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Use of Statistical Techniques to Analyze Textures in Medical Images for Tumor Detection and Evaluation

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Abstract

Detection of malignant tumors in the diagnostic phase is a concern of clinicians, radiologists and oncologists. Medical images contribute greatly to early diagnosis. The use of data extraction techniques from 2D / 3D medical images of human tissues suspected of tumors and the use of statistical techniques are efficient for the detection of these tumors. This paper discusses recent advances in understanding the segmentation and representation of visual textures, in order to show predictive and probabilistic models through the analysis of human tissue textures. Texture feature is an important source of information for the process of image analysis and interpretation.

Keywords

Haralick's Parameters; Region of Interest; Texture Analysis; Tumor

Introduction

One of the most promising applications of texture analysis in medicine is the early detection of tumor signals and prophylaxis of cancer according to Gentillon [1].

The benefit of medical imaging depends on a precise diagnosis and this, in turn, depends on the quality of the image acquisition and its interpretation by specialists. The quality of the image acquired depends on the resolution, sensitivity, bandwidth and signal-to-noise ratio of the imaging system. Computer vision can, for example, be used to assist radiologists in focusing their attention on diagnostically relevant information and to provide quantitative measurements for suspicious regions [2]. Studies on the influence of noise on ultrasound images have been presented by Singh [3]. The experimental results presented show how these features are able to provide an accurate quality measurement that corresponds well with the subjective evaluations performed by clinical experts.

The tumor is an exceptional expansion generated by human cells reproducing in an unrestricted way. This can be identified by a variations in the texture of the human tissue under study, since the information contained in the images is of extreme value. Textures are visual patterns in the image pixels, which have brightness, color, slope, size, and other attributes, but which, once partitioned into sub-images in regions of interest, can be used for classification purposes.

Texture can be characterized by the spatial distribution of the intensity of pixels in a neighborhood. If two contiguous regions in an image have a different surface texture, this may lead to the detection of intermediate texture boundaries. Much of the work on perception is concerned with enabling observers to discriminate, without effort, certain pairs of textures.

In the medical field, radiologists are more interested in Region of Interest (ROI) rather than whole image. ROI is a subpart of the image that contains very important information related to the diagnosis. In addition, ROI size has been known to influence the sensitivity and specificity of the classification [4].

It turns out that human vision, though perfect, cannot accurately distinguish variations between low intensities from neighboring pixels, especially if the quality of the medical image acquired does not have a good resolution, which generally contributes to the noise present in the imaging process. Advancements in medical imaging systems have made it possible to obtain texture information which is not visible to the human eye.

The probabilistic methods initially used in texture analysis in images are the first order statistics, using the histogram of the image, or the probability of occurrence of pixels. The histogram is calculated from the intensity of the pixels, without taking into account any spatial relationships between the pixels within the image. The characteristics are simply statistical parameters of the histogram distribution, such as: mean brightness, variance, skewness, kurtosis and percentiles.

Similar to the first-order characteristics, the histogram of the image gradient is calculated and the statistical parameters of these histograms are determined. Haralick [5] proposed an approach for the development of new algorithms for microtextures analysis. Once the Gray Level Coocurrence Matrix (GLCM) is established, the statistical parameters can be calculated from this matrix. The fourteen textural features described by Haralick provide a wide range of parameters that can be used in image texture analysis, such as contrast, homogeneity, energy, entropy, mean, and variance. GLCM is one of the most studied and extensively used general approaches for texture analysis and has recently become the focus of study of several research groups whose aim is to increase the discriminability of GLCM descriptors [6]. First-order texture analysis measurements use the image histogram, or pixel occurrence probability, to calculate texture.

In similar way to the image histogram features, the histogram of the image gradient is computed and statistical parameters of the histogram distribution are determined. Haralick provided the classic survey of texture measurements.

The statistical approaches are better suited to micro textures, for which Haralick identified analytical techniques based upon auto correlation functions, frequency domain analysis, edge operators, grey-level co-occurrence matrices, grey-level run lengths, and autoregressive models. But it has been contested that the discrimination between two image textures depends in great part of the difference in the second-order statistics of the textures. That is, for two textures with identical second-order statistics, a deliberate quantitative effort is needed to discriminate between them. In contrast, little effort is required when the second-order texture statistics are different. This observation, however, does not extend to textures that differ in a third or higher order, and cannot readily be discerned by the naked eye. Segmentation divides an image into discrete fields, so that the pixels in each region are similar and there is a visible distinction between regions, according to Agrawal [7].

Another statistical method is the Gray Level Run-Length Matrix (GLRLM) that calculates for each ROI features using Spatial Gray Level Dependence Matrices (SGLDM). This is a statistical method which consists in constructing co-occurrence matrices to reflect the spatial distribution of gray levels in the ROI. SGLDM is based on an estimate of the second order conditional probability density g (i, j, d, θ).

This means that a pixel element at location (i, j) of the SGLD matrix signifies the probability that two different resolution cells which are in a specified orientation θ from the horizontal and specified distance from each other, will have gray level values i and j respectively.

Different textural parameters of texture reflect different properties of the image. These parameters, derived from the Haralick matrix, reflect the characteristics such as: contrast, homogeneity, energy, entropy, mean, and variance. The study of developing these perceptual textural spaces was conducted by Rao [8]. Twelve perceptual features aiming to capture different aspects of texture were elaborated selected for psychophysical experiments.

Juelesz [9] verified that discriminating between two image textures depends largely upon the difference in the second-order statistics of the textures. That is, for two textures with identical second-order statistics, a deliberate amount of effort is required to discriminate between them. In contrast little effort is required when the second-order statistics of the textures are different. However, this observation does not extend to textures that differ in third or higher-order statistics, which are not readily discriminated by eye. Image segmentation is one of the widely used methods to organize the pixels of an image accurately in a decision-oriented application. It divides an image into a number of discrete fields so that the pixels have high resemblance in each region and high distinction between regions. The significance of image analysis for cancer was treated by Sela [10].

Related Works

Recently, Vamvakas [11] used texture analysis to distinguish ambiguous imaging on the appearance of Glioblastoma Multiforme (GBM) and solitary Metastasis (MET). This is a particular challenge to conventional Magnetic Resonance Imaging (MRI) based diagnosis, leading to exploitation of an advanced MRI techniques, such as Diffusion Tensor Imaging (DTI), considered 11 first and 16 second order 3D textural features. From the 16 second order features, 11 are based on Gray Level Co-Occurrence Matrices (GLCM) and 5 on Gray Level Run Length Matrices (GLRLM), calculated from DTI isotropic and anisotropic parametric maps, corresponding to a 3D tumor core segmented from the clustering technique.

Jennitta [12] showed the feature extraction approach that aims to extract the texture characteristics present in medical images using the Local Standard Descriptor (LPD) and the Gray Level Coherence Matrix (GLCM) for Medical Diagnosis from MRI Brain Images.

Brain tumor detection and classification methods from Magnetic Resonance Imaging (MRI) brain images by analysis of feature extraction methods was presented by Harshavardhan et al. [13]. The performance of the features derive from the various texture methods such as histogram, Gray Level Co-occurrence Matrix (GLCM), and the Gray-Level Run-Length Matrix (GLRLM). The authors proposed to combine histogram, GLRLM and GLCM in order to study the performance. The Support Vector Machine (SVM) was used to classify the extracted features into benign or malignant. The performance of these texture assessment methods use a variety of statistical performance measurements such as sensitivity, specificity and accuracy. When some texture features are considered, such as GLCM homogeneity and complexity, they have high potential for revealing, for example, tissue pathology. Based on results these features could detect textural brain stem and midbrain differences between Parkinson's disease patients and controls and changes in brain structure textures during disease progress. These features were also capable of revealing textural differences between ipsilateral and unaffected sides of the brain in stroke patients and can be correlated with Diffusion tensor imaging parameters. In addition, these features have been associated with thigh muscle adaptation to exercise [2].

Wibmer [14] showed that the Haralick texture analysis may therefore contribute to prostate cancer detection and risk-stratification, without the need for acquiring additional MRI sequences. Several Haralick-based texture features showed significant differences between non-cancerous and malignant prostate tissue and in tumors with different Gleason Scores.

In a recent lung cancer study, Yoon et al., [15] analyzed texture using standard deviation, skewness, kurtosis, entropy and homogeneity to evaluate histogram and texture parameters on pretreatment Dynamic Contrast material-enhanced (DCE) Magnetic Resonance (MR) images of lungs with cancer in terms of temporal change, optimal time for analysis, and prognostic potential. Linear regression analysis was used to evaluate correlations between tumor size and image area for each of the histogram and texture parameters. Some of the results revealed that the histogram and texture parameter changes varied after contrast material injection. The 120-180 second window after contrast material injection was optimal for the MR imaging-derived texture parameter and the entropy at DCE MR imaging.

As a linear approach, Principal Component Analysis (PCA) and Multidimensional Scaling (MDS) has been broadly used in revealing the mechanisms underlying color and texture perception, [16], as well as visual object classification [17-19].

One predictive and two probabilistic models for detecting cancer in human liver using computed tomography image has been reported by Seal [20]. The marked normal and abnormal lesions were distinguishable by their textures, using Gray Level Co-occurrence Matrices (GLCMs), one of the earliest methods for texture analysis. Thirteen Haralick features were extracted from the GLCMs of abnormal and normal lesions, which were further employed to build two probabilistic models using Logistic Regression (LR), Linear Discriminant Analysis (LDA) and a predictive model using Multilayer Perceptron (MLP) to determine the probability that the patient had liver cancer or not. A comparative study was made based on the prediction accuracies of these three models. Moreover, LR and LDA were used to identify specific features of the thirteen which played a statistically significant role in decision-making by the probabilistic models. On the other hand, MLP doesn't have the ability to select these significant features. Seal's studies indicated that logistic regression (96.67%) was more accurate than LDA (95%) and MLP (94.4%). The proposed method consisted of three basic steps. Initially, a fuzzy c-means (FCM) clustering algorithm was used to segment the lesions from the human liver. Among all the segmented lesions, were marked as abnormal (malignant) and others are marked as normal (benign) by the radiologist.

Pantic [21] has shown that certain parameters of the Gray Level Co-Occurrence Matrix (GLCM) method have discriminatory ability in assessing renal tissue that has sustained reperfusion injury. For each micrograph, the values were calculated for fractal dimension, lacunarity, as well as five GLCM features: angular second moment, entropy, inverse difference moment, GLCM contrast, and GLCM correlation. Discriminatory value of the parameters was tested using Receiver Operating Characteristic (ROC) analysis, by measuring the area below the ROC curve. The results indicated that certain features of the GLCM algorithm have excellent discriminatory ability to evaluate of damaged kidney tissue.

Malathi [22] proposed segmentation of the brain MRI images for detection of tumors using k-means clustering technique. A cluster can be defined as a group of pixels where all the pixels in certain group are defined by similar relationship.

Various data mining techniques have been widely used for breast cancer diagnosis. Kharya [23] discussed some of effective techniques that can be used for breast cancer classification. Among the various data mining classifiers and soft computing approaches, Decision tree has been found to be the best predictor, with 93.62% accuracy related to the benchmark dataset.

Liu [24] applied Hierarchical Cluster Analysis (HCA) and Singular Value De-composition (SVD) to discover the perceptual features used by the observers in grouping similar textures. The results suggested that the existing dimensions as describe in the literature cannot accommodate random textures. Therefore, Isometric feature mapping (Isomap) was used to establish a three-dimensional perceptual texture space which clarifies better the features used by humans in assessing texture similarity.

Doumou [25] analyzed the precision of textural analysis in 18F-fluorodeoxyglucose Positron Emission Tomography (18F-FDG PET) scans of oesophageal cancer and studied the provision of predictive and prognostic information, considering the technical aspects of image processing that can influence parameter measurements, by testing the effects of image smoothing, segmentation and quantization on the accuracy of heterogeneity measurements. The calculations of the textural characteristics were performed through matrices, considering 57 textural features, including GLCM and GLRCM. Isotropic 3D ROIs were considered using cubic interpolation.

Jothi [26] proposed a Computer Aided Diagnosis (CAD) system that semi-automatically segments and classifies H&E-stained thyroid histopathology images into two classes: Normal Thyroid (NT) or Papillary Thyroid Carcinoma (PTC), based on nuclear texture features. This segments the given histopathology image into different binary images using Particle Swarm Optimization (PSO)-based Otsu's multilevel thresholding. From the segmented binary images, a binary image containing the nuclei is chosen manually. Nuclei are extracted from the manually selected binary image by imposing an area constraint and a roundness constraint. The intensity variations of pixels within the nuclei are quantified by extracting texture features. Four GLCM features were used: correlation, contrast, homogeneity and energy. These that were extracted with distance between neighboring pixels d = 1. The results of classification were accurate between 97% and 99%.

The texture analysis classification of primary breast cancer was studied by Waugh [27]. In this study, Texture Analysis (TA) has been used for the first time to prospectively identify whether underlying breast cancer subtypes could be fully classified based on pixel intensity distributions on MR images. The study demonstrated that entropy-based features from the co-occurrence matrix appear to be most crucial in this respect. As the entropy features produced significantly different values between breast cancer subtypes, an accurate classification, was expected using these features. These results reflect the heterogeneity of internal enhancement patterns which may either directly or indirectly reflect underlying growth patterns and, therefore, may prove useful in decisions regarding therapeutic efficacy and in the monitoring and follow-up of breast cancers during and after treatment.

Ko et al., [28] investigated the potential correlation between the heterogeneity obtained from texture analysis of MR images and the heterogeneity observed from histopathological findings in invasive breast cancer. The MRI texture analysis parameters of homogeneity and entropy were correlated with pathological tumor heterogeneity.

Based on a multivariate analysis of several texture features, Liu et al., [29] showed that texture parameters derived from T1-, T2-, and diffusion-weighted MR images combined with supervised machine-learning algorithms could act as imaging biomarkers for the therapeutic response of nasopharyngeal carcinoma to chemo-radiotherapy.

Conclusion

Although there are other methods of texture analysis for tumor detection, statistical models accurately reveal, in the order of 85% to 95%, the clinical diagnoses.

Some research work was related to texture analysis for the detection of tumors in different tissue types. From these articles, their common conclusions, strengths, weaknesses, gaps and a comparisons of suggested techniques were extracted.

The statistical methods analyzed were used to calculate a variety of texture characteristics, through the parameters based on histogram matrices and co-occurrence. In some papers, texture analysis problems such as segmentation and classification were discussed.

Texture analysis uses the changes in the grey value of image pixels and their distribution pattern, to identify microscopic pathological changes that are not visible and that can be used in the analysis of various images. Texture analysis in medical imaging can be a substantial support for the clinical decision-making process in the diagnosis and classification of tumors. This methodology is expected to become more accurate than the human eye and mind in detecting minute deviations in cell and tissue structures. Although the results using statistical techniques were satisfactory, when second order GLCM parameters are used, it is necessary to take some precautions regarding the size of the region of interest. In some cases, the size of the ROI can change values for some parameters. For example, parameters describing the image homogeneity and complexity (angular second moment, entropy, sum entropy, and difference entropy) are examples of parameters that depend on the ROI size, especially with small ROI sizes, and approach a limit value, [2]. The optimal ROI size also reduces the computational cost in extracting the texture features from the smaller ROI. The experimental results encourage the use of 200 × 200 pixels ROI for classifying a mammogram in one of the two (Fatty, Dense) breast density classes [4].

The results demonstrate that histogram parameters are highly dependent on variations in image contrast and brightness, and provide little additional information to that obtained by visual inspection. Features based on the GLCM and GLRLM contain information that cannot be evaluated visually. The size-dependence of specific features should be noted by standardizing the size and shape of the ROI [2].

Statistical methods that use GLCM to perform microtextural analyzes of human tissues and image classification for tumor detection have shown great efficiency. The accuracy of these analyzes reaches the level between 90% and 95%. This shows the effectiveness of second-order statistics.

It is hoped in the future to design and implement these web-based applications in medical-hospital equipment to assist clinicians, oncologists and radiologists in decision-making.

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