

REVIEW

Texture analysis of medical images

G. Castellano*, L. Bonilha, L.M. Li, F. Cendes

Neuroimage Laboratory, Faculty of Medical Sciences, State University of Campinas, Brazil

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The analysis of texture parameters is a useful way of increasing the information obtainable from medical images. It is an ongoing field of research, with applications ranging from the segmentation of specific anatomical structures and the detection of lesions, to differentiation between pathological and healthy tissue in different organs. Texture analysis uses radiological images obtained in routine diagnostic practice, but involves an ensemble of mathematical computations performed with the data contained within the images. In this article we clarify the principles of texture analysis and give examples of its applications, reviewing studies of the technique.

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Introduction

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. 1. 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.

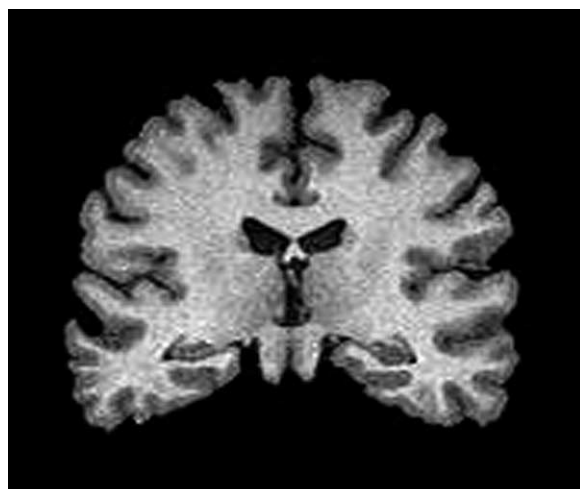
According to the methods employed to evaluate the inter-relationships of the pixels, the forms of texture analyses are categorized as structural, model-based, statistical and transform methods.¹

The structural methods²

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 morphology³ is a powerful tool for structural analysis.

* Guarantor and correspondent: G. Castellano, Neuroimage Laboratory, Faculty of Medical Sciences, State University of Campinas (UNICAMP), 13081-970 Campinas SP, Brazil. Tel.: +55-19-37887292; fax: +55-19-32891395.

E-mail address: gabriela@dca.fee.unicamp.br (G. Castellano).



(a)



(b)

Figure 1 (a) Coronal slice of T1-weighted cerebral MRI. (b) Corresponding three-dimensional map based on the pixel values.

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.

The statistical approaches²

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,⁴ Gabor⁵ or Wavelet transform.⁶ The Wavelet transform 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.⁷⁻¹⁵

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).

We describe those categories in more detail below, and give examples of the sorts of measures (parameters) that can be obtained from them.

Histogram

In digital images, the allowed grey-level values that a pixel may assume are limited. They consist of integer numbers ranging from 0 to $2^b - 1$, where b stands for the number of bits of the image (i.e. this

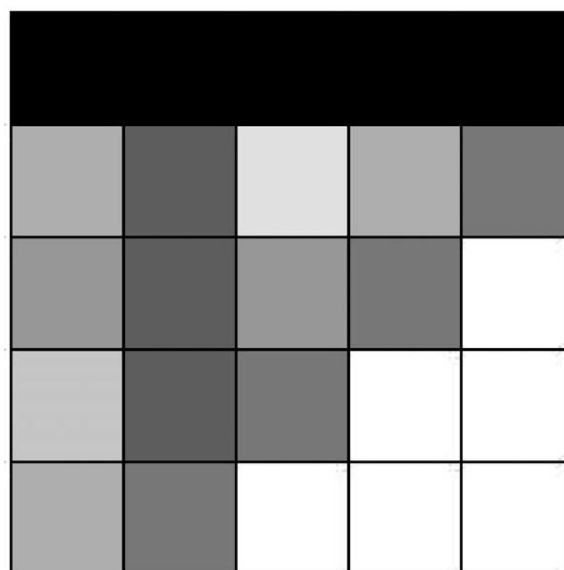
will determine the amount of disk memory occupied by each image pixel). For most digital images 8 bits are sufficient, and therefore the grey-level values range from 0 to 255; but medical MR images normally use 12 bits (which gives more definition of the objects in the image), and therefore the grey-level values range from 0 to 4095. Note that the convention is to attribute lower values to darker grey levels, and higher values to lighter grey levels. Therefore 0 generally represents black, and white is represented by 255 (in an 8 bits image) or 4095 (in a 12 bits image). Fig. 2 shows an example of a 3 bits digital image, with 5×5 pixels.

The histogram of an image is the count of how many pixels in the image possess a given grey-level value. For a 12 bits image, this may be represented by a graph with an x coordinate ranging from 0 to 4095, and a y coordinate representing the respective pixel count. Fig. 3 shows the histogram of the image in Fig. 2.

From the histogram many parameters may be derived, such as its mean, variance and percentiles. The mean of the histogram gives us the mean grey-level value of the image. The variance is a measure of how far from the mean the grey-level values in the image are distributed. For example, if there is an image with 2 pixels with grey-level values 0 and 100, and another image also with 2 pixels with values 49 and 51, the mean will be 50 for both images. However, in the first case there is a huge variance, since 0 and 100 are far from the mean, whereas in the second case the variance is small, since 49 and 51 are close to the mean value. A percentile gives the highest grey-level value under which a given percentage of the pixels in the image are contained; for example, if the 1% percentile of an 8 bits image is 10, the 1% of pixels in the image has a grey-level value from 0 to 9.

Absolute gradient

The gradient of an image measures the spatial variation of grey-level values across the image. Thus, if at a point in the image the grey level varies abruptly from black to white, we have a high gradient value at that point; whereas if it varies smoothly from a dark grey to a slightly lighter grey, we have a low gradient value at that point. The gradient may be positive or negative, depending on whether the grey level varies from dark to light or from light to dark. However, since in general what is of interest is whether we have an abrupt or a smooth grey-level variation, the absolute gradient is used (i.e. the sign is not taken into consideration). Fig. 4(a) shows a coronal slice of a T1-



(a)

0	0	0	0	0
4	1	6	4	2
3	1	3	2	7
5	1	2	7	7
4	2	7	7	7

(b)

Figure 2 Example of a digital image. (a) Image with 5×5 pixels, with grey-level values ranging from 0 (black) to 7 (white). (b) Numerical representation of the image.

weighted cerebral MRI, and Fig. 4(b) shows the corresponding absolute gradient. Note how the gradient image emphasizes the contours of the original one, and how it is strongest (whitest) where the grey-level changes in the original image are greatest.

Examples of texture parameters that may be computed from the absolute gradient are, again, its mean and its variance. The absolute gradient mean will thus be a measure of the mean grey-level variation across the image, and its variance a

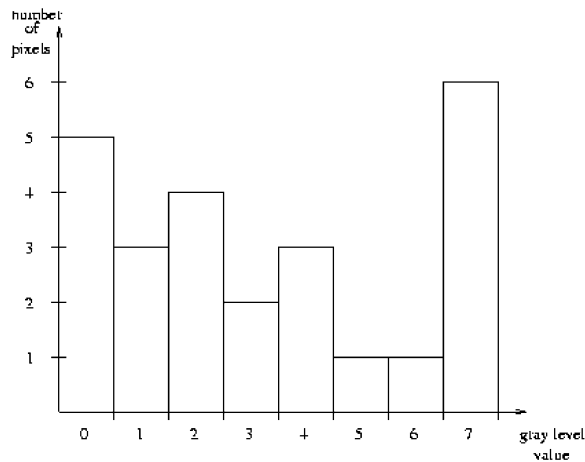
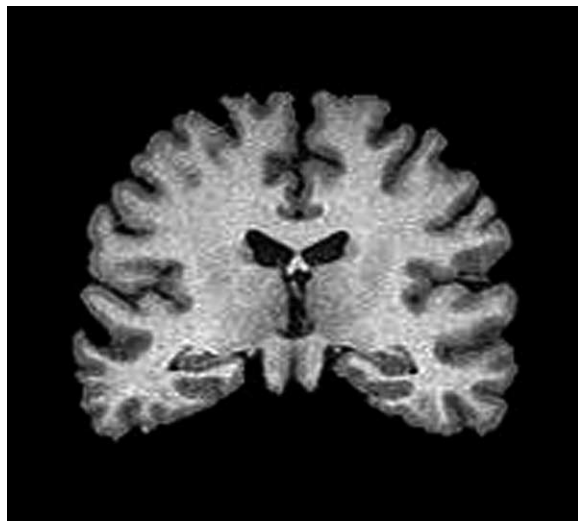


Figure 3 Histogram of the image shown in Fig. 2.



(a)



(b)

Figure 4 (a) Coronal slice of T1-weighted cerebral MRI. (b) Corresponding absolute gradient image.

measure of how far from the mean these variations are.

Run-length matrix

The run-length matrix is a way of searching the image, always across a given direction, for runs of pixels having the same grey-level value. Thus, given a direction (for example, the horizontal direction), the run-length matrix measures for each allowed grey-level value how many times there are runs of, for example, 2 consecutive pixels with the same value. Next it does the same for 3 consecutive pixels, then for 4, 5 and so on. Note that many different run-length matrices may be computed for a single image, one for each chosen direction. In practice normally 4 matrices are computed, for the horizontal, vertical, and two diagonal directions. Fig. 5 shows the horizontal and one of the diagonal run-length matrices corresponding to the example image in Fig. 2. Since this image is small and there is not much space for runs in it, most of the elements of the run-length matrices are zero-valued. The only non-zero-valued elements correspond to the grey-level values 0, 2 and 7, which are the only values giving runs in the selected directions.

Some parameters that may be computed from the run-length matrix are the fraction of image in runs and the short-run emphasis. The fraction of image in runs is a measure of the percentage of image pixels that are part of any of the runs considered for the matrix computing, and the short-run emphasis is a measure of the proportion of runs occurring in the image that have short length.

Co-occurrence matrix

The co-occurrence matrix is a technique that allows

	2	3	4	5	run size
0	4	3	2	1	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	
5	0	0	0	0	
6	0	0	0	0	
7	3	1	0	0	
gray level	runs in the horizontal direction				

	2	3	4	5	run size
0	0	0	0	0	
1	0	0	0	0	
2	3	2	1	0	
3	0	0	0	0	
4	0	0	0	0	
5	0	0	0	0	
6	0	0	0	0	
7	3	1	0	0	
gray level	runs in the 45-degrees direction				

Figure 5 Example of horizontal and 45° run-length matrices for the image shown in Fig. 2.

for the extraction of statistical information from the image regarding the distribution of pairs of pixels. It is computed by defining a direction and a distance, and pairs of pixels separated by this distance, computed across the defined direction, are analyzed. A count is then made of the number of pairs of pixels that possess a given distribution of grey-level values. Each entry of the matrix thus corresponds to one such grey-level distribution. For example, let us define a distance of 3 pixels in the vertical direction, and let us compute the corresponding co-occurrence matrix for an 8 bits image; for such an image, the allowed grey-level values range from 0 to 255. The size of this matrix will then be 256×256 . Thus the element (0, 10) will correspond to the number of pixel pairs that we find in the image having intensity values 0 and 10 respectively, and which are separated by a 3-pixel distance in the vertical direction. Conversely the element (10, 0) will have exactly the same value, since it will correspond to the number of pixel pairs that we find in the image having intensity values 10 and 0, respectively, and which are separated by a 3-pixel distance in the vertical direction.

As in the case of the run-length matrix, there may be many co-occurrence matrices computed for a single image, one for each pair of distances and directions defined. Normally a set of 20 co-occurrence matrices are computed, for distances ranging from 1 to 5 pixels, in the horizontal, vertical, and two diagonal directions. In Fig. 6, a co-occurrence matrix for a distance of 2 pixels in the horizontal direction, for the example image of Fig. 2, is shown. Note that the matrix is symmetrical, as expected.

Since the co-occurrence matrix analyzes the grey-level distribution of pairs of pixels, it is also known as the second-order histogram.

Examples of parameters computed from the co-occurrence matrix are the contrast and the entropy. The contrast of an image refers to how much difference, or definition, there is between grey-level values of different objects in the image. The entropy measures the randomness or homogeneity of the pixel distribution with respect to length or orientation, and it will take a higher value for a more random distribution: it is a measure of the amount of disorder in the image.

Auto-regressive model

The auto-regressive model assumes a local interaction between image pixels in that the pixel grey-level value is a weighted sum of the grey-level values of the neighbouring pixels. In simpler words,

	0	1	2	3	4	5	6	7
0	6	0	0	0	0	0	0	0
1	0	0	1	0	1	0	0	1
2	0	1	0	0	0	1	1	2
3	0	0	0	2	0	0	0	1
4	0	1	0	0	0	0	1	1
5	0	0	1	0	0	0	0	0
6	0	0	1	0	1	0	0	0
7	0	1	2	1	1	0	0	2

co-occurrence within a 2-pixels distance in the horizontal direction

Figure 6 Example of a co-occurrence matrix for a 2-pixels distance in the horizontal direction, computed for the example image of Fig. 2.

it is a way of describing shapes within the image, by finding relations between groups of neighbouring pixels. The auto-regressive parameters are simply the set of weights used to establish these relations. It is expected that these relations are unique for a given type of object (or shape) in an image and, therefore, they may constitute a way of characterizing this object.

Fig. 7 shows an example neighbourhood (white pixels) that could be used to characterize the grey-level value of the centre pixel (black) through the auto-regressive model. In that case, the assumption made is that every pixel in the image has its grey-level

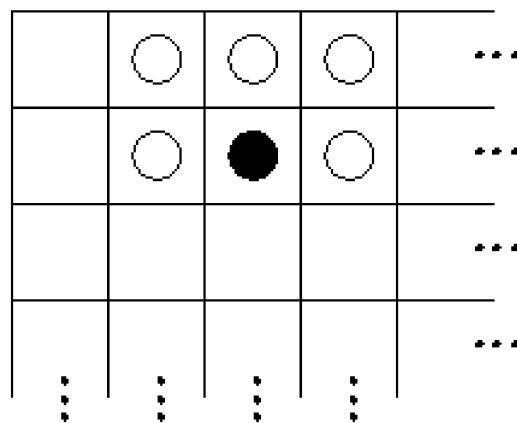


Figure 7 Example of a pixel neighbourhood that could be used to compute the parameters of the auto-regressive model.

value characterized by the grey-level values of the surrounding pixels, according to the pattern shown.

Wavelets

If a one-dimensional signal varies quickly in time, it has a high frequency; if slowly, it has a low frequency. For example in an electrocardiogram we see that fast variations are associated with high frequency, whereas slow variations are associated with low frequency. If the grey-level value of a two-dimensional image varies fast, that is has many variations within a small piece of the image, we associate a high spatial frequency to this part of the image. In turn, if the grey-level value varies slowly, being almost the same throughout a region of the image, the region has a low spatial frequency. The concept of fast or slow grey-level value variations is dependent on the scale of the image region. An example is the picture of a forest: if taken by a satellite (very large scale), it looks like an almost constant green stain; if taken from an aircraft flying at a low altitude (smaller scale), it shows many variations and details. The former picture would have a lower frequency content, and the latter would have a higher frequency content. In addition, the direction of the variations must be taken into account in two dimensions: an image with stripes in the horizontal direction is different from an image with stripes of the same size but in the vertical direction.

Wavelets represent a technique that analyzes the frequency content of an image within different scales of that image. This analysis yields a set of wavelet coefficients corresponding to different scales and to different frequency directions. When computing the wavelet transform of an image, we associate to each pixel a set of numbers (the wavelet coefficients) which characterize the frequency content of the image at that point over a set of scales. From these coefficients we can compute texture parameters. Fig. 8 shows an example of a wavelet transform for the image shown in Fig. 4(a). The top left corner of the image shows a low-frequency small-scale version of the original image, whereas all the other parts of the image show high-frequency versions of the original image on different scales.

An example of a wavelet-derived parameter is the wavelet energy associated with a given scale and direction, so this parameter measures the frequency content of the image on a given scale and in a given direction.

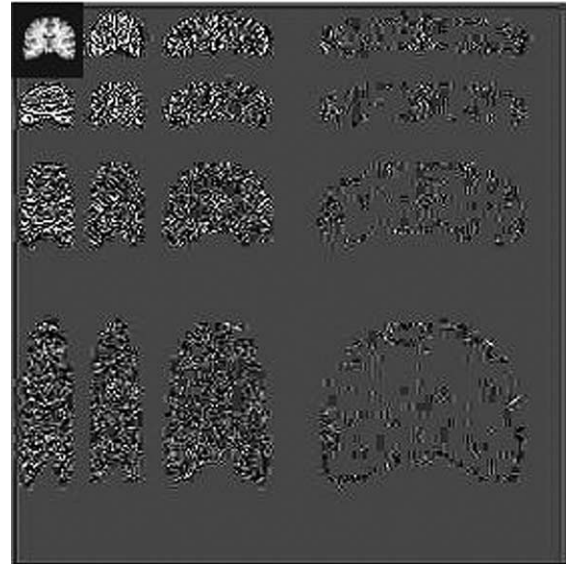


Figure 8 Wavelet transform of the image shown in Fig. 4(a). The top left corner of the image shows a low-frequency, small-scale version of the original image, whereas all other parts of the image show high-frequency versions of the original image on different scales.

Important considerations

The parameters described above give an idea of the type of information that texture analysis may produce from an image, depending on which texture parameters provide the information sought. Most applications use texture measures as a way of classifying regions of interest in images, for example to differentiate between healthy and pathological tissue, or in order to separate different anatomical structures. Therefore, the procedure generally adopted is to compute a large set of texture parameters, and then determine which of them provides the differentiation required. This may be done by simple inspection of the parameter values, or differentiation by parameter group may be performed through discriminant analysis.

There are commercial software packages such as Mazda (https://www.eletel.p.lodz.pl/merchant/mazda/order1_en.epl), developed by A. Materka and his group under the Cost project (http://www.eletel.p.lodz.pl/cost/cost_project.html), which produce a large amount of texture parameters for a given region of interest in an image, and there are many other packages available to perform further data reduction and analysis of the texture parameters.

The effect of external factors on some texture parameters must be taken into consideration before using texture analysis techniques. An example of an external factor is the grey-level

tone variation present in MR images due to lack of homogeneity of the radio-frequency field, which results in different grey-level values for the same tissue type. These changes in grey-level tones affect the histogram of the image and its mean.

Applications

Texture analysis may be applied in a series of studies of medical images. One application is the segmentation of a given anatomical structure, based on the texture characteristics of the structure. However, texture analysis is most important for those cases in which change cannot be detected by direct inspection of the image. For example, in some conditions the tissue of associated anatomical structures suffers alterations. These can normally be detected by histological examination, but sometimes not by visual inspection of the image of the tissue, whereas they may be demonstrated by statistical analysis of the pixel distribution in the image of the structure.

Most applications described above have been performed on MR images because of the great amount of detail provided by this technique. Nevertheless, texture analysis of all sorts of images has been and may be performed.

Segmentation of anatomical structures

Saeed and Puri¹⁶ analyzed texture features in order to segment the cerebellum, using T1-weighted three-dimensional MRI of adult controls and patients. Alejo et al.¹⁷ used neighbourhood analysis of texture-based parameters of MRI for semi-automatic segmentation of the hippocampus and corpus callosum.

Diagnosis of skeletal muscle dystrophy

In an earlier study using texture analysis, Herlidou et al.¹⁸ compared texture with visual analysis of MRI data for the diagnosis of skeletal muscle dystrophy. They concluded that texture analysis can provide useful information contributing to the diagnosis of skeletal muscle disease.

Differentiation between healthy and pathological tissue in the human brain

Kovalev et al.¹⁹ used texture parameters derived from gradient vectors and from generalized co-occurrence matrices for the characterization of texture of some MR-T2 brain images, in order to demonstrate pathological conditions with widespread manifestations, resulting in the change in the textural appearance of

the brain. They used extended multisort co-occurrence matrices that involve intensity, gradient and anisotropy image features in a uniform way, for separation between the brain images of controls and patients suffering from white-matter encephalopathy and/or Alzheimer's disease. They also applied these texture features to the segmentation of diffuse brain lesions.²⁰

Herlidou et al.²¹ used texture parameters based on the histogram, co-occurrence matrix, gradient and run-length matrix for the characterization of healthy and pathological human brain tissues (white matter, grey matter, cerebrospinal fluid, tumours and oedema). They succeeded in distinguishing the different brain tissues, and confirmed that MR images, including those obtained during routine procedures in three different MRI units, contain tissue-specific texture features which can be extracted by mathematical methods.

In a series of studies of T1-weighted cerebral MR images, Bernasconi et al.⁷ and Antel et al.^{22,23} manipulated a combination of texture parameters to determine cortical thickness and hyperintense T1 signal, and to model the blurring of the grey matter/white matter interface. They managed in that way automatically to detect lesions of focal cortical dysplasia, some of which would have been missed by the human eye. They assert that the developed computer-based, automated method may be useful in the presurgical evaluation of patients with severe epilepsy related to focal cortical dysplasia.²³

Mahmoud et al.²⁴ used the texture analysis approach based on a three-dimensional co-occurrence matrix in order to improve brain tumour characterization. They carried out a comparative study to evaluate the performance of this approach compared with the two-dimensional approach, using T1-weighted MRI of 7 patients with glioma to distinguish between solid tumour, necrosis, oedema and surrounding white matter. With the three-dimensional approach they achieved better discrimination between necrosis and solid tumour as well as between oedema and solid tumour. They did not manage completely to separate peritumoral white matter from oedema, nor far ipsilateral matter from contralateral white matter, using either of these methods. They suggest, however, that the proposed three-dimensional approach could provide a new tool for tumour grading and treatment follow-up, as well as for surgery or radiation therapy planning.

Hippocampus and epilepsy

Yu et al.²⁵ performed a study with patients with unilateral temporal lobe epilepsy characterized on

MRI by ipsilateral hippocampal sclerosis and an apparently normal contralateral hippocampus. They first ascertained the existence of texture differences between normal (control) and sclerotic hippocampi. Next they showed that the apparently normal contralateral hippocampi could be classified into three categories in terms of texture: apparently healthy, similar to sclerosis; or different from either healthy or sclerotic. They attributed these findings to a certain degree of hippocampal alteration, requiring further investigation to improve characterization. Bonilha et al.⁸ and Coelho et al.¹⁰ confirmed the findings using texture parameters based on run-length and co-occurrence matrices. A similar study was undertaken by Jafari-Khouzani et al.,²⁶ this time using wavelet-based texture features in order to distinguish healthy from pathological hippocampal tissue, aiming to aid physicians in the determination of candidates for epilepsy surgery.

Multiple sclerosis

Mathias et al.¹³ applied texture analysis to MRI of the spinal cord in an attempt to quantify pathological changes that occur in multiple sclerosis (MS). Texture differences were detected between normal controls and relapsing-remitting MS patients before spinal cord atrophy was visually detectable. They also found a significant correlation between texture changes and disability.

Cervix lesions classification

Ji et al.¹² used texture analysis for characterizing and recognizing typical, diagnostically most important, vascular patterns relating to cervical lesions from colposcopic images. They introduced a generalized texture analysis technique, where conventional statistical and structural textural analysis approaches were combined, thus creating a set of texture measures that described the specific characteristics of cervical textures as perceived by medical examinations. With those measures they demonstrated the effectiveness of the proposed approach in discriminating between cervical texture patterns indicative of different stages of cervical lesions.

Obstructive lung diseases

Chabat et al.¹⁵ used 13 texture parameters, derived from the histogram, co-occurrence matrix and run-length matrix categories, to differentiate between a variety of obstructive lung diseases in thin-section

(CT) images. A set of CT images was obtained from healthy subjects and from patients with panlobular emphysema, centrilobular emphysema and constrictive obliterative bronchiolitis. They demonstrated the feasibility of textural distinction between those diseases, which cause decreased attenuation of the lung parenchyma, and the lungs of healthy subjects. They concluded that the accuracy of the method was high, and suggested that it should be included as one of the main CT feature extractors for the automated detection of obstructive lung diseases.

Conclusions

We have described here the technique of texture analysis in medical images. Texture parameters are simply a mathematical representation of image features that can be characterized in words as smooth, rough, grainy and so on. This implies that in principle, texture analysis may be applied to any set of image regions that may be differentiated by such description.

In outlining the main categories of texture parameters, and the several uses of each technique, MRI applications have been emphasized except in the work of Ji et al. with colposcopic images¹² and Chabat et al. with CT.¹⁵ MRI applications dominate in the literature about this technique because, although texture analysis is a method devised to extract from medical images additional information that is not easily depicted by visual inspection, such analysis remains limited by the restricted resolution of images. It is therefore a promising method linked to future improvement in the quality of medical images.

However, the technique is by no means limited to MRI, and can be applied in the setting of different image applications, taking into consideration the limitations of each imaging method. Furthermore, the application of texture parameters is not specific to the illnesses discussed herein, but is helpful in the investigation of other pathological conditions in which imaging is an appropriate investigation method.

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