local jets decompose the image based on partial derivatives highlighting textural patterns.
- Six local jet components are generated from 0th, 1st and 2nd-derivative.
- The combination of the local jet space and texture feature extractors improves the texture pattern recognition.

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ABSTRACT

The proposal of this study is to analyze the texture pattern recognition over the local jet space looking forward to improve the texture characterization. Local jets decompose the image based on partial derivatives allowing the texture feature extraction be exploited in different levels of geometrical structures. Each local jet component evidences a different local pattern, such as, flat regions, directional variations and concavity or convexity. Subsequently, a texture descriptor is used to extract features from 0th, 1st and 2nd-derivative components. Four well-known databases (Brodatz, Vistex, Usptex and Outex) and four texture descriptors (Fourier descriptors, Gabor filters, Local Binary Pattern and Local Binary Pattern Variance) were used to validate the idea, showing in most cases an increase of the success rates.

1. Introduction

Local jets make a decomposition of the image, that is an intensity function, based on partial derivatives [1–3]. This approach can be seen as a model of receptive fields of human cortex [4]. Receptive fields are able to discriminate geometric characteristics of the visual scene like lines, edges, orientations, or curvatures. In Ref. [3], a local jet space framework was developed to process and represent images extracting relevant information over the decomposition of the image by a set of functions, demonstrating its efficiency in optical flow estimation, non-local means filtering, background subtraction and image and object characterization. Moreover, this framework can be used in a wide range of applications, such as real time video processing, detecting, predicting and filtering.

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In the context of image representation, the behavior of local jet can be used to highlight the geometric characteristics of texture patterns. Furthermore, the local jet decomposition creates a similarity space of image that can be explored to classify texture images. Texture descriptors have played a significant role in pattern recognition and image analysis, including applications using real and synthetic images in several fields, for example plant analysis and identification [5–8], medical image analysis [9–11] and many others. Aiming to increase the potential of traditional texture descriptors, our proposal is to enhance the texture feature extraction process using the local jet decomposition as initial transformation. The texture image is represented by a set of features composed by the result of the application of a texture descriptor on the local jet components.

The performance of the proposal is assessed over four databases: Brodatz [12], Usptex [13], Vistex [14], and Outex [15]; using four texture feature descriptors: Fourier, Gabor, Local Binary Pattern and Local Binary Pattern Variance. A principal component analysis (PCA) [16] was performed to reduce the dimension of features and linear discriminant analysis (LDA) is used to perform the classification. In most experiments, the proposed approach obtained higher success rate compared to the feature descriptors applied without the local jet decomposition.

Additionally, another experiment was performed to verify the resistance to noise of our proposal. Gaussian noise was artificially added to the test images in order to validate the efficiency of local jet approach. The results have shown that the new methodology has achieved higher success rate in most of the cases.

The remainder of this paper is organized as follows. Section 2 presents the theory of local jet. Section 3 describes the process of feature extraction in the local jet space as well as each of the texture extractors used in the experiments. Section 4 outlines the experiments to validate the proposal, detailing the databases and procedures for classification. The results and discussion of the classification experiments are reported in Section 5, and, finally, conclusions are presented in Section 6.

2. Local jet

To extract the basic local representation of images, we have used the multiscale local jet, which can be used as a similarity space [2], based on the approximation provided by the Taylor expansion. For a function $f : \mathbb{R}^2 \to \mathbb{R}$, at order r, the Taylor expansion is

$$f(x+c_1, y+c_2) = \sum_{k=0}^{r} \sum_{i=0}^{k} \binom{k}{i} c_1^{k-i} c_2^{i} \frac{\partial^k f}{\partial x^i \partial y^{k-i}}(x, y) + \mathcal{O}(\|\mathbf{c}\|^r), \tag{1}$$

where $\mathbf{c} = (c_1, c_2)$ is the residual. The notation of partial derivatives can be changed to $f_{ij} = \frac{\partial^{i+j} f}{\partial x^i \partial y^j}$. In image processing context, $f : \Omega \in \mathbb{R}^2 \to \mathbb{R}$ is the original image and the derivatives are estimated at a certain scale [1], by convolving the image with Gaussian derivatives, as

$$f_{ij}^{\sigma} = f \star \frac{\partial^{i+j} G_\sigma}{\partial x^i \partial y^j}, \tag{2}$$

where G_σ is the bi-dimensional Gaussian filter with standard deviation σ, which represents the estimation scale. Hence, the local jet space is the set $\{f_{ij}^{\sigma} \,|\, i+j \leqslant r, \sigma \in S\}$. In this work, the scale parameter is set to 1 (i.e. only one scale is used), and the order of derivation is set to 2. Thus, the local jet space of image $f : \Omega \in \mathbb{R}^2 \to \mathbb{R}$ is the collection $\{f_{00}, f_{10}, f_{01}, f_{20}, f_{02}, f_{11}\}$. Fig. 1 shows this decomposition applied to a texture image.

Each image in local jet space highlights different geometric properties of scene image. Fig. 2 shows the isolines of a texture image and the isolines of some local jet components. We can see that the peaks in original image is blurred in f_{00} component in which flat regions can be better analyzed. On f_{10} resulting image, the intensity of directional variation is evidenced and the intensities in second order components represent the measure of concavity or convexity of each pixel neighbor on the image surface, emphasizing the different local variations.

3. Texture feature extraction on local jet space

The primary goal of the proposed approach was to emphasize the intrinsic content in texture images that cannot be extracted directly from the original image. The local jet decomposition enhances geometric properties in texture images to improve the action of feature extractors.

The flow in Fig. 3 summarizes the idea where local jet decomposition until the second order on Eq. (2) is applied in all images of the database, i.e., six local jet components are calculated for each image. A texture feature extractor is used on these local jet components characterizing each image in six n-dimensional feature vectors. The dimension n of each feature vector is dependent on the feature extractor. The PCA transformation is applied to the resulting set of feature vectors of each texture descriptor. This procedure aims to find the directions of the feature space along which the variability of feature vectors is maximal, allowing to reduce the dimension of the feature space.

Different feature extractors are used in this approach based on their different analysis of geometric properties. The application of this methodology is not limited to these feature extractors. They were chosen due to the well-known applications of these descriptors in the literature. In the remainder, each descriptor is presented.