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Analysis of Doppler Ultrasound Signals: Ophthalmic Arterial Disorders Detection Case

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Abstract— **The paper includes illustrative and detailed information about implementation of automated diagnostic systems and feature extraction/selection from signals recorded from ophthalmic arteries. The major objective of the paper is to be a guide for the readers, who want to develop an automated diagnostic systems for detection of arterial disorders. Toward achieving this objective, this paper present the techniques which should be considered in developing automated diagnostic systems. The paper will assist to the people in gaining a better understanding of the techniques in the detection of arterial disorders.**

Key Words: Spectral analysis techniques, Automated diagnostic systems, Feature extraction/selection, Ophthalmic arterial disorders

I. Introduction

Automated diagnostic systems are important applications of pattern recognition, aiming at assisting doctors in making diagnostic decisions. Automated diagnostic systems have been applied to and are of interest for a variety of medical data, such as electrocardiogram (ECGs), electroencephalogram (EEGs), ultrasound signals/images, X-rays, and computed tomographic images [1-4]. Conventional methods of monitoring and diagnosing the diseases rely on detecting the presence of particular signal features by a human observer. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated diagnostic systems have been developed in the past ten years to attempt to solve this problem. Such techniques work by transforming the mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem [5-7].

Medical diagnostic decision support systems have become an established component of medical technology. The main concept of the medical technology is an inductive engine that learns the decision characteristics of the diseases and can then be used to diagnose future patients with uncertain disease states. A number of quantitative models including multilayer perceptron neural networks (MLPNNs), combined neural networks (CNNs), mixture of experts (MEs), modified mixture of experts (MMEs), probabilistic neural networks (PNNs), recurrent neural networks (RNNs), and support vector machines (SVMs) are being used in medical diagnostic support systems to assist human decision-makers in disease diagnosis [3,4,7,8]. Artificial neural networks (ANNs) have been used in a great number of medical diagnostic decision support system applications because of the belief that they have greater predictive power. Unfortunately, there is no theory available to guide an intelligent choice of model based on the complexity of the diagnostic task. In most situations, developers are simply picking a single model that yields satisfactory results, or they are benchmarking a small subset of models with cross validation estimates on test sets [2-8].

As in traditional pattern recognition systems, the present model consists of three main modules: a feature extractor that generates a feature vector from the raw Doppler ultrasound signals, feature selection that composes diverse and composite features (the model-based power spectral density values, the eigenvector power spectral density values, wavelet coefficients), and a feature classifier that outputs the class based on the diverse and composite features. Data acquisition from ophthalmic arteries (OA), spectral analysis techniques, feature extraction/selection, review of different classifiers, experiments for implementation of classifiers, measuring performance of classifiers are presented in this paper.

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II. DATA ACQUISITION FROM OPHTHALMIC ARTERIES

Doppler ultrasound provides a noninvasive assessment of the hemodynamic flow condition within arteries including OA. Diagnostic information is extracted from the Doppler blood flow signal which results from the backscattering of the ultrasound beam by moving red blood cells. Doppler devices work by detecting the change in frequency of a beam of ultrasound that is scattered from targets that are moving with respect to the ultrasound transducer. The Doppler shift frequency f_D is proportional to the speed of the moving targets:

$$f_D = \frac{2vf \cos\theta}{c} \tag{1}$$

where v is the magnitude of the velocity of target, f is the frequency of transmitted ultrasound, c is the magnitude of the velocity of ultrasound in blood, and θ is the angle between ultrasonic beam and direction of motion [9].

Since flow in arteries is pulsatile and the red blood cells have a random spatial distribution, the Doppler signals are highly nonstationary. The stationarity of the signal is further reduced if the flow pattern is disturbed as a result of an obstructed artery. If the blood flow over the cardiac cycle is to be observed, it is necessary to use time frames that are no longer than the length of time that the signal can be considered stationary. If longer time frames are used, the frequency spectra will be smeared and the consecutive frames will not provide a detailed indication of how the velocities within the artery are changing with respect to time. The Doppler power spectrum has a shape similar to the histogram of the blood velocities within the sample volume (in the arteries) and thus spectral analysis of the signal produces information concerning the velocity distribution in the artery [2,3,9-12]. The estimation of the power spectral density (PSD) of the signal is performed by applying the spectral analysis methods.

OA examinations were performed with Doppler units. The measurement systems consisted of five units. These were ultrasonic transducers (10 MHz), analog Doppler units (Diasonics Synergy color Doppler ultrasonography), recorder (Sony), analog/digital interface board (Sound Blaster Pro-16 bit), and a personal computer with a printer. The probe was most often placed at an angle of 60 degrees from the midline pointing towards the arteries. The OA Doppler signals were obtained from 169 subjects (63 healthy subjects, 52 subjects suffering from OA stenosis, 54 subjects suffering from ocular Behcet disease). The group consisted of 81 females and 88 males with ages ranging from 19 to 65 years and a mean age of 32.5 years (standard deviation-SD 9.1).

III. SPECTRAL ANALYSIS TECHNIQUES

The basic problem that considered in this paper is the estimation of the PSD of a signal from the observation of the signal over a finite time interval. The signals recorded from OA is conventionally interpreted by analyzing its spectral content. Diagnosis and disease monitoring are assessed by analysis of spectral shape and parameters [2,3,9-12]. OA arterial signals are processed by the spectral analysis methods to achieve the PSD estimates and then OA disorders can be determined.

In order to obtain the PSD estimates which represent the changes in frequency with respect to time, the classical methods (nonparametric or fast Fourier transform-based methods), model-based methods (autoregressive, moving average, and autoregressive moving average methods), time-frequency methods (short-time Fourier transform, Wigner-Ville distribution, wavelet transform), eigenvector methods (Pisarenko, multiple signal classification, Minimum-Norm) can be used [13,14].

IV. FEATURE EXTRACTION/SELECTION

Features are used to represent patterns with minimal loss of important information. The feature vector, which is comprised of the set of all features used to describe a pattern, is a reduced-dimensional representation of that pattern. One purpose of the dimensionality reduction is to meet engineering constraints in software and hardware complexity, the computing cost, and the desirability of compressing pattern information. In addition, classification is often more accurate when the pattern is simplified through representation by important features or properties only [2,3,5-8,12].

Feature extraction is the determination of a feature or a feature vector from a pattern vector. For pattern processing problems to be tractable requires the conversion of patterns to features, which are condensed representations of patterns, ideally containing only salient information [2,3,5-8,12].The feature selection process performed on a set of predetermined features. Features are selected based on either 1) best representation of a given class of signals, or 2) best distinction between classes. Therefore, feature selection plays an important role in classifying systems such as neural networks. In the feature extraction stage, numerous different methods can be used so that several diverse features can be extracted from the same raw data. To a large extent, each feature can independently represent the original data, but none of them is totally perfect for practical applications. Moreover, there seems to be no simple way to measure relevance of the features for a pattern classification task. For this kind of pattern classification tasks, diverse features often need to be jointly used in order to achieve robust performance. This kind of pattern classification tasks are called as classification with diverse features. In order to perform a classification, two different methods are used. One is the use of a composite feature formed by lumping diverse features together and the other is combination of multiple classifiers that have been already trained on diverse feature sets. Several problems given as follows occur with the usage of composite feature:

- Its dimension is higher than that of any component feature and it is well known that high-dimension vectors will not only increase computational complexity but will also produce implementation problems and accuracy problems.
- It is difficult to lump several features together due to their diversified forms, e.g., they may be continuous variables, binary values, discrete labels, structural primitives.
- Those component features are usually not independent.

In general, therefore, the use of a composite feature does not provide a significantly improved performance. However, the combination of multiple classifiers is a good solution for the problem involving a variety of features [15]. An appropriate automated diagnostic systems would help to achieve higher model accuracy.

V. EXPERIMENTS FOR IMPLEMENTATION OF DIFFERENT AUTOMATED DIAGNOSTIC SYSTEMS

The key design decisions for the neural networks used in classification are the architecture and the training process. The MLPNN, CNN, ME, MME, PNN, RNN, SVM are used for classification of the OA Doppler signals. The adequate functioning of neural networks depends on the sizes of the training set and test set. To comparatively evaluate the performance of the classifiers, all the classifiers can be trained by the same training data set and tested with the evaluation data set. In the developed automated diagnostic systems for classification of the OA Doppler signals 60 (20 from each class) of 169 subjects were used for training and the rest for testing.

The expectation-maximization (EM) algorithm can be used to train the MME and ME classifiers and the Levenberg-Marquardt algorithm employing the cross-entropy error function as cost function can be used to train the RNNs, CNNs and MLPNNs. Training algorithm of the SVM, based on quadratic programming, incorporates several optimization techniques such as decomposition and caching. The quadratic programming problem in the SVM was solved by using the MATLAB optimization toolbox. The SVMs and the error correcting output codes (ECOC) algorithm can be used to classify the signals. There is an outstanding issue associated with the PNN concerning network structure determination, that is determining the network size, the locations of pattern layer neurons as well as the value of the smoothing parameter. The objective is to select representative pattern layer neurons from the training samples. The output of a summation layer neuron becomes a linear combination of the outputs of pattern layer neurons.

Different experiments are performed during implementation of these classifiers and the number of support vectors in the SVMs, pattern layer neurons in the PNNs, expert networks in the MEs and MMEs, recurrent neurons in the RNNs, hidden layers and hidden neurons in the MLPNNs are determined by taking into consideration the classification accuracies. Table I defines the network parameters of the classifiers [3].

TABLE I
NETWORK PARAMETERS OF THE CLASSIFIERS

Classifier (features)	Dataset
SVM (composite feature)	41·9·3[a]
RNN (composite feature)	41·20r·3[b] 600[c]
PNN (composite feature)	41·21·3·1[d]
MME (diverse features)	5·25·3[e], 4·25·3[e], 28·25·3[e], 4·25·3[e], 5·25·3[f], 4·25·3[f], 28·25·3[f], 4·25·3[f], 500[c]
ME (composite feature)	41·25·3[e], 41·25·3[g], 700[c]
CNN (composite feature)	41·25·9[h], 9·30·3[i] 1200[c]
MLPNN (composite feature)	41·25·3[j], 1900[c]

[a]Design of SVMs: Number of input neurons · support vectors · output neurons, respectively.
[b]Design of RNNs: Number of input neurons · recurrent neurons in the hidden layer · output neurons, respectively.
[c]Number of training epochs.
[d]Design of PNNs: Number of input neurons · pattern layer neurons · summation layer neurons · output layer neurons, respectively.
[e]Design of expert networks: Number of input · hidden · output neurons, respectively.
[f]Design of gating networks in gate-bank: Number of input · hidden · output neurons, respectively.
[g]Design of gating network: Number of input · hidden · output neurons, respectively.
[h]Design of first level network: Number of input · hidden · output neurons, respectively.
[i]Design of second level network: Number of input · hidden · output neurons, respectively.
[j]Design of neural network: Number of input · hidden · output neurons, respectively.

VI. CLASSIFICATION ERRORS AND ROC ANALYSIS

The test performance of the classifiers can be determined by the computation of specificity, sensitivity and total classification accuracy. In order to compare the classifiers used for classification problems, the classification accuracies (specificity, sensitivity, total classification accuracy) on the test sets and the central processing unit (CPU) times of training of the classifiers can be evaluated. The classification accuracies (specificity, sensitivity, total classification accuracy) of the OA Doppler signals test sets and the CPU times of training of the classifiers are presented in Table II [3]. Receiver operating characteristic (ROC) plots provide a view of the whole spectrum of sensitivities and specificities because all possible sensitivity/specificity pairs for a particular test are graphed. The performance of a test can be evaluated by plotting a ROC curve for the test and therefore, ROC curves are used to describe the performance of the classifiers [9]. A good test is one for which sensitivity rises rapidly and 1-specificity hardly increases at all until sensitivity becomes high (Fig. 1). ROC curves of the SVM, MME and MLPNN implemented for the OA Doppler signals are shown in Fig. 1 [3].

VII. CONCLUSIONS

The Doppler ultrasound signals classification is considered as a typical problem of classification with diverse features since the methods used for feature extraction have different performance and no unique robust feature has been found. The inputs (diverse or composite features) of the automated diagnostic systems are obtained by preprocessing of the signals with various spectral analysis methods. The superiorities of the wavelet transform and eigenvector methods will make them useful in spectral analysis of the signals recorded from OA. The performance of the ME, RNN, PNN, CNN, and MLPNN are not as high as the SVM and MME. This may be attributed to several factors including the training algorithms, estimation of the network parameters and the scattered and mixed nature of the features. Based on the drawn conclusions, the SVM and MME trained on the features extracted by especially the wavelet transform and eigenvector methods can be useful in detection of OA disorders.

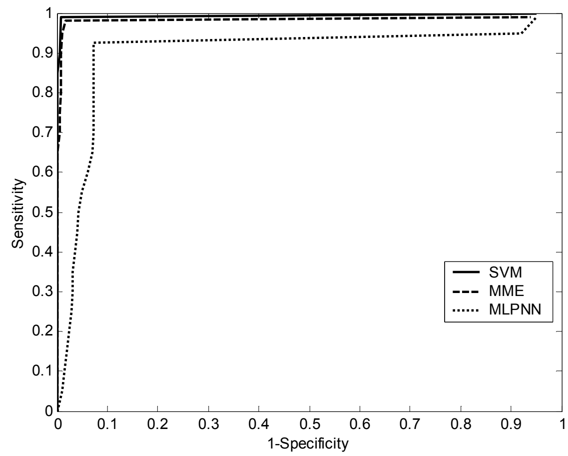

Fig. 1. ROC curves of the classifiers

TABLE II
THE CLASSIFICATION ACCURACIES AND THE CPU TIMES OF TRAINING OF THE CLASSIFIERS

Classifier (features)	Classification Accuracies (%)				CPU time (min:s)
	Specificity	Sensitivity (OA stenosis)	Sensitivity (Ocular Behcet disease)	Total classification accuracy	
SVM (composite feature)	100.00	100.00	97.06	99.08	8:11
RNN (composite feature)	95.35	96.88	94.12	95.41	11:45
PNN (composite feature)	95.35	96.88	97.06	96.33	12:09
MME (diverse features)	97.67	100.00	97.06	98.17	7:32
ME (composite feature)	97.67	96.88	94.12	96.33	9:05
CNN (composite feature)	95.35	96.88	97.06	96.33	12:41
MLPNN (composite feature)	93.02	93.75	91.18	92.66	13:28

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