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A Review on Texture Analysis Methods in Biomedical Image Processing

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Introduction

Imaging physics as a developed field of study provide different diagnosis tools for different researchers such as clinicians and biologists. Popular imaging modalities are X-ray, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), 3-D ultrasound and whole slide microscopy images which widely used in clinical routine for different aims. For example, MRI imaging is a common and powerful approach to represent the soft tissues of the human body, which can be used for three-dimensional visualization of the body organs [1]. Extraction of target tissues, tumors and lesions like MS are the preliminary step in many medical procedures. For instance, extraction of three main cerebral tissues such as white matter, gray matter and cerebrospinal fluid is an important step for different diagnosis and treatment procedures such as 3D-brain visualization, heterotopia, and brain atrophy [2,3]. Currently, computerized analysis of image data has become one of the main subjects in diagnostic procedures. This important field of research area is known as computer-aided diagnosis (CAD). These methods mainly provide a description of pathologic tissues for radiologists, biologist and, so forth for detection and diagnosis of normal and pathological tissues [4].

Textures are one of the vital features in image processing and especially biomedical image analysis. Although, textures look intuitive, so far a single unifying of them have not been suggested, which could present a comprehensive definition for textures. Therefore, researchers proposed different methods for extraction of texture features, which each group of features have their positive and negative properties as well. Textures as an important property in medical images have attracted much attention in CAD systems [5]. Texture analysis methods can be divided in different sub-categories. In this paper we present some of the most important branches of texture analysis methods which find a proper application in medical image analysis.

Statistical Methods

Statistical features consist of different categories such as first-order, second-order statistical methods, Local Binary Pattern (LBP) methods and so forth. These features especially LBP have been the center of attention because of obtaining promising results which they recently have achieved in different applications with changing in level of noises, illumination, sizes of textures. As medical images are affected by many artifacts during imaging providing an invariant group of features is crucial in these applications. In the following subsections we describe some of the important methods of the statistical approaches for texture analysis.

First order and second order methods

The first order statistical features include the features which are extracted from the statistical property of image histogram including mean, variance, standard deviation and etc. Although these features are very straightforward and simple, they provide a good description of texture in the image. Moreover, there are three main sub-categories which have been proposed for second-order statistical features including Spatial Grey-level Difference Method based on the analysis of co-occurrence matrix [6], the Grey-Level Difference and the Grey-Level Run Method. Statistical features have widely been used for extraction of relevant features in CAD systems [7].

LBP Methods

The other important category of statistical methods is Local Binary Pattern (LBP) based approaches [8]. In [9] a new LBP method has been proposed which tries to incorporate spectral features into LBP method. Therefore, LBP will be more robust and powerful to invariant texture analysis in this case. Different types of this method have been proposed for texture analysis of biomedical applications and find a great attention in CAD systems [10,11].

Model Based Approaches

Some researchers have tried to model contextual, textural and spatial properties of images and then texture features can be extracted by incorporating these features during image analysis. The main categories of model based methods which have been considered for this aim are Markov models. These methods have different types including the Gaussian Markov random fields and Gibbs random fields. In fact, Markov random field method is an optimization method which defines an energy function on a label field and the goal is to minimize the energy function. This energy function must be defined in a way that textural features and also spatial relationships of neighbourhood pixels to be considered. Methods based on auto-regressive and Hidden Markov Model have been proposed for texture classification and have had good results in this field [12].

Filter Banks Based Methods

The other important groups of texture analysis methods which have been considered in biomedical image analysis applications are filter bank based methods [13]. The filter bank methods consist of three main sub-categories including the frequency, spatial and spatial-frequency approaches. Frequency filter banks mainly use Fourier transform and discrete cosine transform for extraction of features and try to extract the texture feature in frequency domain. On the other hand, spatial methods just apply filter banks on spatial domain of textures and then extract the texture features from the image.

Spatial filter banks and frequency analysis based approaches

Spatial filter banks have long history for biomedical feature extraction. These methods are containing of two important groups such as smoothing filters like Gaussian filters and sharpening filters like Laplacian and Sobel filters. However, recently, different authors inspired from the visual cortex, try to use a bank of oriented spatial filters in different scales for modelling of texture images [14,15].

Spatial-frequency based methods

Frequency analysis just decomposes each signal into frequency components of the signal and completely ignores the spatial domain. Moreover, spatial filters just consider the spatial information; therefore, these two groups of methods intrinsically have limitation for analysis of textures. These shortcomings could be solved if both the spatial and spectral information considered because appropriate analysis of real world images needs both information. Spatial-frequency methods include a range of filter banks which wavelet transform and Gabor filter are among the most important ones. In most feature based methods such as pyramid-structured wavelet transforms and tree-structured wavelet transform (TSWT), texture features are extracted by some features in different resolution and channels. In [16,17], two way for combination of DWT method with spatial filter banks is proposed and try to incorporate spectral information in multi-resolution analysis methods like DWT for extraction of invariant features. DWT based methods are very important for biomedical image analysis [18,19]. The other important multi resolution based methods are Gabor filters and Gabor wavelets. According to the ability of Gabor filters for invariant texture analysis these methods have provided good results in biomedical image analysis applications [20].

Conclusion

In this paper, a review on different groups of texture methods which find an application in biomedical image analysis and CAD systems was presented. Texture analysis is an active research area of study and many researchers in different fields (including the medical image analysis) work on this topic. This paper tried to summarize some of the original methods which have been proposed in computer vision and image processing community for texture analysis and some of their biomedical applications have been considered.

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