Graph-based Analysis of Textured Images for Hierarchical Segmentation

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The analysis and extraction of textural information from image data is a relevant topic in the image analysis and processing domains, mainly due to the large number of application areas that it concerns.

The Hierarchical Multiple Markov Chain (H-MMC) family of models has been recently introduced [2] to provide a simple and effective tool to represent the visual properties of an image at any scale of observation, by means of its "broad sense" textural information: the core of the modeling strategy is the joint definition of texture components (patterns) at different scales and spatial interactions among them. The *Texture Fragmentation and Reconstruction* (TFR) algorithm has been proposed as a hierarchical segmentation technique based on the H-MMC model. In this work, we carry on with the development of these tools by enriching the modeling approach with the use of a *graph based image representation*.

The original TFR algorithm consists of three steps: a *color-based classification* (CBC), a *spatial context based clustering* (SBC) and an iterative *texture merging* procedure. The first two steps constitute the fragmentation phase: first, a map of color-homogeneous areas is generated (the unsupervised TS-MRF segmentation algorithm described in [1] is used) and then a clustering of the connected components (fragments) within each color class finally provides a partition of the image into a set of elementary image patterns, homogeneous for both color and spatial context. The hierarchical texture reconstruction is performed in the last step, where these elementary patterns are merged two-by-two resorting to a hierarchy of nested segmentation maps at different scales of observation.

The scope of this work is limited to the SBC block. It is based on a characterization of each connected component of the color map (output of CBC) by means of a suitable description of its color context: given Ω the set of color classes available, S_ω a subset of pixels of the same color class $\omega \in \Omega$, and ω_k the label of its k-th connected component, the latter is associated with a $|\Omega| \times 8$ matrix of transition probabilities:

$$p_j(\omega'|\omega_k) = |S_{\omega_k \xrightarrow{j} \omega'}|/|S_{\omega_k}| \qquad j \in \{N,NE,E,SE,S,SW,W,NW\}, \quad (1)$$

representing the probability of finding a pixel of color ω' when moving from a location of the fragment ω_k in the direction j. In the original version of the algorithm, these matrices are reduced through Principal Component Analysis and used as fragment features in a simple K-means clustering. This generally leads to a quick and reliable output. However, in more complex cases, for example when color information is limited or in presence of significant scale differences, K-means is likely to perform unsatisfactorily, mainly due to the insufficient number of samples for a statistical clustering and the absence of a spatial constraint (position of the fragments is not taken into account).

To overcome this limitations, our key idea is to consider the spatial proximity among fragments and measure context differences locally instead of relying on global statistics. This is realized by associating to each map of color-uniform fragments a graph based representation that allows for the definition of *neighbourhood relationships*, allowing for a cluster formation aided by an superimposed topology. Two main issues have been dealt with: the *definition of suitable graph structures*, to be associated to each partial map of generally non-adjacent fragments, and the *definition of the clustering method* and the metrics on which it relies.

Building the Graph Representation: for each map of fragments from the same color class ω, see for example Fig. 1(b) and the *red* subset of Fig. 1(a), a graph G_ω is needed where each node is associated to a fragment and a link exists between two nodes if the corresponding fragments are *neighbours* in some sense. To define neighbouring relationships, we generate adjacencies among fragments by means of *uniform-speed label propagation*. This is here realized using a simple queue-based algorithm

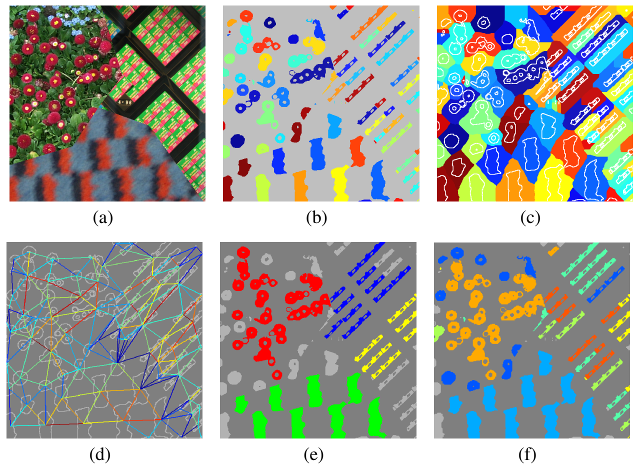

Figure 1: Toy example for the new SBC block: 1(a) a sample texture mosaic, 1(b) *red* image subset, 1(c) label propagated sub-map, 1(d) corresponding region adjacency graph with annotated links, result of the clustering with 1(e) the new and 1(f) the old SBC version.

derived from mathematical morphology [3]. For the toy example of Fig. 1, the result of the procedure is shown in Fig. 1(c). The desired representation corresponds to the region adjacency graph of this map (see Fig. 1(d)).

The Linked Spatial Based Clustering (L-SBC): the new SBC block here proposed relies on a modified definition of finest-scale pattern: beside being a set of spectrally homogeneous connected regions exhibiting similar spatial contexts, we also require each of these patterns to be "connected", in the sense of the graph based representation introduced above. Detecting image patters is hence equivalent to retrieving the corresponding subgraphs. To achieve this goal, links are annotated by means of a context similarity metric derived by the probabilities in Eq. 1, namely:

$$CS_{ij} = \Big[\frac{1}{8(|\Omega|-1)} \sum_{r,s} (A^i_{rs} - A^j_{rs})^2 \cdot \frac{1}{|\Omega|-1} \sum_s \Big(\frac{1}{8}\sum_r A^i_{rs} - \frac{1}{8}\sum_r A^j_{rs}\Big)^2\Big]^{-1},$$

with A^k_{rs} being a $(|\Omega|-1) \times 8$ matrix whose element r,s equals to $p_r(s|\omega_k)$ (see Eq. 1) and where transition to the same color class of the fragment are neglected. Once a threshold CS_{th} is chosen as to keep only a fixed percentage ψ_L of the total number of links from the entire $|\Omega|$-color graph representation, all links below this threshold are suppressed resorting to the desired graph partitions. A (partial) result for the toy example is shown in 1(e), along with the one for the old SBC version in 1(f).

The texture merging is obtained using the procedure described in [2]: sequentially, the image segment that exhibits the lowest *Texture Score*, a measure of "texture completeness", is merged with the neighbouring region with which it shares the largest part of its boundary.

Assessment of the new version of the algorithm has provided promising results, both on a texture segmentation benchmark and on real-world images from the remote sensing domain.

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