Chaos-Wavelet-Neural Network Models for Automated EEG-Based Diagnosis of the Neurological Disorders

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Abstract—In this keynote lecture the author presents a research ideology, a novel multi-paradigm methodology, and advanced computational models for automated electroencephalogram (EEG)-based diagnosis of neurological disorders. The methodology is based on adroit integration of three different computing technologies and problem solving paradigms: neural networks, wavelets, and the chaos theory. Examples of the research performed by the authors and his associates for automated diagnosis of epilepsy, the Alzheimer's Disease, and Attention Deficit Hyperactivity Disorder are discussed

I. INTRODUCTION

The author started this research track about a decade ago with the general goal of helping neurologists in their diagnosis of neurological disorders. Highly trained neurologists and epileptologists currently *read* EEGs, that is, try to identify visual markers of EEGs. But, EEGs can include markers invisible to the eyes of neurologists. The author's research also challenges the assumption that the EEG represents the dynamics of the entire brain as a unified system and needs to be treated as a whole. On the contrary, an EEG is a signal that represents the effect of the superimposition of diverse processes in the brain. There is no good reason why the entire EEG should be more representative of brain dynamics than the individual frequency sub-bands. In fact, the sub-bands may yield more accurate information about constituent neuronal activities underlying the EEG and, consequently, certain changes in the EEGs that are not evident in the original full-spectrum EEG may be amplified when each sub-band is analyzed separately. This has been a fundamental premise of the author' approach which is presented in a new treatise (Adeli and Ghosh-Dastidar, 2010).

Over the years research on EEG analysis was focused mostly on seizure detection and epilepsy diagnosis. In recent years the research has extended into other neurological issues and disorders (Kramer et al., 2007; Montina et al., 2007; Wang et al., 2007; Chiappalone et al., 2007; Postnov et al., 2007; Chen et al., 2007; Chakravarthy et al., 2007; Osterhage et al., 2007; Lee et al., 2007; Ghosh-Dastidar and Adeli, 2009a&b; Osorio et al., 2009; Shoeb et al., 2009; Good et al., 2009).

II. EPLEPSY

About one percent of the people in the world suffer from epilepsy and 30% of epileptics are not helped by medication. Careful analyses of the EEG records can provide valuable insight and improved understanding of the mechanisms causing epileptic disorders. Wavelet transform is particularly effective for representing various aspects of non-stationary signals such as trends, discontinuities, and repeated patterns where other signal processing approaches fail or are not as effective (Pakrashi et al., 2007; Su et al., 20007; Xie et al., 2007; Spanos et al., 2007; Montejo and Kowalsky, 2008; Umesha et al., 2009; Yazdani and Takada, 2009; Rizzi et al., 2009). Earlier, Adeli et al. (2003) investigated discrete Daubechies and harmonic wavelets for analysis of epileptic EEG records. Wavelet transform is used to analyze and characterize epileptiform discharges in the form of three-Hz spike and wave complex in patients with absence seizure. Through wavelet decomposition of the EEG records, transient features are accurately captured and localized in both time and frequency context. The capability of this mathematical microscope to analyze different scales of neural rhythms was shown to be a powerful tool for investigating small-scale oscillations of the brain signals.

Adeli, Ghosh-Dasidar, and Dadmehr (2007) present wavelet-chaos methodology for analysis of EEGs and delta, theta, alpha, beta, and gamma sub-bands of EEGs for detection of seizure and epilepsy diagnosis. The non-linear dynamics of the original EEGs are quantified in the form of the correlation dimension (CD, representing system complexity) and the largest

Lyapunov exponent (LLE, representing system chaoticity). The wavelet-based methodology isolates the changes in CD and LLE in specific sub-bands of the EEG. The methodology is applied to three different groups of EEG signals: (a) healthy subjects (b) epileptic subjects during a seizure-free interval (interictal EEG), and (c) epileptic subjects during a seizure (ictal EEG). It is observed that while there may not be significant differences in the values of the parameters obtained from the original EEG, differences may be identified when the parameters are employed in conjunction with specific EEG sub-bands.

Ghosh-Dastidar, Adeli, and Dadmehr (2007) present a novel wavelet-chaos-neural network methodology for classification of EEGs into healthy, ictal, and interictal EEGs. Three parameters are employed for EEG representation: standard deviation (quantifying the signal variance), correlation dimension, and largest Lyapunov exponent. The classification accuracies of the following techniques are compared: a) unsupervised k-means clustering, b) linear and quadratic discriminant analysis, c) radial basis function neural network, and d) Levenberg-Marquardt backpropagation neural network (LMBPNN). It is concluded that all three key components of the wavelet-chaos-neural network methodology are important for improving the EEG classification accuracy. Judicious combinations of parameters and classifiers are needed to accurately discriminate between the three types of EEGs. It was discovered that a particular mixed-band feature space consisting of nine parameters and LMBPNN result in the highest classification accuracy, a high value of 96.7%.

Ghosh-Dastidar, Adeli, and Dadmehr (2008) present a two-stage principal component analysis (PCA)-enhanced cosine radial basis function neural network classifier and integrate it with the aforementioned mixed-band wavelet-chaos methodology for accurate and robust classification of EEGs into healthy, ictal, and interictal EEGs. A nine-parameter mixed-band feature space discovered in previous research for effective EEG representation is used as input to the two-stage classifier. In the first stage, PCA is employed for feature enhancement. The rearrangement of the input space along the principal components of the data improves the classification accuracy of the cosine radial basis function neural network (RBFNN) employed in the second stage significantly. The new wavelet-chaos-neural network methodology yields high EEG classification accuracy (96.6%) and is quite robust to changes in training data with a low standard deviation of 1.4%. For epilepsy diagnosis, when only normal and interictal EEGs are considered, the classification accuracy of the proposed model is 99.3%. This statistic is especially remarkable because even the most highly trained neurologists do not appear to be able to detect interictal EEGs more than 80% of the times.

III. ALZHEIMER'S DISEASE

Prediction or early-stage diagnosis of Alzheimer's disease (AD) requires a comprehensive understanding of the underlying mechanisms of the disease and its progression. Researchers in this area have approached the problem from multiple directions by attempting to develop (a) neurological (neurobiological and neurochemical) models, (b) analytical models for anatomical and functional brain images, (c) analytical feature extraction models for electroencephalograms (EEGs), (d) classification models for positive identification of AD, and (e) neural models of memory and memory impairment in AD. Adeli, Ghosh-Dastidar, and Dadmehr (2005a) present a review of research performed on computational modeling of AD and its markers covering computer imaging, classification models, connectionist neural models, and biophysical neural models. It is concluded that a mixture of markers and a combination of novel computational techniques such as neural computing, chaos theory, and wavelets can increase the accuracy of algorithms for automated detection and diagnosis of AD.

The popularity of imaging techniques for detection and diagnosis of possible AD stems from the relative ease with which neurological markers can be converted to visual markers. However, due to the expense of specialized experts and equipment involved in the use of imaging techniques, a subject of significant research interest is detecting markers in EEGs obtained from AD patients. Adeli, Ghosh-Dastidar, and Dadmehr (2005b) present a review of models of computation and analysis of EEGs for diagnosis and detection of AD covering three areas: time-frequency analysis, wavelet analysis, and chaos analysis. The vast number of physiological parameters involved in the poorly understood processes responsible for AD yields a large combination of parameters that can be manipulated and studied. The authors conclude that a combination of parameters from different investigation modalities seems to be more effective in increasing the accuracy of detection and diagnosis.

Adeli, Ghosh-Dastidar, and Dadmehr (2008) present a spatio-temporal wavelet-chaos methodology for analysis of EEGs and their *delta*, *theta*, *alpha*, and *beta* sub-bands for discovering potential markers of abnormality in Alzheimer's disease. The non-linear dynamics of the EEG and EEG sub-bands are quantified in the form of CD and LLE. The methodology is applied to two groups of EEGs: healthy subjects and AD patients. The eyes open and eyes closed conditions are investigated to evaluate the effect of visual input and attention. EEGs from different loci in the brain are investigated to discover areas of the brain responsible for or affected by changes in CD and LLE. It is found that the wavelet-chaos methodology and the sub-band analysis developed in this research accurately characterize the nonlinear dynamics of non-stationary EEG-like signals with respect to the EEG complexity and chaoticity. It is concluded that changes in the brain dynamics are not spread out equally across the spectrum of the EEG and over the entire brain, but are localized to certain frequency bands and electrode loci. New potential markers of abnormality were discovered in this research for both eyes open and closed conditions.

IV. ATTENTION-DEFICIT/HYPERACTIVITY DISORDER

Ahmadlou and Adeli (2010) present a multi-paradigm methodology for EEG-based diagnosis of Attention-Deficit/Hyperactivity Disorder (ADHD) through adroit integration of nonlinear science, wavelets, and neural networks. The selected nonlinear features are generalized synchronizations known as synchronization likelihoods (SL), both among all electrodes and among electrode pairs. The methodology consists of three parts: first detecting the more synchronized loci (group 1) and loci with more discriminative deficit connections (group 2). Using SLs among all electrodes, discriminative SLs in certain sub-bands are extracted. In part two, SLs are computed, not among all electrodes, but between loci of group 1 and loci of group 2 in all sub-bands and the band-limited EEG. This part leads to more accurate detection of deficit connections, and not just deficit areas, but more discriminative SLs in sub-bands with finer resolutions. In part three, a classification technique, radial basis function neural network, is used to distinguish ADHD from normal subjects. Using the RBF neural network classifier the methodology yielded a high accuracy of 96.5% for diagnosis of the ADHD.

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