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Feature saliency using signal-to-noise ratios in automated diagnostic systems developed for Doppler ultrasound signals

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Abstract

Artificial neural networks (ANNs) have been used in a great number of medical diagnostic decision support system applications and within feedforward ANNs framework there are a number of established measures such as saliency measures for identifying important input features. By identifying a set of salient features, the noise in a classification model can be reduced, resulting in more accurate classification. In this study, a signal-to-noise ratio (SNR) saliency measure was employed to determine saliency of input features of multilayer perceptron neural networks (MLPNNs) used in classification of Doppler signals. The SNR saliency measure determines the saliency of a feature by comparing it to that of an injected noise feature and the SNR screening method utilizes the SNR saliency measure to select a parsimonious set of salient features. Ophthalmic and internal carotid arterial Doppler signals were decomposed into time–frequency representations using discrete wavelet transform. Input feature vectors were extracted using statistics over the set of the wavelet coefficients. The MLPNNs used in classification of the ophthalmic and internal carotid arterial Doppler signals were trained for the SNR screening method. The application results of the SNR screening method to the ophthalmic and internal carotid arterial Doppler signals demonstrated that classification accuracies of the MLPNNs with salient input features are higher than that of the MLPNNs with salient and non-salient input features.

Keywords: Feature saliency; Signal-to-noise ratio; Doppler signal

1. Introduction

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 linear discriminant analysis, logistic regression, k nearest neighbor, kernel density, recursive partitioning, and neural networks are being used in medical diagnostic support systems to assist human decision-makers in disease diagnosis. 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 (West and West, 2000a, b; Kordylewski et al., 2001). Various methodologies of automated diagnosis have been adopted, however the entire process can generally be subdivided into a number of disjoint processing modules: preprocessing, feature extraction/selection, and classification. 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. Medical diagnostic accuracies can be improved when the pattern is simplified through representation by important features (Kordylewski et al., 2001; Kwak and Choi, 2002).

There are numerous methods to represent patterns as a grouping of features. The choice of methods appropriate for a given pattern analysis task is rarely obvious. At each level (feature extraction, feature selection, classification) many methods exist. Conventional methods of monitoring

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and diagnosing arterial diseases rely on detecting the presence of particular Doppler signal features by a human observer. Doppler ultrasound is widely used as a non-invasive method for the assessment of blood flow both in the central and peripheral circulation. It may be used to estimate blood flow, to image regions of blood flow and to locate sites of arterial disease as well as flow characteristics and resistance of ophthalmic and internal carotid arteries. Due to large number of patients in intensive care units and the need for continuous observation of such conditions, several techniques for automated diagnosis of arterial diseases have been developed 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. Several techniques have been used to address this problem such as the analysis of Doppler signals for detection of arterial diseases using various standard waveform indices (Evans et al., 1989; Miao et al., 1996; Beksaç et al., 1996) and spectral analysis methods (Baykal et al., 1996; Wright et al., 1997; Wright and Gough, 1999; Güler and Übeyli, 2003; Übeyli and Güler, 2003; Güler and Übeyli, 2004, 2005). Our previous studies (Güler and Übeyli, 2003; Übeyli and Güler, 2003; Güler and Übeyli, 2004, 2005) and the studies existing in the literature (Baykal et al., 1996; Wright et al., 1997; Wright and Gough, 1999) have shown that standard waveform indices are inadequate to evaluate Doppler waveforms. Therefore, we performed spectral analysis of the Doppler signals in order to extract features for the proposed automated diagnostic system.

Feedforward ANNs have received a great deal of attention for their application to pattern recognition and function prediction problems (Basheer and Hajmeer, 2000; Chaudhuri and Bhattacharya, 2000; Haykin, 1994). Within the feedforward ANNs framework, there are a number of established measures for identifying important input features. Such measures are known as saliency (importance) measures (Steppe and Bauer, 1997). Saliency measures can be used for assessing relative importance of a feature. In recent years, the general problem of selecting a parsimonious salient feature set for ANNs has generated a great deal of interest (Steppe and Bauer, 1996; Steppe et al., 1996; Steppe and Bauer, 1997; Polakowski et al., 1997; Bauer et al., 2000; Laine et al., 2002). Non-salient input features to an ANN classifier can have negative results. First of all, insignificant input features may reduce classification accuracy. In addition, as the number of features grows, the number of training vectors required grows exponentially. The signal-to-noise ratio (SNR) saliency measure determines the saliency of a feature by comparing it to that of an injected noise feature (Bauer et al., 2000).

Up to now, there is no work relating to the SNR saliency measure for determining the saliency of input features of ANNs used in classification of Doppler signals in the literature. In the present study, feature extraction from ophthalmic and internal carotid arterial Doppler signals for diagnosis of arterial diseases was performed using discrete wavelet transform (DWT). In order to reduce the dimensionality of the extracted input feature vectors, statistics over the set of the wavelet coefficients were used. Then SNR saliency measure was employed to identify salient input features of the proposed multilayer perceptron neural networks (MLPNNs). The SNR saliency measure was chosen because of its versatility during the training cycle. In addition to this, the SNR saliency measure appears highly robust relative to the effects of the weight initialization, ANN architecture, and the selection of training and test sets. The SNR screening method, which utilizes the SNR saliency measure to select a parsimonious set of salient features, was applied to the ophthalmic and internal carotid arterial Doppler signals. Some conclusions were drawn concerning the improvement of classification accuracies of the MLPNNs with salient input features determined by the SNR saliency measure.

The outline of this study is as follows. In Section 2, we explain SNR saliency measure. In Section 3, we describe SNR screening method for SNR saliency measure application. In Section 4, we present a brief description of neural network models including MLPNN and neural network architecture used in this study. In Section 5, we perform spectral analysis of the ophthalmic and internal carotid arterial Doppler signals using DWT in order to extract features characterizing the behavior of the signals under study. We present the application results of the SNR screening method to the ophthalmic and internal carotid arterial Doppler signals. Finally, in Section 6 we conclude the study.

2. SNR saliency measure

Feature saliency measures provide a way to measure the relative usefulness of features and a means to rank order the features. A partial derivative based saliency measure calculates the impact of each feature on a single hidden layer ANN output by calculating the sum of the partial derivatives of the outputs to that feature. The derivative can be written as a function of the input vector and the weights as follows:

$$\Lambda_i = \frac{1}{K} \cdot \frac{1}{M_{\text{train}}} \cdot \sum_{k=1}^{K} \sum_{m=1}^{M_{\text{train}}} \left| \frac{\partial z_{k,m}(\mathbf{x_m}, \mathbf{W})}{\partial x_{i,m}} \right|, \tag{1}$$

where Λ_i is the partial derivative-based saliency measure for feature $i = 1, \ldots, I$, K is the total number of output nodes, M_{train} is the total number of exemplars in the training set, $z_{k,m}(\mathbf{x_m}, \mathbf{W})$ is the actual output of output node k with input vector $\mathbf{x_m}$ for exemplar $m = 1, \ldots, M_{\text{train}}$ with the trained ANN weight matrix $\mathbf{W}$. All feature inputs are standardized. The partial derivative-based saliency measure can be used to rank order the features from least salient to most salient where lower saliency measure values indicate lower relative saliency and higher values indicate higher relative saliency.