Lecture 9
Fourth stage

Medical Imaging Processing II

Image Texture Analysis

By

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1. Medical Image Texture Analysis

medical imaging is conventionally assessed visually or qualitatively, with a lot of the latent information in the images remaining unused. One way of accessing this hidden information is by using radiomics, which is the extraction of quantitative information from clinical imaging. In particular, heterogeneity in imaging data is not adequately assessed on visual assessment. Intratumoral heterogeneity is associated with tumor aggressiveness and poor patient outcomes. Some radiomic metrics, particularly texture analysis metrics, have been reported to assess intratumoral heterogeneity in studies assessing the diagnosis, prognosis, and treatment response of cancer. Typical radiomic assessment includes analysis of texture, shape, and size. The underlying assumption of the technique is that the grayscale values creating the image of the tumor and the spatial and temporal in terrelationships of these values reflect the phenotypic variations of the tumor, which are indicative of genetic and other molecular variations. Although there is a lot of interest in using radiomics for noninvasive tumor assessment, poor standardization and generalization of radiomic results hinder the translation of radiomics in clinical practice.

2. Texture Analysis

In material science, texture is defined as a measure of the variation of a surface; a rough-textured material would have a high rate of change in the high and low points of a surface, compared with a smooth-textured material. In radiology, image texture refers to differences in the grayscales representing an ROI. The image of a rough textured material would have a high rate of change in the high and low points of a surface (the grayscale value), compared with a smooth-textured material. On a simplistic level, a typical radiomics workflow comprises four modules: image acquisition, image segmentation, feature extraction, and statistical analysis (Fig. 1). Additional modules, such as image registration, data formatting, de-noising, and other modules, are used; however, they are modality and application specific.

2.1. Image Acquisition

Image acquisition is the first stage of the radiomics workflow. Currently available clinical imaging modalities allow wide variations in acquisition and image reconstruction protocols. This is not a limitation for visual or ***qualitative evaluation*** of imaging. However, when images are ***quantitatively* assessed** to extract meaningful data, variations in acquisition and image reconstruction parameters lead to inconsistent findings between different datasets, particularly in multicenter studies. Image Segmentation The image segmentation step involves identifying an ROI, which could be done automatically, semi automatically, or manually. **Although *manual segmentation* is accurate, it is more tedious and subjective**. ***Automatic segmentation*** is objective but error prone, especially when imaging artifacts and noise are encountered. Some of the commonly used automated segmentation algorithms include active contour–based , level set–based , and region- and graph-based methods. No established segmentation standard currently exists. More recently, deep learning techniques, such as convolutional

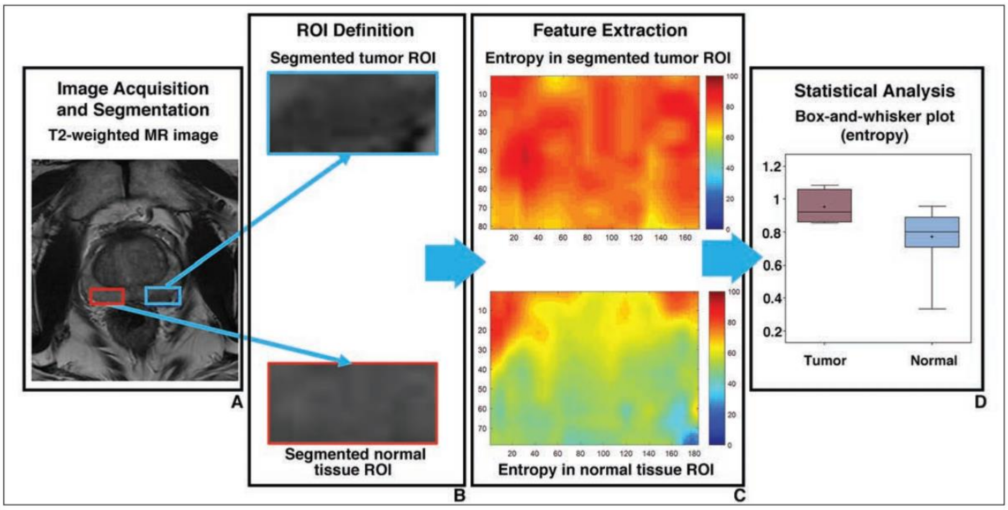

Fig. 1—Schematic of typical radiomics workflow showing four basic modules.

A. The structural methods

This represents texture by the use of well-defined primitives. In other words, a square object is represented in terms of the straight lines or primitives that form its border. *The advantage of these methods are that they provide a good symbolic description of the image*. On the other hand, it is better for the synthesis of an image than for its analysis. The theory of ***mathematical morphology*** is a powerful tool for structural analysis.

B. The model-based methods

Here an attempt is made to represent texture in an image using sophisticated mathematical models (such as fractal or stochastic). The model parameters are estimated and used for the image analysis. The disadvantage is the ***computational complexity*** involved in the estimation of these parameters.

C. **The statistical approaches.**

These are based on representations of texture using properties governing the distribution and relationships of grey-level values in the image. These methods normally achieve higher discrimination indexes than the structural or transform methods. *The transform methods* The texture properties of the image may be analyzed in a different space, such as the frequency or the scale space. These methods are based on the Fourier, **Gabor or Wavelet transform**.

Gabour Transform – Wavelet

LOW LOW LL	LOW HIGH LH
HIGH LOW HL	HIGH HIGH HH

D. The Wavelet transform

It is the most widely used because of the ease with which it may be adjusted to the problem in question. Texture parameters Medical images possess a vast amount of texture information relevant to clinical practice. For example, current magnetic resonance (MR) images of tissues are not capable of providing microscopic information that can be assessed visually. However, histological alterations present in some illnesses may bring about texture changes in the MR image that are amenable to quantification through texture analysis. ***This has been successfully applied to the classification of pathological tissues from the liver, thyroid, breasts, kidneys, prostate, heart, brain and lungs***. We describe the main parameters used in texture analysis, selecting four categories of parameter from the statistical class (which is the most widely used for medical applications), one from the model-based class and one from the transform class. The structural class is omitted because we did not find any example of its application to medical images. The most commonly used texture parameters come from six main categories.

1. Histogram (statistical class)
2. Absolute gradient (statistical class)
3. Run-length matrix (statistical class)
4. Co-occurrence matrix (statistical class)
5. Auto-regressive model (model class)
6. Wavelets (transform class).

The texture of images refers to the ***appearance, structure and arrangement of the parts of an object within the image.*** Images used for diagnostic purposes in clinical practice are digital. A two dimensional digital image is composed of little rectangular blocks or pixels (picture elements), and a three-dimensional digital image is composed of little volume blocks called voxels (volume elements); each is represented by a set of coordinates in space, and each has a value, representing the grey-level intensity of that picture or volume element in space. Since most medical images are two-dimensional we will restrict the discussion to pixels, bearing in mind that the extension to voxels and volumetric images is straightforward. We may attribute the texture concept in a digital image to the distribution of grey-level values among the pixels of a given region of interest in the image. One way of depicting this is to display the digital data as a three-dimensional map based on the pixel values, as shown in Fig. 2. Thus, texture analysis is in principle a technique for evaluating the position and intensity of signal features, i.e. pixels, and their grey-level intensity in digital images. Texture features are, in fact, mathematical parameters computed from the distribution of pixels, which characterize the texture type and thus the underlying structure of the objects shown in the image. According to the methods employed to evaluate the inter-relationships of the pixels, the forms of texture analyses are categorized as structural, model-based, statistical and

transform methods.

Figure 2 (a) Coronal slice of T1-weighted cerebral MRI. (b) Corresponding three-dimensional map based on the pixel values.

2.2. Image Segmentation for texture images

The image segmentation step involves identifying an ROI, which could be done automatically, semiautomatically, or manually. Although manual segmentation is accurate, it is more tedious and subjective. Automatic segmentation is objective but error prone, especially when imaging artifacts and noise are encountered. Some of the commonly used automated segmentation algorithms include active contour–based , level set–based , and region- and graph-based methods . No established segmentation standard currently exists. *More recently, deep learning techniques, such as convolutional neural networks, have been used for segmentation.* Texture analysis has been incorporated into the radiomics workflow at various stages. At the preprocessing stage, images could be segmented into contiguous regions on the basis of the texture properties of each region; at the feature extraction and classification stages, texture features could provide cues for classifying patterns or identifying objects.

2.3. Feature Extraction

Statistical, transform-based, and structural-based texture assessment are the three main approaches used to describe texture (Table 1). Statistical characterization of texture is based on the assessment of texture as a measure of the statistical properties of the gray levels creating the ROI. These properties are conventionally computed from first order statistical methods, such as histogram analysis in which the analysis is based on grayscale values only and spatial information is lost. These first-order methods and analysis are relatively easier to implement and understand. Among the higher-order texture methods, which include both grayscale values and spatial orientation, are the gray-level co-occurrence matrix and the gray-level difference matrix. In recent studies, gray-level run-length matrix metrics and gray-level size zone matrix metrics have also been reported. Transform-based analysis involves extraction of texture metrics on the basis of properties of a wave spectrum and describes the global periodicity of the gray levels of a surface by identifying high-energy peaks in the spectrum and their variations. Structural methods involve techniques of decomposing an image into basic units and identifying the rules required to construct that given image from these basic units. Some examples of structural methods of texture assessment include fractal analysis. The use of a large number of radiomic metrics and the lack of uniformity of these measures and their selective use, which may be correlated, have led to studies with results that are nonreproducible and noncomparable

TABLE 1: Texture Metrics Extracted in the Radiomic Analysis of Imaging Data

Texture Metric	Method(s)	Descriptors	Imaging Modalities [Reference(s)]
First-order (statistical)	Histogram analysis	Mean, median, SD, kurtosis, skewness, quartiles, minimum, maximum, and other descriptors	CT MRI PET US
Second-order (statistical)	Gray-level co-occurrence matrix method, gray-level difference matrix, and other methods	Contrast, energy, entropy, correlation, inertia, cluster, prominence, cluster shade, and other descriptors (Haralick metrics)	CT MRI PET US
Transform analysis	Fourier, wavelets, discrete cosine, Gabor, and Law methods	Metrics assessing magnitude, phase, direction, and other descriptors	CT MRI US
Structural analysis	Fractal analysis	Fractal dimension	CT MRI PET US

Statistical Analysis

The choice of statistical methods used in radiomics depends on multiple factors (e.g., whether the radiomic features are used as the outcome or the predictor or whether radiomics analysis is part of a pilot or confirmative study). When radiomic features are used as the outcome, the assumption of the data normality will need to be tested first. Statistical bias can be introduced on the basis of the choice of the statistical tests used as well as on the basis of the inherent noise and skewness of the medical data. Some of the commonly used statistical tests for normality include the t test, ANOVA.

A number of radiomics studies include scans from different centers. Although this increases the cohort size, it increases the number of variables and confounds the imaging data, leading to systematic errors and poor reliability. To this end, reliable metrics (i.e., metrics that are reproducible [i.e., their value remains unchanged across different scanners of a given imaging modality] and repeatable [i.e., their value remains the same when repeated multiple times on a single scanner]) need to be identified (Fig. 3). The two popular statistical indexes to assess reliability include the intraclass correlation coefficient (ICC) and the concordance correlation coefficient. When reproducibility alone is assessed without repeated measures for a given scanner or modality, the ICC2 (two-way random ICC) and ICC3 (two-way mixed ICC) are identical to the concordance correlation coefficient. However, if reproducibility is assessed with repeated measures, which is equivalent to assessing reproducibility and repeatability at once, only the ICC3 is identical to the concordance correlation coefficient. In general, the concordance correlation coefficient or the ICC2 and ICC3 are the preferred assessment methods, with a heat map used as a visualization tool to illustrate the pattern of reliability.