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Parsimonious classification of binary lacunarity data computed from food surface images using kernel principal component analysis and artificial neural networks

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ABSTRACT

Lacunarity is about quantifying the degree of spatial heterogeneity in the visual texture of imagery through the identification of the relationships between patterns and their spatial configurations in a two-dimensional setting. The computed lacunarity data can designate a mathematical index of spatial heterogeneity, therefore the corresponding feature vectors should possess the necessary inter-class statistical properties that would enable them to be used for pattern recognition purposes. The objectives of this study is to construct a supervised parsimonious classification model of binary lacunarity data–computed by Valous et al. (2009)–from pork ham slice surface images, with the aid of kernel principal component analysis (KPCA) and artificial neural networks (ANNs), using a portion of informative salient features. At first, the dimension of the initial space (510 features) was reduced by 90% in order to avoid any noise effects in the subsequent classification. Then, using KPCA, the first nineteen kernel principal components (99.04% of total variance) were extracted from the reduced feature space, and were used as input in the ANN. An adaptive feedforward multilayer perceptron (MLP) classifier was employed to obtain a suitable mapping from the input dataset. The correct classification percentages for the training, test and validation sets were 86.7%, 86.7%, and 85.0%, respectively. The results confirm that the classification performance was satisfactory. The binary lacunarity spatial metric captured relevant information that provided a good level of differentiation among pork ham slice images.

1. Introduction

Textural patterns are often complex, exhibit scale-dependent changes in structure and are difficult to identify and describe (Plotnick, Gardner, Hargrove, Prestegaard, & Perlmutter, 1996). Various studies have shown that the fractal dimension alone is not a sufficient metric for the characterization of most textures (Moghaddam, 1991), because fractal dimension only measures how much space is filled. The lacunarity metric complements fractal dimension by measuring how the data fill the space (Tolle, McJunkin, & Gorsich, 2008). Lacunarity can describe the spatial distribution of real datasets. This is an advantage over fractal dimension and has been commonly used as a texture descriptor of images that often exhibit limited self-similarity. Lacunarity has been proposed as a general method for the analysis of a number of spatial patterns (Chmiela, Słota, & Szala, 2006; Feagin, Wu, & Feagin, 2007; Dong, 2009).

Lacunarity has several practical advantages for the assessment of spatial heterogeneity, i.e. sensitivity to local aggregation or clustering (Henebry & Kux, 1995). The algorithm for the lacunarity computation analyzes deviations from translational invariance of an image's intensity distribution using gliding box sampling (Pendleton, Dathe & Baveye, 2005). In this method, a square structuring element or moving window of side length b is placed in the upper left-hand corner of a binary image (Fig. 1a) of side length T (pixels), such that $b \leq T$. The algorithm records the number or "mass" m of pixels that are associated with the image underneath the moving window. The window is then translated by one pixel to the right and the underlying mass is again recorded (Fig. 1b). When the moving window reaches the right-hand side of the image, it is moved back to its starting point at the left-hand side of the image and is translated by one pixel downward. The computation proceeds until the moving window reaches the lower right-hand edge of the image. The essential feature of a sliding scan is that the gliding box moves over the image overlapping itself at each slide, thus compared to a fixed scan, a sliding scan is considerably slower. Allain & Cloitre (1991) defined lacunarity Λ measured with a moving window of side length b, as:

$$\Lambda = \left(\sigma^2 / \mu^2\right) + 1 \tag{1}$$

where the ratio of σ (standard deviation) to μ (mean) changes with window size which signifies that lacunarity depends on the scale

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