Texture-Based Computational Models of Biomedical Tissue in Radiological Images: Unveiling the Invisible

Modern multi-dimensional imaging in radiology yields much more information than the naked eye can appreciate. As a result, errors and variations in interpretations are currently the weakest aspect of clinical imaging. Computerized image analysis may provide solutions for ensuring the quality of medical image interpretation by yielding exhaustive, comprehensive and reproducible analysis of imaging features that are difficult to recognize with the naked eye.

We developed computational models of multi-dimensional morphological properties of biomedical tissue. The Riesz transform and support vector machines are used to learn the organization of image scales and directions that is specific to a given biomedical tissue type. The models obtained can be "steered" analytically to enable rotation-covariant image analysis. While most rotation-invariant approaches discard precious information about image directions, rotation-covariant analysis enables modeling the local organization of image directions independently from their global orientation. Although already being important in 2D images, this becomes crucial to adequately leverage directional image information in 3D images.

We evaluated and compared our approach to other state-of-the-art methods using benchmark collections of non-medical natural textures. Experimental evaluation reveals high classification accuracies for even orders of the Riesz transform, and suggests high robustness to changes in global image orientation and illumination. In a second step, we demonstrated the ability of the framework to model biomedical tissue. Computational models of descriptive terms about liver lesions seen in CT slices were built. The models were used to predict the presence of 18 descriptors about liver lesions with an average area under the ROC curve of 0.853. The Euclidean distances between all descriptor models are calculated to establish a non–hierarchical computationally–derived ontology containing inter-term synonymy and complementarity. It was found to be complementary to the RadLex ontology, and constitutes a potential method to link the image content to visual semantics.

Overall, the proposed computational models were able to fit a wide range of textures and tissue structures. They can be trained to segment, classify and retrieve desired tissue categories. We are currently extending the framework to 3D, which is expected to fully leverage the wealth of modern radiology images.