Neurocomputing 170 (2015) 161–167

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Evaluating Quantum Neural Network filtered motor imagery brain-computer interface using multiple classification techniques

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ARTICLE INFO

Article history:
Received 29 July 2014
Received in revised form
6 November 2014
Accepted 12 December 2014
Available online 17 July 2015

Keywords:
Recurrent Quantum Neural Network (RQNN)
Brain-computer interface (BCI)
EEG
Filtering

ABSTRACT

The raw EEG signal acquired non-invasively from the sensorimotor cortex during the motor imagery (MI) performed by a brain-computer interface (BCI) user is naturally embedded with noise while the actual noise-free EEG is still unattainable. This paper compares the enhancement in information when filtering these noisy EEG signals while using a Schrodinger wave equation (SWE) based Recurrent Quantum Neural Network (RQNN) model and a Savitzky–Golay (SG) filtering model, while investigating over multiple classification techniques on several datasets. The RQNN model is designed to efficiently capture the statistical behavior of the input signal using an unsupervised learning scheme. The algorithm is robust to parametric sensitivity and does not make any *a priori* assumption about the true signal type or the embedded noise. The performance of both the filtering approaches, investigated for the BCI competition IV 2b dataset as well as the offline datasets on subjects in the BCI laboratory, over multiple classifiers shows that the RQNN can potentially be a flexible technique that can suit different classifiers for real-time EEG signal filtering. The average classification accuracy performance across all the subjects with the RQNN technique is better than the SG (and the unfiltered signal) by approximately 5% (and 7%) and 1% (and 4%) during the training and the evaluation stages respectively.

1. Introduction

Brain-Computer Interface (BCI) technology is a possible mode of communication for individuals with severe movement disability. It enables people to communicate and control assistive robotic devices using their electroencephalogram (EEG) or other brain signals. A typical BCI scheme (cf. Fig. 1) consists of signal acquisition, pre-processing, feature extraction, classification and feedback as well as device commands. Motor Imagery (MI) i.e. mental imagination of movement plays a very important role in various BCI applications. However, the raw MI signals acquired from the sensorimotor cortex region have a very low Signal-to-Noise (SNR) ratio because of the presence of artifacts due to interference from the electrical power line, impedance fluctuation due to minor body movements leading to electrode movements over the skin, electromyogram (EMG)/electrooculogram (EOG) interference, noise introduced due to instrumentation or electronic devices etc. Thus, most of the BCI systems involve pre-processing or filtering to remove such unwanted components that are embedded within the EEG signal which otherwise may bias the analysis of the EEG and lead to wrong conclusions [1]. Suitable pre-processing within the BCI system leads to cleaner EEG signals, thereby enhancing the classification results. This paper focuses on the quantum mechanics motivated pre-processing stage within the BCI system, to extract more information from the acquired noisy EEG signals, and thus lead to an increase in the classification accuracy even when classified using multiple classification approaches.

Conventional architectures such as basic filtering using band pass [2], adaptive filtering [3] and blind source separation [3] have been investigated for EEG signal filtering. However, it is said that EEG signals are a realization of a random or a stochastic process [4]. Therefore, when an accurate description of the system is not available, a stochastic filter based on the concepts of quantum mechanics, such as the Recurrent Quantum Neural Network (RQNN) [5], can be designed on the basis of probabilistic measures. The work presented in this paper builds on the foundations of EEG signal filtering using the RQNN model laid in our previous work [6]. Here, the RQNN approach is used on multiple classification techniques to confirm its suitability for complex EEG filtering. The

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http://dx.doi.org/10.1016/j.neucom.2014.12.114
0925-2312/

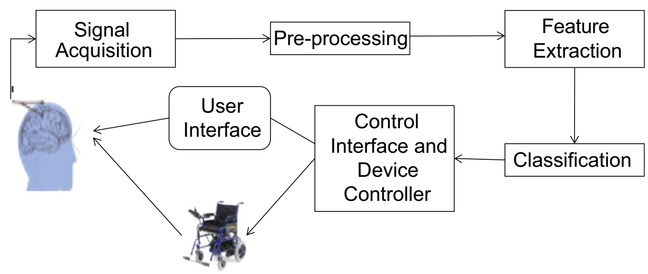

Fig. 1. Basic Design of a simple BCI system.

RQNN involves the computation of a time varying probability density function (*pdf*) on the state space of the observed system. The architecture of the RQNN model is based on the principles of quantum mechanics (QM) with the Schrodinger wave equation (SWE) [7] playing a major part that enables online estimation of a time varying *pdf* which allows estimating and removing the noise from the EEG [6]. The quantum state, in quantum terminology, is represented by ψ (a vector in the Hilbert space and also referred to as a wave amplitude function or a probability amplitude function). The time evolution of this quantum state ψ is described by the SWE [7] as

$$i\hbar\frac{\partial\psi(x,t)}{\partial t} = -\frac{\hbar^2}{2m}\nabla^2\psi(x,t)+V(x,t)\psi(x,t) \quad (1)$$

where H is the Hamiltonian or the energy operator and is given as $i\hbar\frac{\partial}{\partial t}$ where $2\Pi\hbar$ (i.e. h) is the Planck constant (which denotes the size of quanta in QM) [8]. $\psi(x,t)$ is the wave (probability amplitude) function associated with the quantum object at space-time point (x, t) and represents the solution of this equation, while $V(x)$ is the spatial potential field. As $V(x)$ sets up the evolution path of the wave function, any desired response can be obtained by properly modulating the potential energy.

For *pdf* computation, each neuron within the architecture of the RQNN model mediates a spatio-temporal field with a unified quantum activation function in the form of a Gaussian that aggregates the *pdf* information from the observed noisy input signal. The solution of the SWE localizes the position of the quantum object in the vector space and gives us the activation function. The RQNN filtering approach has been implemented successfully in many practical applications such as robot control [9], eye tracking [10], physiological signal filtering [6,11] and stock market prediction [12].

2. RQNN architecture within the BCI system

This section describes the RQNN architecture implemented within the BCI system. The raw EEG signal is first scaled in the range 0–2 before it is fed to the RQNN model (cf. Fig. 2). Scaling helps reduce the range to be covered by the wave packet, potentially enhancing the speed of the filtering process, thereby making it practically conceivable. The RQNN estimates the true EEG from the scaled EEG, which is then used to obtain Hjorth features [13]. These features are then fed as input to train the offline classifier. In this paper, Linear Discriminant Analysis (LDA), Regression (REG) and LD5 (CSP motivated) classifiers are investigated. The parameters/weight vector from the offline classifier analysis is stored for use with the corresponding classifier to identify the unlabeled EEG data during the online analysis. The weight update process of the RQNN model is continuous during both the offline and the online process, thereby enabling the model to capture the dynamic property of the continuous EEG signal. However, the parameters of the classifier are tuned offline and then kept fixed during the online (evaluation) classification process.

The theory in the RQNN is that the average behavior of a neural lattice that estimates the EEG signal is a time varying *pdf*, which is mediated by a quantum object placed in the potential field $V(x,t)$ and modulated by the input EEG signal so as to transfer the information about the *pdf* [14]. The SWE is used to track this *pdf* since it is a well-known fact that the square of the modulus of the ψ function, the solution of this wave equation, is also a *pdf* (denoted as ρ ((.)).The potential energy modulates the non-linear SWE described by Eq. (1), and is calculated as below:

$$V(x) = \zeta W_i(x,t)\phi_i(v(t)) \quad (2)$$

where

$$\phi(x,t) = e^{\frac{-(x-y(t))^2}{2\sigma^2}} - |\psi(x,t)|^2 \quad (3)$$

where $y(t)$ is the input signal and the synapses are represented by the time varying synaptic weights $W(x,t)$. The variable ζ represents the scaling factor to actuate the spatial potential energy $V(x,t)$ and σ is the variance that is taken here as unity.

The filtered estimate is calculated using Maximum Likelihood Estimate (MLE) as

$$\hat{y}(t) = \int \psi(x,t)^* x(t)\psi(x,t)dx \quad (4)$$

where x represents the different possible values that may be taken by the random process y. Based on ML estimation, the weights are updated and thus establishing a new potential $V(x,t)$ for the next time evolution. When the estimate $\hat{y}(t)$ is the actual or true signal, then the signal that generates the potential energy $v(t)$ is simply the noise that is embedded in the signal. If the statistical mean of the noise is zero, then this error correcting signal $v(t)$ has little effect on the movement of the wave packet. Precisely, it is the actual signal content in the input $y(t)$ that moves the wave packet along the desired direction, which in effect achieves the goal of the EEG signal filtering. It is expected that the synaptic weights $W(x,t)$ evolve in such a manner so as to drive the ψ function to carry the exact information of the *pdf* of the filtered EEG signal $\hat{y}(t)$. To achieve this goal the weights are updated using the following learning rule

$$\frac{\partial W(x,t)}{\partial t} = -\beta_d W(x,t) + \beta\phi(x,t)(1+v(t)^2) \quad (5)$$

where, β_d is the de-learning parameter, used to prevent unbounded increase in the values of the synaptic weights W.

The parameters $\beta = 2.7$, $\beta_d = 1$, $m = 0.25$ and $\zeta = 15$ have been set heuristically, after suitable trial and experimentation over a small set of EEG data, for the RQNN with non-linear modulation of the potential field. The parameter $\hbar$ (reduced Planck's constant) has been set as unity[1]. A particular computational sampling instant of the EEG signal is iterated 20 times for the response of the wave equation to reach a steady state. The values of the weight and the potential function evolve in this iterative loop. All the above parameters have been kept the same for all the subjects.

3. Savitzky–Golay approach

The performance of the RQNN filtering process has been compared with the unfiltered EEG as well as with the well-established SG technique [15], investigated over multiple classification techniques. The SG technique can smoothen out the signal without destroying the original properties of the signal. The SG technique has been utilized as a noise removal approach (in a way it is thus similar to the RQNN) in biological signals such as the ECG [16] and the EEG [17,18]. Hence, the

[1] The Planck constant is an atomic-scale constant. The atomic units are a scale of measurement in which the units of energy and time are defined so that the value of the reduced Planck constant is exactly one.