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Computer Aided Diagnosis Based on Medical Image Processing and Artificial Intelligence Methods

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Abstract

With the recent advances in the field of computer science and technology, enhancement in the interpretation of the medical images has contributed to the early diagnosis of various diseases. In this paper Computer Aided Diagnosis systems design and development are demonstrated by two examples. The first example helps us understand the difference between symptomatic and asymptomatic carotid atheromatous plaques. For each plaque the estimated vector of texture and the motion feature is reduced to the most robust one by ANalysis Of VAriance (ANOVA). Further the features were clustered into two classes using fuzzy C-means. The second example supports the diagnosis of focal liver lesions and also characterize liver tissue from Computed Tomography (CT) images as normal, hepatic cyst, hemangioma and hepatocellular carcinoma. Five texture feature sets were extracted from each lesion. A genetic algorithm based feature solution method was applied to identify the most robust feature. The selected feature set was the fed into an ensemble of neural network classifiers, from where the classification performance was achieved. It can be concluded that computerized analysis of medical images in combination with artificial intelligence can be used in clinical practices which helps contribute to more efficient diagnosis.

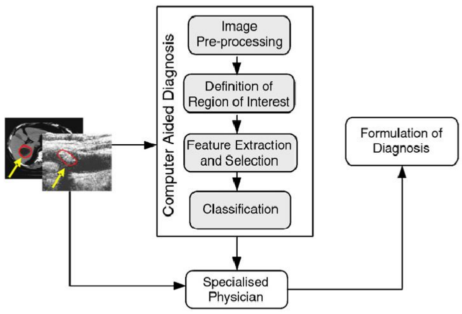
1. Introduction

Computer Aided Diagnosis provides computerized aid to the physicians that serves as a second opinion in the detection of abnormalities, quantification of disease progress and differential diagnosis of lesions.CAD can be applied to digital images for the purpose of addressing a variety of diagnostic problems. At present CAD systems are used to support the detection and characterization of breast lesions from digital mammography and ultrasound images, for assisting the diagnosis of lung cancer using chest radiography and Computed Tomography (CT) images, to distinguish Tourette's syndrome from chronic tic disorder based on Single Photon Emission Computed Tomography (SPECT) brain imaging and for supporting the diagnosis of functional brain disorders using Positron Emission Tomography (PET) images.The aim of the present paper is to demonstrate the principles underlying the design and development of 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 lesion from CT images.

2. General Architecture of Cad Systems

A CAD system is made up of four main modules:

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.



A. Image Preprocessing

The main idea behind image processing is creating a better quality data by applying certain methods. These methods include:

i) Methods of denoising – which includes application of mean filters, median filters, Laplacian filters and Gaussian filters.
ii) Enhancing the edges of image structures – which includes unsharping and wavelet transform.
iii) Enhancing image contrast – which includes histogram equalization

B. Definition of Region(s) of Interest

The normal and abnormal anatomical structures that appear in the patient's images may be defined using manual (semiautomatic methodologies) or by using fully automated methodologies. An example of semi-automatic method which is extensively used for the definition of ROIs in medical images is Seeded region growing. Automated methodology includes active contour models that automatically define and track anatomical contours in 2-dimensional(2D) medical images due to their capability to approximate the random shapes of the organ boundaries accurately.

C. Extraction and Selection of Features

Feature extraction can be carried out in a spectral or spatial domain. During feature extraction various quantitative measurements of medical images are taken for making decisions with respect to the pathology of a structure or tissue. After the extraction of features, selection of a subset of the most robust features is carried out so as to reduce the overall complexity by improving the classification accuracy.

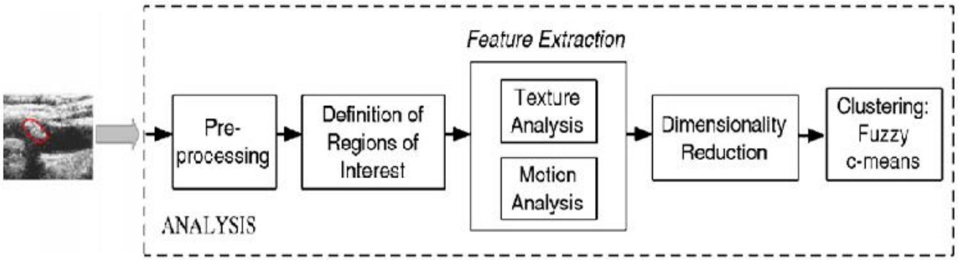
D. Classification of selected ROI

Classification of a set of features into the proper class is one of the most common problems of pattern recognition of image analysis. Classification of features from a given set may be supervised or unsupervised. In the supervised classification, the feature set is 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 neighbour and Bayesian classifiers, and NN classifiers.

E. Computer-aided diagnosis of carotid atherosclerosis from b-mode US images

Currently, the diagnosis of carotid atherosclerosis and decisions on patient management are based on past occurrences of clinical symptoms (e.g. stroke) and the degree of stenosis caused by the plaque which is usually estimated with US imaging. However, there is evidence thatatheromatous plaques with relatively low stenosis degree may produce symptoms and that the majority of asymptomatic patients with highly stenotic plaques remain asymptomatic. Analysis of digitized ultrasound images for estimating the quantitative indices that characterize the severity of plaque may be used to assist the diagnosis of carotid atherosclerosis. More specifically, use of image texture analysis to quantify plaque echogenicity, and movement of the carotid artery wall and plaque may be estimated from temporal image sequences 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 aid interpretation of vascular ultrasound images. To demonstrate the potential of ANALYSIS we used it to differentiate between 10 symptomatic and 9 asymptomatic atheromatous plaques with no 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 (68 features) and the fractal dimension (one feature). Estimation of motion of selected rectangular ROIs on the surface of plaque from temporal image sequences was carried out using region tracking and block matching. The following indices of motion were estimated for each plaque:



Motion and texture features of symptomatic and asymptomatic plaques

	Symptomatic	Asymptomatic	p-value
Texture features			
HW–Mask L^TE	38.3 ± 8.74	46.11 ± 12.95	0.0328
STD–Mask L^TE	17.46 ± 4.01	21.76 ± 5.41	0.0428
Entr–Mask E^TS	2.87 ± 0.50	2.36 ± 0.42	0.0182
IMC	0.93 ± 0.02	0.95 ± 0.01	0.0062
FD	2.21 ± 0.09	2.14 ± 0.04	0.0381
Motion features			
MSV (cm/sec)	1.84 ± 1.00	0.75 ± 0.73	0.0102
MRSV (cm/sec)	2.85 ± 1.69	0.52 ± 0.53	0.0009

F. Differential diagnosis of focal liver lesions from CT images

The combined applicability of texture features and classifiers has been considered for the characterization of liver tissue either from CT or US images [13,19]. The concept conferred 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 described with precision by an experienced radiologist in abdominal non-enhanced CT images. For every ROI a set of texture features was estimated using five texture analysis methods,this provides input to an EC. CAD system presented in Fig[20,21] was a result of comparative appraisal of various architectures in terms of used features and ECs. The design, development, and testing of the CAD system was established using 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. In the feature extraction module, 89 features from five texture analysis methods (five sets of features) for each and every ROI were calculated: 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).

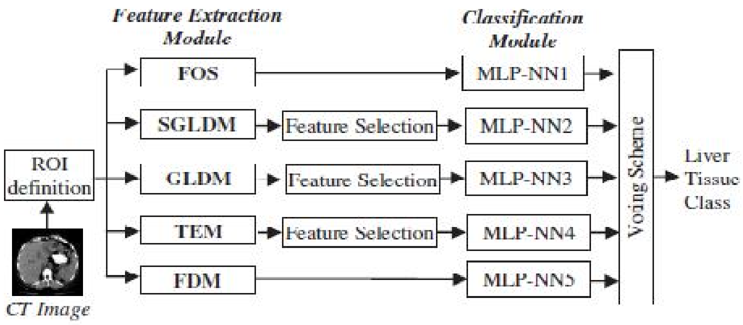


Fig. 3. CAD architecture for the characterization of liver tissue from CT images.

Table 2
Confusion Matrix of the CAD (C1: Normal, C2: Cyst, C3: Hemangioma, C4: Hepatocellular carcinoma)

	Actual diagnosis							
	Validation set				Testing set			
CAD diagnosis	C1	C2	C3	C4	C1	C2	C3	C4
C1	17	0	0	0	17	0	0	0
C2	0	4	0	0	0	4	0	0
C3	1	0	5	0	1	0	4	1
C4	1	0	0	4	1	0	0	4

3. Conclusion

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

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