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Classification of mild cognitive impairment EEG using combined recurrence and cross recurrence quantification analysis

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ABSTRACT

The present study is aimed at the classification of mild cognitive impairment (MCI) EEG by combining complexity and synchronization features based on quantifiers from the common platform of recurrence based analysis. Recurrence rate (RR) of recurrence quantification analysis (RQA) is used for complexity analysis and RR of cross recurrence quantification analysis (CRQA) is used for synchronization analysis. The investigations are carried out on EEG from two states (i) resting eyes closed (EC) and (ii) short term memory task (STM).The results of our analysis show lower levels of complexity and higher levels of inter and intra hemispheric synchronisation in the MCI EEG compared to that of normal controls (NC) as indicated by the statistically significant higher value of RQA RR and CRQA RR. The results also evidence the effectiveness of memory activation task by bringing out the characteristic features of MCI EEG in task specific regions of temporal, parietal and frontal lobes under the STM condition.A new approach of combining complexity and synchronization features for EEG classification of MCI subjects is proposed, based on the geometrical signal separation in a feature space formed by RQA and CRQA RR values. The results of linear classification analysis of MCI and NC EEG also reveals the effectiveness of task state analysis by the enhanced classification efficiency under the cognitive load of STM condition compared to that of EC condition.

1. Introduction

Dementia caused by Alzheimer's disease (AD) is one of the most common cognitive disorders in geriatric population. Mild Cognitive Impairment (MCI), which is generally considered as an early stage of AD, is defined as a condition with memory deficits greater than normal elderly, but do not fulfil the criteria for clinically probable AD (Petersen et al., 1999). MCI is considered as a challenging condition as it is characterised by only memory impairment, leaving functions involving daily activities unaffected (Petersen et al., 2001; Petersen et al., 2009). MCI subjects are at increased risk of developing AD with a conversion rate of 12% per year (Petersen, 2004). Hence, preclinical discrimination of MCI from normal subjects has great significance in current research scenario and deserves much attention.

EEG signals are the representation of the complex electrical activity of the brain and hence they have the potential of providing useful information about the various dynamical features of the underlying cortical process.Conventional linear analyses of EEG signals have identified characteristic features of different brain states as well as various pathological conditions like seizures, psychiatric disorders,Alzheimer's and Parkinson's disease and toxic states (Rice et al., 1990; Bennys et al., 2001). However, considering the complex interconnections and interactions of the underlying neuronal networks and the identification of nonlinear nature of EEG signals, nonlinear analysis is found to provide important supplementary information in most of these cases (Park et al., 2007; Faust and Bairy, 2012; Stam, 2005; Jelles et al., 2008;Kannathal et al., 2005).

In the case of AD, the established methods of spectral analysis have identified characteristic features of decreased mean frequency and coherence (Jeong, 2004; Dauwels et al., 2010a). Taking into account the nonlinear and nonstationary nature of the EEG signals, dynamical systems theory based methods are successfully applied to EEG signals for effective characterisation of AD and MCI condition. Various entropy measures like Renyi's entropy, Shannon spectral entropy, Approximate entropy, Transfer entropy, Tsalli's entropy, Lempel Ziv's complexity have indicated lower level of complexity of the EEG in MCI and AD patients compared to age matched subjects (Dauwels et al., 2011; Faust and Bairy, 2012; Abasolo et al., 2005; McBride et al., 2015; Sneddon et al., 2004; Labate et al., 2013). Entropy measures characterise the

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diversity in patterns generated over space and time and hence the complexity of evolution. Entropy of a time series characterise its information capacity and thereby its level represents the related predictability. Complexity of EEG as evidenced by entropy measures are characteristic of the number of underlying independent neural sources (Stam, 2005; Ibáñez-Molina and Iglesias-Parro, 2016), thereby indicating its level of dynamic richness. Thus the observed reduction in complexity of AD/MCI EEG are suggested as due to the lowering of dynamism or loss of brain responsivity, caused by neuronal death, cholinergic deficits and other network disconnections (Jeong, 2004; Jeong, 2002; McBride et al., 2014).

Spectral analysis of AD EEG using coherence has reported a decrease in coherence of fast bands as well as an increase in coherence of slow bands indicating disruption of long cortico-cortical cholinergic connections (Jeong, 2004; Jeong, 2002). Resting state studies using nonlinear measures of synchronisation like synchronisation likelihood, omega complexity, S estimator and phase synchronisation measures like phase coherence, imaginary coherence, global field synchronisation (GFS) and phase lag index (PLI) have indicated lowered synchrony in AD EEG compared to that of controls indicating impaired neuronal coordination (Dauwel et al., 2009; Dauwels et al., 2010b; Ma et al., 2014). Loss of synchronisation between different cortical regions is the mainly observed EEG feature in AD condition (Stam et al., 2003; Kramer et al., 2007) and is considered as the outcome of structural/functional disconnections among cortical areas (Delbeuck et al., 2003; Stam et al., 2006) resulting from axonal pathology or death of cortical neurons (Jeong, 2002 and Jeong, 2004).

Nonlinear analysis applied to study the synchronisation or rather the relationship between two or more EEG, can reveal to some extent the cognitive dynamics with respect to functional connectivity and thereby provide information on functional interactions between different brain regions (Stam, 2005). In the case of MCI EEG, the synchronisation pattern is usually found to show high variability with respect to frequency bands, cortical regions and cognitive states. Resting state EEG studies of MCI have indicated a decrease of mean frequency and associated decrease in synchronisation (Stam et al., 2003; Koenig et al., 2005; Moretti et al., 2008; Gómez et al., 2009; Zeng et al., 2015), whereas other studies found no significant difference in synchronisation patterns between MCI and normal subjects (Jiang, 2005). Studies based on state space measures have found a loss of synchrony in resting state, which were found to be nonsignificant after statistical correction (Tao and Tian, 2005; Dauwels et al., 2010b). Several EEG/MEG studies have indicated higher synchronisation levels between different cortical regions in MCI compared to normal subjects under short term memory conditions (Dauwels et al., 2010b; López et al., 2014; Pijnenburg et al., 2004; Jiang and Zheng, 2006), suggestive of a compensatory mechanism in their cortical dynamics (Bajo et al., 2010; Bajo et al., 2012; Cantero et al., 2009). Even in the resting state, a few studies have identified hypersynchronisation in the posterior networks which overlapped with regions of decreased oxygen and glucose metabolism (Knyazeva et al., 2013). The synchronisation of cerebral activity is an important physiological mechanism for the functional integration of different brain regions (Vysata et al., 2014) and the main basic functions of such synchronous activity of neuronal oscillators are neural communication and plasticity (Fell and Axmacher, 2011). Thus functional connectivity methods identify brain regions that possess correlated activity which can help in investigation of pathological connectivity in neurological disorders (Bowyer, 2016).

EEG analysis of cognitive deficit conditions of AD and MCI have been conducted using complexity and synchronisation measures and these features are found to be the most significant ones to characterise such EEG (Abasolo et al., 2006; Stam et al., 2003).However, the focus of these studies was either on complexity or on synchronisation analysis. No studies have been carried out based on the combined use of complexity and synchronisation characteristics on a single platform for any application. EEG complexity is found to be related to the amount of independent cortical generators and therefore, can be sensitive to cortical synchrony (Stam, 2005; Ibáñez-Molina and Iglesias-Parro, 2016). In the neural context, dynamical complexity is interpreted as randomness or lack of interaction between the elements of the dynamical system, hence related to lack of functional sources (Stam, 2005). Considering these interrelations and the fact that complexity and synchronisation are the most important characteristic features of AD/MCI EEG, we propose to investigate the effectiveness of the combined use of complexity and synchronisation features to form a common platform of recurrence quantification methods for the purpose of classification of MCI EEG. The recurrence based quantification methods are found to be highly efficient in characterising nonlinear system dynamics (Kurths et al., 1994). These methods do not require the assumption of stationarity of the data and are highly effective for short noisy signals (Zbilut et al., 1998) making them ideal for the dynamical analysis of real-world signals. Due to these significant characteristics, recurrence methods have found applications in varied fields like engineering, biomedical, geophysics, astrophysics, and economics (Nichols et al., 2006; Rangaprakash and Pradhan, 2014; Marwan et al., 2002; Zolotova and Ponyavin, 2006; Holyst et al., 2001).

The present study aims at classification of MCI EEG based on the combined use of recurrence quantification analysis (RQA) and the cross recurrence quantification analysis (CRQA). The recurrence rates (RR) of RQA and CRQA analysis which are efficient indicators of complexity and synchronisation levels are suitably chosen from the common platform of recurrence based dynamical analysis. The recurrence rate of RQA is the measure of the density of the recurring points in a recurrence plot and hence represents the probability of repetition of a dynamical state. CRQA is the bivariate extension of RQA and recurrence rate of CRQA is the density of cross recurrence points, which is the probability of occurrence of similar states in two systems. These measures have found applications in characterisation of epileptic, anaesthetic, multiple sclerotic EEG, as well as climatological and behavioural signals. RQA measures of RR and DET are effectively used to identify loss of complexity in EEG of multiple sclerosis (Carrubba et al., 2012) and in pre-ictal state of epileptic EEG (Zhang et al., 2008). Similarly, CRQA measures are applied to characterise the effect of anaesthesia on coupling relationships in EEG (Nicolaou and Georgiou, 2014) and the detection of increased synchronisation between thumb and index finger caused by peripheral median nerve block (Li and Li, 2013). CRQA is also used for quantifying the temporal organization of interacting behavioural signals, thus identifying the temporal phases during which interactions take place (Coco and Dale, 2014) and in the analysis of climatological signals for the investigation of palaeo-climatic conditions (Marwan and Kurths, 2004).

Here, classification of MCI EEG is carried out using RQA RR and CRQA RR independently as well as in a combined manner by including both these measures collectively in the classification procedure. In addition, these two features are projected onto a feature space wherein support vector machine (SVM) is applied for classification procedure. The method of using feature space for signal separation has earlier been applied for vocal disorders (Matassini et al., 2000; Manfredi and Matassini, 2002) and fault in induction motors (Stefan and Holger, 2000). To study the effectiveness of the proposed method, EEG analysis is carried out in MCI and normal subjects under resting eyes closed (EC) and a cognitively active state of short term memory task (STM). From the present results, it is found that with the inclusion of complexity and synchronisation features into a single analysis, the classification efficiency is enhanced especially in the STM condition. The present study supports the effectiveness of recurrence based methods for EEG signal analysis and moreover the efficiency of combining the two characteristic features of complexity and synchronisation for enhanced classification efficiency. The study also indicates the effectiveness of applying such methods under the cognitively active state of short term memory task condition.