Subband Spectral Complexity Distance for Cortical Health Evaluation and Monitoring in Ischemic Brain Injury

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ABSTRACT - A quantitative electroencephalogram (qEEG) index for the evaluation and monitoring of cortical health in ischemic brain injury is presented. The proposed qEEG index, called the subbands spectral complexity distance (SSCD), measures the distance between a vector of subbands spectral complexities computed from the investigated EEG and a one computed from normal EEG. For the computation of the SSCD, the spontaneous power spectral density of the EEG signal is estimated using the time-varying autoregressive (TV-AR) model, decomposed into subbands and the spectral complexity of each subband is computed. Results of evaluating human EEG data are presented to show the usefulness of the proposed SSCD index. It is shown that the index increases during the time-segments of ischemic brain injury while decreases during the normal and recovery segments. This can be explained by the fact that the ischemic brain injury may increase the irregularity of the EEG signal and therefore the power spectral density becomes more complex with ischemic brain injury.

INTRODUCTION

CARDIAC arrest affects about 200,000 to 375,000 patients annually in the USA and it is therefore a common problem [1]. After cardiopulmonary resuscitation from cardiac arrest, brain damage due to hypoxic-ischemic encephalopathy is considered one of the leading causes of morbidity and mortality. Intensive care requires tracking the electrical brain activity post cardiac arrest in order for clinicians to be ready for neuroprotective intervention. The electroencephalogram (EEG) is a noninvasive indication for the brain electrical activity. Since injury causes death of many thousands of brain cells, this results in change in the EEG signal amplitude, power spectrum and complexity. For the evaluation of the cortical health during ischemic brain injury and recovery based on EEG signal, various quantitative measures, such as temporal amplitude-based entropy, time-varying spectral distance and Itakura distance have been used [4]-[8]. The spectral distance expresses the sum of square-differences between the spectral lines of the baseline (normal) EEG and the injury-related one [13]. The spectral distance then reflects the similarity/dissimilarity of the spectral lines, their values and corresponding frequencies with respect to the baseline EEG signal. For the computation of the power spectrum, a time-varying autoregressive (TV-AR) modeling is often employed [4], [11], [12], [13]. The amplitude-based entropy has been used as a measure of the information contents of the EEG signal [4], [5], [7], [8]. This is implemented by treating the EEG amplitude as a random variable within a sliding window; then the probability distribution function and time-dependent entropy have been computed. As known, the amplitude is very sensitive to additive noise.

In this paper, a spectral complexity distance (SSCD) is proposed for quantitatively measuring and monitoring the ischemic brain injury post cardiac arrest. The proposed distance evaluates how far the subband spectral complexities of the investigated EEG signal are from those of the normal EEG signal. In Section 2 we presents description of the computation of the proposed spectral complexity distance, a brief review for the TV-AR modeling and a brief description for the employed human real-world EEG data. Section 3 presents the results of applying the proposed SSSSCD to 4 real-world EEG data of human subjects. Finally in Section 4, the conclusions are drawn.

METHOD AND DATA

A. Spectral Complexity

The time-varying spectral entropy can be computed by [2], [3], [4]

\[ v(n) = - \sum_f H(f,n) \log(H(f,n)) \],

where \( H(f,n) \) is the normalized power spectral density, \( f \) is the discrete normalized frequency and \( n \) is the time-sample number. If the logarithmic base is 2, then spectral entropy based complexity (simply, spectral complexity) measure can be obtained as follows:

\[ s(n) = 2^{v(n)} \]

It is simple to demonstrate that the spectral complexity (SC) increases with the increase of the randomness, i.e. it reaches its maximum value when the signal is white.
constant for each process, then the normalized power spectral density is equal to \( \log(N) \) and therefore the SC is equal to \( N \). It is also simple to prove that the spectral entropy of a single sinusoid is zero and therefore the SC is equal to 1. If \( x(n) \) consists of three sinusoids of equal amplitudes, the normalized power spectral density shows three lines each of amplitude \( 1/3 \). The SC is therefore equal to 3.

B. Subband Complexities and Complexity Distance

The normalized power spectral density \( H(f, n) \) is decomposed into \( M \) of either equal- or non equal-width subbands, i.e.,

\[
H(f, n) = H_1(f, n) + H_2(f, n) + \ldots + H_M(f, n)
\]  

The subband spectral entropy \( v_i(n) \) and the subband spectral complexity \( s_i(n) \) are computed as follows [10]

\[
v_i(n) = \sum_f -H_i(f, n) \log(H_i(f, n))
\]

\[
s_i(n) = 2^{v_i(n)}
\]

The subbands can be selected to cover the clinical EEG rhythms. The subband complexities can be converted into various single measures. Of these measures, the complexity distance which measures how far the spectral complexity of the investigated EEG signal from a baseline EEG signal. The Euclidian distance as an example is computed as follows

\[
u(n) = \left( \sum_{i=1}^M (s_i(n) - r_m(n))^2 \right)^{1/2}
\]

where \( r_m(n) \) represent the subband-spectral complexities of the baseline EEG.

C. TV-AR Power Spectral Model

The EEG signal, \( x(n) \), could be modeled as a time-varying autoregressive (TV-AR) process given by [11], [12].

\[
x(n) = -\sum_{i=1}^p a_i(n)x(n-i) + e(n)
\]

where \( p \) is the AR model order. This implies that \( x(n) \) is generated as the output of the all-poles system

\[
1/ \left(1 + \sum_{i=1}^p a_i(n)z^{-i}\right) = 1/A(z, n)
\]

as driven by the unpredictable (white noise) process \( e(n) \). Since the system coefficients are time-varying, the power spectral density is time-varying as well. For the computation of the TV-AR coefficients, Burg’s method is applied to a sliding window of size \( W \) samples. Burg’s method finds an all-pole model that minimizes the sum of the squares of both the forward and backward prediction errors [11], [12]. As time increases by \( \Delta \) samples, the sliding window is moved to the advance by \( \Delta \) samples as well. This implies that the analysis window is overlapped on the previous one by \((W-\Delta)\) samples. More details about Burg’s method and its lattice realization are found in [10], [12]. The computation of the TV-AR coefficients in (7), the power spectral density of the EEG signal \( x(n) \) versus the time-sample \( n \) is given by

\[
H(f, n) = 1/ |A(e^{i2\pi f}, n)|^2
\]

D. Data

The SSSCD described in this paper are computed for the EEG of 4 subjects. Each EEG signal was acquired using sampling frequency of 256 Hz. The signals were filtered with a digital bandpass filter between 1 and 70 Hz with a notch at 60 Hz in order to remove the out-of-EEG-band noise and the power line interference. Each subject was later evaluated at discharge using a functional outcome measure, the Cerebral Performance Category (CPC) which is of 5 point scale further divided as good and poor outcome [9], [10]. Table 1 presents the CPC outcomes that we used.

**RESULTS**

For the computation of the TV-AR coefficients, the windowed Burg’s method has been used with window size of 2 sec overlapped by 1 sec. The TV-AR model order \( p \) is chosen 8, generally, the order of such model is determined by using Akaake criteria [14]. Various model orders greater than 8 have also been examined and have shown no significant improvement. The SSSCD is computed using the schematic diagram shown in Fig. 1. Fig. 2 shows the spectral complexity of 6 equal-width subbands of the EEG recorded from the normal subject and the one with severe injury. Subbands can be adjusted to cover the EEG wave rhythms. Results of other subjects were omitted for the paper space limitation. It is obvious that there are valuable changes in the subband complexities of the subject having CPC of grade 5 in comparison with the normal subject.

<table>
<thead>
<tr>
<th>Grades</th>
<th>Cerebral Performance Category (CPC)</th>
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<tbody>
<tr>
<td>1</td>
<td>Conscious and alert with normal function or slight disability</td>
</tr>
<tr>
<td>2</td>
<td>Conscious and alert with moderate disability</td>
</tr>
<tr>
<td>3</td>
<td>Conscious and alert with severe disability</td>
</tr>
<tr>
<td>4</td>
<td>Comatose or persistent vegetative state</td>
</tr>
<tr>
<td>5</td>
<td>Brain death or death from other causes</td>
</tr>
</tbody>
</table>

Fig. 3 shows a bar plot of the spectral complexities of the 6 subbands of the EEG of the four subjects. Fig. 4 shows the ongoing SSSCD of the four EEG subjects and the normal subject. It is obvious that the online SSSCD
changes with ischemic brain injury grade. The SSCD of the normal subject and the one performing good outcomes are very close. However the SSCD of the subject with CPC of grade 5 who died after 24 Hours is very far from the normal subject. It is also obvious that the one with CPC 5 died after 72 Hours is separated from the subject with CPC of grade 5 who died after 24 Hours. Therefore the SSCD could distinguish between the different injury levels. The spectral complexity distance shows that the subject with CPC of grade 5 and died after 24 Hours is far from the normality while the subject with good outcome is close to the normal one.

CONCLUSIONS

In this paper, a subbands spectral complexity distance (SSCD) of EEG signal has been proposed as a quantitative EEG (qEEG) index to evaluate and monitor ischemic brain injury. The qEEG index has been formatted as the Euclidean distance between a vector of subbands spectral complexities computed from the patient investigated EEG and the one from a control (normative) subject. The real-time power spectral density is estimated using the time-varying autoregressive (TV-AR) model computed by applying Burg’s method to a sliding window. The SSCD obtained from EEG data recorded from four human subjects with ischemic brain injury and a normative subject has shown the significant usefulness of the approach. It has been noticed that the SSCD value increases with the increase of the grade of the cortical injury. The subject with brain injury and good outcomes provides a very close distance from the normal subject.

ACKNOWLEDGMENT

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REFERENCES


Fig. 1. A schematic diagram for the spectral complexity distance (SSCD) computation approach.
Fig. 2. Real-time subband complexities for 6 subbands of the four EEG examples: a, normal subject; and b, cortical brain injury subject with CPC of grade 5 (died within 24 H after cardiac arrest).

Fig. 3. Bar plots of the 6 subbands complexities time-average: title #1, normal subject; #2, ischemic cortical brain injury with good outcomes (diagnosed later that his cerebral performance category (CPC) is of grade 2); #3, ischemic cortical brain injury subject with CPC of grade 5 (died within 72 H after cardiac arrest); and #4, ischemic cortical brain injury subject with CPC of grade 5 (died within 24 H after cardiac arrest).

Fig. 4. The real-time SSCD of the four EEG examples: ◊, normal subject; □, ischemic cortical brain injury subject with good outcome (CPC is of grade 2); ○, ischemic cortical brain injury subject with CPC of grade 5 (died within 72 H after cardiac arrest); and +, ischemic cortical brain injury subject with CPC of grade 5 (died within 24 H after cardiac arrest).