Computer aided diagnosis based on medical image processing and artificial intelligence methods

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Abstract

Advances in imaging technology and computer science have greatly enhanced interpretation of medical images, and contributed to early diagnosis. The typical architecture of a Computer Aided Diagnosis (CAD) system includes image pre-processing, definition of region(s) of interest, features extraction and selection, and classification. In this paper, the principles of CAD systems design and development are demonstrated by means of two examples. The first one focuses on the differentiation between symptomatic and asymptomatic carotid atheromatous plaques. For each plaque, a vector of texture and motion features was estimated, which was then reduced to the most robust ones by means of ANalysis of VAriance (ANOVA). Using fuzzy c-means, the features were then clustered into two classes. Clustering performances of 74%, 79%, and 84% were achieved for texture only, motion only, and combinations of texture and motion features, respectively. The second CAD system presented in this paper supports the diagnosis of focal liver lesions and is able to characterize liver tissue from Computed Tomography (CT) images as normal, hepatic cyst, hemangioma, and hepatocellular carcinoma. Five texture feature sets were extracted for each lesion, while a genetic algorithm based feature selection method was applied to identify the most robust features. The selected feature set was fed into an ensemble of neural network classifiers. The achieved classification performance was 100%, 93.75% and 90.63% in the training, validation and testing set, respectively. It is concluded that computerized analysis of medical images in combination with artificial intelligence can be used in clinical practice and may contribute to more efficient diagnosis.

1. Introduction

Advances in the area of computer science and Artificial Intelligence (AI) have a tremendous impact on the interpretation of medical images [1]. Computer Aided Diagnosis (CAD) aims to provide a computer output as a second opinion in order to assist physicians in the detection of abnormalities, quantification of disease progress and differential diagnosis of lesions (Fig. 1).

To detect an abnormality, the physician usually performs visual scanning of the images of many healthy subjects. The procedure of image scanning lends itself to CAD, since it is a repetitive, burdensome task involving mostly normal images—a situation prime for oversight errors. In the case of lesion characterization, complex anatomy, variation in the presentation of benign and malignant states, and the varying abilities of the physicians may result in interpretation errors. CAD systems aim to facilitate lesion detection and characterization tasks by enhancing the physicians’ capabilities and reducing the time required for accurate diagnosis.

CAD can be applied to digital images obtained from a number of imaging modalities, to address a variety of diagnostic problems. CAD systems have been implemented to support the detection and characterization of breast...
lesions from digital mammography [2] and Ultrasound (US) images [3], to assist the diagnosis of lung cancer using chest radiographs and Computed Tomography (CT) images [4], to distinguish Tourette’s syndrome from chronic tic disorder based on Single Photon Emission Computed Tomography (SPECT) brain imaging [5], and to support the diagnosis of functional brain disorders using Positron Emission Tomography (PET) images [6]. Recently, CAD systems based on the combination of AI techniques and data fusion approaches were proposed [7].

The aim of the present paper is to describe the basic principles underlying the design and development of CAD systems, and to demonstrate these principles in two CAD systems aiming at assisting (a) the characterization of carotid atheromatous plaques from B-mode US images and (b) the differential diagnosis of focal liver lesions from CT images.

2. Generic architecture of CAD systems

The typical architecture of a CAD system (Fig. 1) comprises four main modules for (i) image pre-processing, (ii) definition of region(s) of interest (ROI), (iii) extraction and selection of features, and (iv) classification of the selected ROI.

The objective of image pre-processing is to improve the quality of data through the application of methods for denoising (application of mean filters, median filters, Laplacian filters and Gaussian filters), enhancing the edges of image structures (unsharping, wavelet transform), and enhancing image contrast (histogram equalization) [8]. Image standardization, i.e. a gray scale transformation using linear or non-linear scaling, represents another pre-processing task, which allows comparison of images obtained using different devices and/or different machine settings. Pre-processing is crucial, because the effectiveness of subsequent tasks, including definition of ROIs and feature extraction, depends highly on the quality of the used images.

Anatomical structures, both normal and abnormal, appearing in patients’ images may be defined using (a) manual or semi-automatic methodologies, where the user interacts with the system, or (b) fully automated methodologies.

Seeded region growing is an example of semi-automatic method widely used for the definition of ROIs in medical images [9]. Active contour models have been used for automatic definition and tracking of anatomical contours in 2-Dimensional (2D) medical images due to their ability to approximate accurately the random shapes of organ boundaries [10].

Feature extraction refers to various quantitative measurements of medical images typically used for decision making regarding the pathology of a structure or tissue. Feature extraction can be carried out in the spectral or the spatial domain. Once the features have been extracted, selection of a subset of the most robust features is essential, aiming at improving classification accuracy and reducing the overall complexity. Feature selection methods use search strategies, which can be categorized as exhaustive, heuristic and non-deterministic.

Heuristic techniques have been applied, in order to select the most appropriate features for the differentiation of five types of leukocyte from blood microscope images [11]. Non-deterministic techniques like Genetic Algorithms (GAs) have been applied for feature selection aiming at lung nodule detection [12], and liver tissue characterization [13], from CT images.

One of the most common problems of pattern recognition in medical image analysis is the classification of a set of features into the proper class. Given a set of features its classification can be supervised or unsupervised. In the supervised classification, the feature set is identified as a member of a predefined class, while in unsupervised classification, the feature set pattern is assigned to an unknown class.

Supervised classification can be based on statistical classifiers such as decision trees, \(k\) nearest neighbor and Bayesian classifiers, and NN classifiers. Recently, more sophisticated supervised classification methods have also been proposed e.g. the use of an Ensemble of Classifiers (EC) for the detection of colonic polyps in CT colonography [14]. C-Means and Self-Organizing Map, or Kohonen Map are examples of commonly used unsupervised classification methods. Various supervised and unsupervised classification methods have been comparatively assessed within the framework of breast tumour diagnosis [15].


Diagnosis of carotid atherosclerosis and decisions on patient management are currently based on previous occurrence of clinical symptoms (e.g. stroke) and the degree of stenosis caused by the plaque, usually estimated...
with US imaging. However, there is evidence that atheromatous plaques with relatively low stenosis degree may produce symptoms and that the majority of asymptomatic patients with highly stenotic plaques remain asymptomatic. To assist diagnosis of carotid atherosclerosis, quantitative indices characterizing plaque severity may be estimated from the analysis of digitized ultrasound images. More specifically, image texture analysis may be used to quantify plaque echogenicity [16], and movement of the carotid artery wall and plaque may be estimated from temporal image sequences [17] and be used as an index of plaque strain. The combination of texture and motion features, estimated using computerized analysis, may be useful in the diagnosis of this disease.

ANALYSIS is a CAD system designed to assist interpretation of vascular ultrasound images [18] (Fig. 2). To demonstrate the potential of ANALYSIS we used it to differentiate between 10 symptomatic and 9 asymptomatic atheromatous plaques with no statistically significant differences in their ages and degrees of stenosis. ROIs corresponding to plaques were selected manually by a specialized physician. Texture features for each ROI were estimated using, first order statistics (16 features), second order statistics (14 features), Laws’ texture energy (14 features), Laws’ texture entropy (16 features), and the fractal dimension (one feature). Motion of selected rectangular ROIs on the surface of the plaque was estimated from temporal image sequences using region tracking and block matching [17]. The following indices of motion were estimated for each plaque: a/ Maximal Surface Velocity (MSV) and b/Maximal Relative Surface Velocity (MRSV), defined as the maximum of differences in their ages and degrees of stenosis. ROIs of different types of atheromatous plaque, and might have implications on the management of patients with carotid atherosclerosis.

4. Differential diagnosis of focal liver lesions from CT images

The combined use of texture features and classifiers has been proposed for the characterization of liver tissue either from CT or US images [13,19]. The approach presented in this paper refers to the classification of four types of hepatic tissue: normal liver (C1), hepatic cyst (C2), hemangioma (C3), and hepatocellular carcinoma (C4), from CT images. ROIs were delineated by an experienced radiologist in abdominal non-enhanced CT images. For each ROI a set of texture features, using five texture analysis methods, was estimated, providing input to an EC. The comparative assessment of various architectures, in terms of used features and ECs, resulted in the CAD system presented in Fig. 3 [20,21].

The design, development, and testing of the CAD system was based on 147 free-hand ROIs (C1:76, C2: 19, C3:28, C4:24), which were divided into three disjoint data sets: training, validation and testing sets. For each ROI a total of 89 features from five texture analysis methods (five sets

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Motion and texture features of symptomatic and asymptomatic plaques</th>
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<tbody>
<tr>
<td>Texture features</td>
<td>Symptomatic</td>
</tr>
<tr>
<td>HW–Mask (L^T E)</td>
<td>38.3 ± 8.74</td>
</tr>
<tr>
<td>STD–Mask (L^T E)</td>
<td>17.46 ± 4.01</td>
</tr>
<tr>
<td>Entr–Mask (E_1^S)</td>
<td>2.87 ± 0.50</td>
</tr>
<tr>
<td>IMC</td>
<td>0.93 ± 0.02</td>
</tr>
<tr>
<td>FD</td>
<td>2.21 ± 0.09</td>
</tr>
<tr>
<td>Motion features</td>
<td></td>
</tr>
<tr>
<td>MSV (cm/sec)</td>
<td>1.84 ± 1.00</td>
</tr>
<tr>
<td>MRSV (cm/sec)</td>
<td>2.85 ± 1.69</td>
</tr>
</tbody>
</table>

Fig. 2. Architecture of ANALYSIS—a CAD system to support diagnosis of carotid atherosclerosis.
of features) were calculated in the feature extraction module: Six (6) features from First Order Statistics (FOS), 48 features from Spatial Gray-Level Dependence Matrix (SGLDM), 20 features from Gray-Level Difference Matrix (GLDM), twelve (12) features from Laws’ Texture Energy Measures (TEM), and three (3) features from Fractal Dimension Measurements (FDM).

Feature selection based on GAs was then applied using as fitness function the maximum squared Mahalanobis distance among the four classes of liver tissue. Feature selection was applied to SGLDM, GLDM and TEM feature sets as their dimensionality was greater than a predefined threshold (used dimensionality threshold = 10).

The features were fed to the EC, which comprised five Multi-layer Perceptron NNs (MLP-NN). Each MLP-NN based classifier, fed with one of the texture feature sets, was trained, by the batched Back-Propagation (BP) algorithm with adaptive learning rate and momentum. The optimal number of hidden neurons, as well as the appropriate values of momentum and initial learning rate were estimated using the performance of each MLP-NN in the validation set. A weighting voting scheme was used to combine the predictions of the individual MLP-NNs.

The performance of the developed CAD system was 100%, 93.75% and 90.63% in the training, validation and testing set, respectively. The confusion matrix of the CAD system, for the validation and testing sets, is shown in Table 2.

From the above results it can be deduced that the proposed CAD architecture can achieve satisfactory performances in the differential diagnosis of focal liver lesions from CT images. More elaborate sampling schemes, such as bootstrapping, are under investigation, in order to validate more systematically the overall system performance. Furthermore, the proposed CAD system can be extended to other classes of liver lesions, and/or to liver images from other types of medical imaging devices.

5. Conclusions

Advanced techniques for medical image processing and AI can be successfully incorporated into clinical diagnostic procedures. The use of quantitative image analysis tools, in conjunction with the experience of the physician, can improve diagnostic sensitivity and specificity and reduce interpretation time. A number of issues regarding the application of CAD systems into clinical practice remain to be investigated.

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References