Computerized Medical Imaging and Graphics 41 (2015) 67–79

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

A multiresolution clinical decision support system based on fractal model design for classification of histological brain tumours

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ARTICLE INFO

Article history:
Received 5 January 2014
Received in revised form 25 March 2014
Accepted 29 May 2014

Keywords:
Texture analysis
Fractal dimension
Brain tumours
Tissue classification

ABSTRACT

Tissue texture is known to exhibit a heterogeneous or non-stationary nature; therefore using a single resolution approach for optimum classification might not suffice. A clinical decision support system that exploits the subbands' textural fractal characteristics for best bases selection of meningioma brain histopathological image classification is proposed. Each subband is analysed using its fractal dimension instead of energy, which has the advantage of being less sensitive to image intensity and abrupt changes in tissue texture. The most significant subband that best identifies texture discontinuities will be chosen for further decomposition, and its fractal characteristics would represent the optimal feature vector for classification. The performance was tested using the support vector machine (SVM), Bayesian and *k*-nearest neighbour (kNN) classifiers and a leave-one-patient-out method was employed for validation. Our method outperformed the classical energy based selection approaches, achieving for SVM, Bayesian and kNN classifiers an overall classification accuracy of 94.12%, 92.50% and 79.70%, as compared to 86.31%, 83.19% and 51.63% for the co-occurrence matrix, and 76.01%, 73.50% and 50.69% for the energy texture signatures; respectively. These results indicate the potential usefulness as a decision support system that could complement radiologists' diagnostic capability to discriminate higher order statistical textural information; for which it would be otherwise difficult via ordinary human vision.

1. Introduction

Meningioma tumours usually occur in adults, with a marked female bias represented by a one to three man to women ratio [1]. It also accounts for 27% of all primary brain tumours, making it the most common tumour of that type [2]. An automated meningioma diagnosis system is essential in improving reproducibility by overcoming subjective diagnosis due to variability associated with expert's evaluation. That is, when differences become minor between tumour subtypes of the same grade this might trigger for an increase in intra-observer variability, i.e. pathologist not being able to give the same reading of the same image at more than one occasion, and inter-observer variability, i.e. increase in classification variation between different pathologists; and thereby increasing uncertainty that may impact patient outcome. While the dataset could be acquired at fixed magnification and microscope settings, and with the same staining protocol, the variability in the reported diagnosis may still occur [3,4]. This could be attributed to the non-homogeneous nature of the diseases, namely, not all samples referring to a certain tumour subtype look identical; raising the issue of misclassification. The automated diagnosis system could also assist in overcoming other diagnosis variability-related subjective factors such as, preconception, expectations, relying on diligence, and fatigue, which could cause differences in image perception. Meningiomas can have three grades numbered from I till III, over here we are more concerned with classifying different subtypes within the same grade, which is considered a more challenging task compared to grade classification, as histopathological features tend to become easier to differentiate by the naked eye in the latter compared to the former case.

The main concern in the texture analysis problem is two-fold: to capture distinctive characteristics that will maximise the difference between the various image regions, and the selection of the best pattern classifier that can give the optimal performance. Some examples of the different methods used for cytopathological diagnosis include immunocytochemistry, cytophotometry, flow cytometry, and microarray-based comparative genomic hybridisation. However, nuclear texture or chromatin granularity is also considered an important measure in cytopathological diagnosis for its capability of characterising disease or abnormality in cell structures, based on the assumption that different tumour grades tend to form different shapes and behaviours and hence reflect on

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http://dx.doi.org/10.1016/j.compmedimag.2014.05.013
0895-6111/

the tissue texture general appearance; and thus could be easily characterised and captured by a machine learning algorithm. Moreover, approaching the problem for a texture analysis perspective can provide the capability of discriminating higher order statistical textural information for which it would be otherwise difficult via ordinary human vision. However, histopathological tissue texture is known to be heterogeneous, and a varying degree of texture heterogeneity exists. The non-stationary nature of this kind of texture weakens the ability for an effective automated classification from a monoresolution viewpoint, and image pre-processing prior to feature extraction might not suffice. On the other hand, viewing texture from a multiresolution perspective can filter out irrelevant features and noise while simultaneously giving more emphasis on the features that contribute to better distinction. Techniques such as wavelet transform can break down textures' statistical complexity to distinguish between different texture regions, and their high sensitivity to local features facilitates the processes of preattentive or subtle texture discrimination as well [5]. Furthermore, according to the uncertainty principle, the wavelet transform can achieve an optimal joint spatial-frequency localisation, i.e. simultaneously maintain a good boundary accuracy and frequency response [6].

Wavelet packet (WP) is a generalised framework of the multiresolution analysis and comprises all possible combination of subbands decomposition. However, it is unwieldy to use all frequency subbands for texture characterisation as not all of them have the same discriminating power, and inclusion of weak subbands would have a negative impact on the classifier's performance. Whereas using an exhaustive search would be computational expensive as the number of decomposition levels grows higher. Therefore an adaptive approach is required for selection of the basis with prominent discriminating power.

2. Overview of previous work

The WP subbands selection can be performed either by selecting the best bases from a library of WPs or in a tree-structured approach. Coifman and Wickerhauser proposed to choose the best basis which gave the most compact representation after transforming the signal into different WP bases [7]. The entropy was used as the cost function for selection of the decomposition levels, where the subband that minimises the cost function, from a comparison between the nodes and its leaves in the WP decomposition tree, was considered the optimal choice. By extending the additive cost function in [7] to an arithmetic hence a geometric mean, Dansereau et al. proposed a generalised rényi entropy for best basis search [8], allowing for different moment orders and inclusion of possible incomplete probabilities in the search as well. Saito et al. estimated the probability density of each class in each coordinate in the WP and local trigonometric bases, then applied the Kullback–Leibler divergence as a distance measure among the densities for selection of the most discriminating coordinates [9]. While Rajpoot compared the discrimination energy between the subbands by using four different distance metrics [10]. The Kullback–Leibler divergence, Jensen–Shannon divergence, Euclidean distance, and Hellinger distance were used to assess the dissimilarities in-between the WPs for selection of the most discriminant bases. Others excluded the set of frequency subbands whose energy signatures showed a degree of dependence identified by mutual information [11]. Huang and Aviyente developed an algorithm for subband selection based on the dependency of the extracted energy features. A compact feature representation was achieved when the dependence between the subbands and the evaluated score of individual subbands was incorporated [12]. Another related work was based on best clustering bases, wherein clustering basis functions are selected according to their ability to separate the fMRI time series into activated and non-activated clusters [13]. The basis that concentrates the most discriminatory power on a small number of basis functions is selected. On the other hand, a tree-structured technique for best basis selection was proposed by Chang and Kuo, where only the subbands with the highest energy are selected for further decomposition [14]. An averaged l_1-norm was used as the energy function for location of the dominant frequency channels, and decomposition is stopped if subbands' energy is less than a factor of the maximum energy at that resolution. Acharyya and Kundu used M-band WP decomposition that resulted in a large number of subbands, therefore they decomposed the subbands whose total energy value are greater than the energy of all subbands at the same resolution [15].

Regarding application of WPs to meningiomas, Lessmann et al. employed a self-organising map in order to link the morphological histopathological image characteristics to the space spanned by features derived from hue, saturation and brightness colour model and WP transform [16]. For four different subtypes of meningiomas, an average of 79% for the entire dataset was classified correctly. Also Wirjadi et al. applied a supervised learning method for classification of meningioma cells [17], using a decision tree, the most relevant features were selected from a base of grey and coloured image features. Others extracted features from four meningioma subtypes using adaptive WP transform and local binary patterns (LBP) methods [18,19]. In the applied WP technique, the best sets of subbands are selected by simply measuring the discriminating power between all decomposed subbands at a certain level using Hellinger distance. While for the LBP method, first order statistics were derived from its histogram; both studies reported a classification accuracy of 82.1%.

Having a relatively good feature extraction method that can characterise the underlying physiology of the examined tissue texture would be considered a half way through designing a robust histopathological meningioma subtype decision support system. The other necessary step that could complete the picture is choosing an appropriate machine-learning algorithm that can assist in improving the classification accuracy, when the quality of the extracted features might degrade due to tissue heterogeneity. In our earlier work [20,21], we proposed a different approach for best basis selection for the processes of histopathological meningioma classification, and in this work we develop a clinical decision support system based on an improvement of the best basis selection method and further integrate it with the optimal classifier model design which would yield more significantly sensitive and specific results. Major additional technical details in this paper are as follows:

(i) The fractal model design used in the wavelet packet decomposition was described in details and an algorithm for implementation was provided. The algorithm was modified as well to include the computation of the texture lacunarity to work along with the fractal dimension for determination of the optimal decomposition levels. Also an example was provided that illustrates the capability of higher frequency channels of meningioma to provide stronger Fourier spectrum, and hence more information.
(ii) The selection of the lambda threshold, which determines how deep the image resolution can be probed, was experimentally justified and results illustrated.
(iii) The resulting subbands spanned from our best basis selection method were indicated for all four meningioma subtypes, and further illustrated via classification accuracies for each decomposition level.
(iv) Since a feature set may be performing better than others only because its distribution is a better fit for the assumptions underlying the classifier model, the proposed method