Automatic Gabor-like Filter Generation using Adaptive-Subspace Self-Organizing Maps

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The automatic segmentation of textures is a long-standing field of research in which many different paradigms have been proposed. Among them, the *Joint Spatial/Frequency* paradigm is of great interest, because it is biologically based and because by using it, it is possible to achieve high resolution in both the spatial and the frequency domains. Moreover, computational methods based on this paradigm are able to decompose textures into different orientations and frequencies (scales), which allows one to characterize them. This kind of characterization is very useful in the analysis of natural textures. Spatial/Frequency-based methods are based on the use of a bank of oriented filters, normally Gabor Filters, to extract a set of invariant features from the input textures. Then, these invariant features are used to classify the textures. The main drawbacks of this kind of methods are the necessity of a large number of filters, which slows down the segmentation process, and the a priori knowledge required to determine the filters' parameters. These drawbacks can be overcome by the automatic generation of the filter bank using neural networks. This neural approach is based on the adaptation process of the receptive fields of the simple and complex cells of the mammalians' primary visual cortex, which is carried out during the first few months of life through example-based learning.

Taking as starting point the ASSOM (Adaptive-Subspace SOM) proposed by Kohonen [3], three growing self-organizing networks based on adaptive-subspace are proposed for the automatic generation of Gabor-like filters. The advantage of this new kind of adaptive-subspace networks with respect to ASSOM is that they overcome problems like the a priori information necessary to choose a suitable network size (number of filters) and topology in advance. In fact, one of the main drawbacks of SOM-based neural models (ASSOM included) in covering input spaces of rather complex morphology seems to be its rigid grid of fixed size and regular rectangular or hexagonal topology. The *Growing Cell Structures (GCS)* and shortly after the *Growing Neural Gas (GNG)*, proposed in [1] and [2], precisely address this issue. Both networks start with a very small number of neurons and, while adapting the underlying prototype vectors, add neurons to the network. In order to determine where to insert a neuron, on-line counters for each neuron are used. These counters are updated every time a neuron results the *winner neuron*. Accordingly, zones of high input activity result in neurons having high counters where consequentially new neurons are inserted. The same idea is used to delete neurons from the network. We have borrowed this growing scheme for the development of three new neural models, ASGCS (Adaptive-Subspace GCS), ASGFC (Adaptive-Subspace Growing Filter Clusters) and SASGFC (Supervised ASGFC).

While a large number of natural images or even artificial bi-dimensional sinusoids generate a nice array of Gabor Filters using either ASSOM or ASGCS, using a limited number of textures to grow a small number of filters seems to be a more difficult task. One way to understand this is to look at the textures in the frequency domain. Typically, each texture has pronounced clusters scattered over the Fourier domain. This suggests a strongly disconnected input space, where the number of filters and their freedom to move around without altering neighboring filters may be critical. ASGCS adds neurons to its network while adapting the underlying subspaces. Filters are inserted where the relationship between input activity and the number of filters is most critical. The topology of the network formed by the neurons and their connections is a regular two-dimensional graph where each neuron belongs at least to one triangle. ASGFC is very similar to ASGCS. The main difference is that filters are inserted where the relationship between matching error and the number of filters is most critical, which gives a more uniform distribution of the filters in the input space and generally a greater variety of filters. Also, the topology of ASGFC is looser; only pair-wise connections between neurons are used, resulting in network graphs with no closed paths. Moreover, connections might break down according to an aging scheme borrowed from GNG, which may create disconnected subgraphs and even isolated neurons. SASGFC is almost identical to ASGFC, but the filters carry a label relating the filter to one texture a priori and, accordingly, only adapt themselves to input episodes belonging to their texture. SASGFC starts with one filter for each texture and grows more filters just like ASGFC does, but the decision where to insert a filter is dramatically stressed since the new filter necessarily will belong to a certain texture. ASGCS, ASGFC and SASGFC will be detailed described in this contribution.

References

[1] B. Fritzke, “Growing Cell Structures - A self-organizing network for unsupervised and supervised learning”, *Neural Networks*, Vol. 7, No. 9, 1994, pp. 1441-1460.

[2] B. Fritzke, “A Growing Neural Gas Network Learns Topologies”, *Advances in Neural Information Processing Sy*stems, 7, MIT Press, 1995.

[3] T. Kohonen, “Emergence of invariant-feature detectors in the adaptive-subspace self-organizing map”, *Biol. Cyber.* 75 (4), 1996, pp. 281-291.