QUANTIFICATION OF INJURY-RELATED EEG SIGNAL CHANGES USING ITAKURA DISTANCE MEASURE

Xuan Kong

Department of Electrical Engineering
Northern Illinois University
DeKalb, IL 60115

Vaibhava Goel and Nitish Thakor

Department of Biomedical Engineering
The Johns Hopkins University
Baltimore, MD 21218

ABSTRACT

Accurate detection and characterization of changes in EEG signal is crucial for clinical assessment of the neurological system condition. Several distance measures are tested and evaluated for their effectiveness of detecting injury-related changes in EEG. Itakura distance is found to be a very efficient means to characterize changes in EEG for both signaling injury and predicting recovery. The efficiency of the Itakura distance measure is further established through a comparison study of spectral distance measure and KL information.

1. INTRODUCTION

It is very important to determine the degree of brain damage following birth hypoxia/asphyxia in neonatal intensive care[1]. An early indicator of this type of injury is critical for the management of infants with hypoxic-asphyxic encephalopathy. Clinical evaluation, imaging, and biochemical methods are a few techniques being frequently used, but they are of value only after first few days of birth.

There have been many attempts to study brain injuries through EEG analysis (e.g., [2] and [3]). In [2], changes in frequency distribution of EEG were studied in the event of hypoxia/asphyxia. A coherence-based linearity index was developed in [3] to characterize changes in event-related EEG when hypoxic injury occurs.

Here, we attempt to answer the following question: how to quantify the changes in EEG signal through a distance measure. To accurately quantify changes in EEG, we parameterize EEG signal with an autoregressive (AR) process. It is conjectured that as the state of the brain changes (especially when injuries occur), the properties of the EEG signal will also change. Such change will be reflected in the parameters of the AR process modeling the EEG signal.

In digital speech processing, a similar question was addressed. In applications like objective speech quality measurement and speech recognition, it is desirable to determine the degree of similarity between two speech utterances[4]. A speech signal can be modeled as the output of an AR process driven by either a white noise (for unvoiced speech) or an impulse train (for voiced speech). The task becomes how to measure the distance between two sets of AR parameters modeling the two utterances. Various distance measures have been proposed for this purpose. One of the most successful methods is Itakura distance measure[5].

In this paper we evaluate the effectiveness of using Itakura distance[5] for measuring the changes in EEG signals with special emphasis on the changes related to injury (hypoxia/asphyxia). The performance of Itakura distance measure is compared with the performance of other methods, such as spectral distance measure[6] and Kullback-Leibler (KL) information[7], for quantifying the injury-related changes in EEG signals.

The rest of the paper is organized as follows: Section 2 summarizes various distance measures to be employed: Itakura distance, spectral distance, and KL information. Data collection procedure is briefly introduced in Section 3. Analysis results are presented in Section 4. Some conclusion remarks are given in Section 5.

2. DISTANCE MEASURES

2.1. Itakura Distance

Suppose that the following AR model of order M is obtained for a reference signal $r[k]$

$$r[k] = \sum_{i=1}^{M} a_i^r r[k-i] + n_r[k], \qquad (1)$$

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where $n_r[k]$ is the unpredictable part of $r[k]$ (white noise). Similarly, an AR model is obtained for a test signal $t[k]$

$$t[k] = \sum_{i=1}^{M} a_i^t t[k-i] + n_t[k]. \tag{2}$$

The distance between the reference and test signals may be reflected by a proper distance measure between the two sets of AR parameter coefficients. Euclidean distance is not appropriate because the individual AR parameters may be highly correlated.

Itakura measure calculates the distance between the two sets of AR parameters as follows: Let us denote the AR parameter sets as two vectors

$$\alpha = [1 \ -a_1^r \ -a_2^r \ \cdots \ -a_M^r]^T$$

$$\beta = [1 \ -a_1^t \ -a_2^t \ \cdots \ -a_M^t]^T.$$

Let R_r be the correlation matrix for $r[n]$

$$R_r = \begin{pmatrix} \gamma_r(0) & \gamma_r(1) & \cdots & \gamma_r(M) \\ \gamma_r(1) & \gamma_r(0) & \cdots & \gamma_r(M-1) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_r(M) & \gamma_r(M-1) & \cdots & \gamma_r(0) \end{pmatrix}$$

where $\gamma_r(i)$ is the autocorrelation of $r[n]$. Similarly we can define R_t. Itakura distance can now be defined

$$d_I'(r,t) = \log \frac{\xi_\alpha}{\xi_\beta} = \log \frac{\beta^T R_r \beta}{\alpha^T R_r \alpha}. \tag{3}$$

If the AR parameters α are obtained by minimizing the mean square error (MSE)

$$\min_\alpha E(r[k] - \sum_{i=1}^{M} a_i^r r[k-i])^2$$

the minimized MSE is given by $\alpha^T R_r \alpha$. Any other AR parameter set $\beta \neq \alpha$ will result in

$$\beta^T R_r \beta > \alpha^T R_r \alpha \quad \Rightarrow \quad d_I'(r,t) \geq 0.$$

Intuitively, Itakura distance can be understood as follows: By passing the reference signal $r[k]$ through an inverse filter

$$H_r(z) = 1 - \sum_{i=1}^{M} a_i^r z^{-i} \tag{4}$$

we obtain a residue error $n_r[k]$ at output. The energy of this error is denoted as ξ_α. Similarly, we can pass $r[k]$ through the inverse filter

$$H_t(z) = 1 - \sum_{i=1}^{M} a_i^t z^{-i} \tag{5}$$

and denote the energy of the output as ξ_β. The closer to α the parameter set β is, the smaller the residue energy ξ_β, since α is so obtained to minimize the residue energy. A distance closer to zero indicates an energy ratio closer to one, thus a closer match between reference and test signals. Itakura distance sometimes is also called energy ratio distance for this reason.

We can also find out how well the parameter set α models the test signal by calculating

$$d_I'(t,r) = \log \frac{\alpha^T R_t \alpha}{\beta^T R_t \beta}. \tag{6}$$

Combining (3) and (6) we have a symmetric distance measure

$$d_I(r,t) = \frac{1}{2}(d_I'(r,t) + d_I'(t,r)). \tag{7}$$

Note that $d_I(r,t)$ is still not a metric because the triangular inequality is not satisfied.

2.2. Spectral Distance

Another means to measure the difference between two AR processes is through spectral distance. Based on its AR parameters, spectrum magnitude for an AR process $r[k]$ can be obtained as follows:

$$S_r(e^{j\Omega}) = \frac{1}{\left|1 - \sum_{n=1}^{M} a_n^r e^{-j\Omega n}\right|}. \tag{8}$$

The gain factor is ignored so that we can obtain the normalized spectrum. Similarly we can calculate the spectrum magnitude $S_t(e^{j\Omega})$ for $t[k]$.

The spectral distance is defined as follows

$$d_S(r,t) = \left\{ \frac{1}{L} \sum_{l=0}^{L-1} |S_r(e^{j\Omega_l}) - S_t(e^{j\Omega_l})|^p \right\}^{1/p} \tag{9}$$

where

$$\Omega_l = \frac{\pi l}{L}, \quad \text{for} \quad l = 0, 1, \cdots, L-1.$$

This measure is commonly referred to as the linear unweighted spectral distance in speech processing[6].

Various weighted spectral distances have been developed in speech quality assessment applications where the characteristics of the frequency response of human auditory system are taken into consideration. These weighting factors are not applicable here. Further research perhaps can reveal the relative clinical importance of the various spectral components of EEG and better weighted spectral distance measures can be developed. For our purpose here we will use the definition in (9) with $p = 1$ or $p = 2$ and $L = 256$.

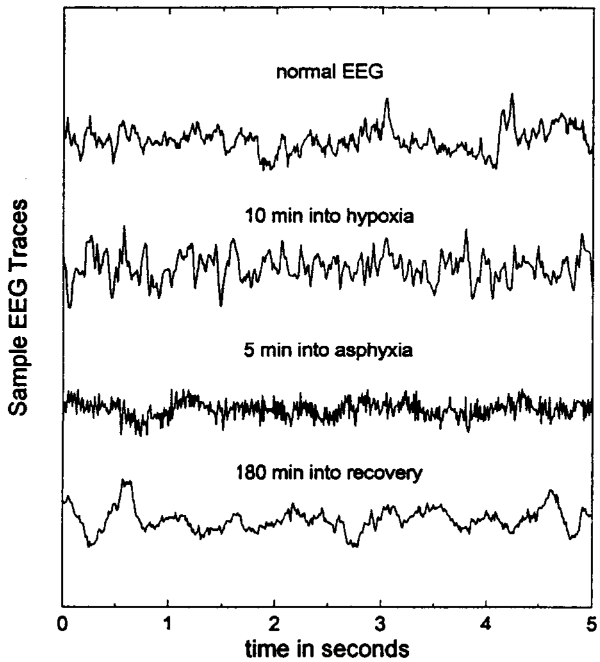

Figure 1: Sample traces of EEG signal at various stages of the experiment. Each trace has a duration of five seconds. DC bias was removed and the amplitude is normalized.

2.3. Kullback-Leibler Information

Aside from being modeled as the output of an AR process, EEG signals have also been studied as a stochastic process with a given distribution. It is reasonable to assume that injury to the brain causes changes in the distribution of the EEG signals. Thus injury-related changes in EEG can also be detected through quantifying the changes of the distribution function of the EEG signals.

The KL information[7] measures the distance between the test distribution with the probability density function $p_t(x)$ and the reference distribution with the probability density function $p_r(x)$. The KL information is defined as follows:

$$d_K(r,t) = \int_{-\infty}^{\infty} p_t(x) \ln \frac{p_t(x)}{p_r(x)} dx. \tag{10}$$

We always have $d_K(r,t) \geq 0$ and the equal sign is valid if and only if $p_t(x) = p_r(t)$. The smaller $d_K(r,t)$ is, the closer the test signal's distribution is to the reference signal's distribution.

3. DATA COLLECTION

Neonatal piglets (1–2 weeks old) were exposed to a sequence of 30 minutes hypoxia, five minutes of room air, and seven minutes of asphyxia followed by a four hour recovery period. Continuous two channel cortical EEG signals were recorded throughout. In data analysis, EEG from a sleeping uninjured piglet serves as the reference signal $r[k]$ and the current EEG from the same piglet is used as the test signal $t[k]$. The EEG signals are sampled at 100 Hz. Sample traces of EEG signal at various stages of the experiment are shown in Figure 1.

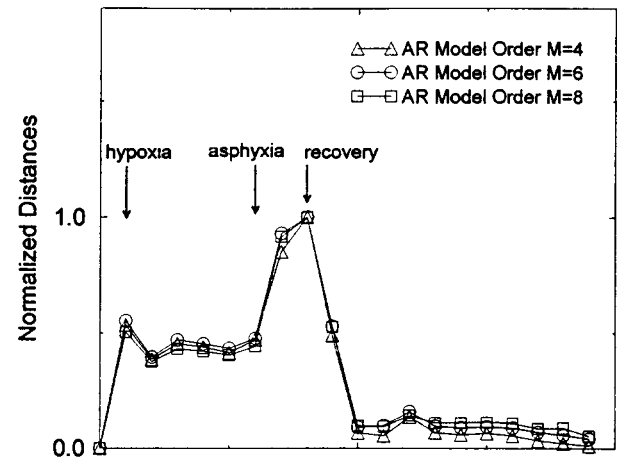

Figure 2: Itakura distances obtained with different AR model orders. Regardless of the model order, the Itakura distance changes significantly when brain's condition changes. Arrow indicates the first data segment processed for that period.

4. DATA ANALYSIS

One minute segments of data at various stages of experiment are analyzed and the distances between these data segments and the reference data segment are computed. Autocorrelation method is used to find the AR model parameters for each segment of EEG. Distances between current and reference EEGs for both left and right channels are calculated and they vary in a very similar fashion. This is true for all three distance measures investigated. Thus, in the following analysis, left and right channel distances are additively combined.

Figure 2 shows the Itakura distances between current and reference EEGs at various stages of experiment. Three different AR model orders ($M = 4, 6, 8$) are used and the results are almost identical. The Itakura distance is very sensitive to the injury-related changes in EEG. Compared to the distance for EEG at hypoxia stage, the distance between EEGs at asphyxia stage and normal stage rises sharply, indicating a much more severe insult to the brain had occurred. As re-

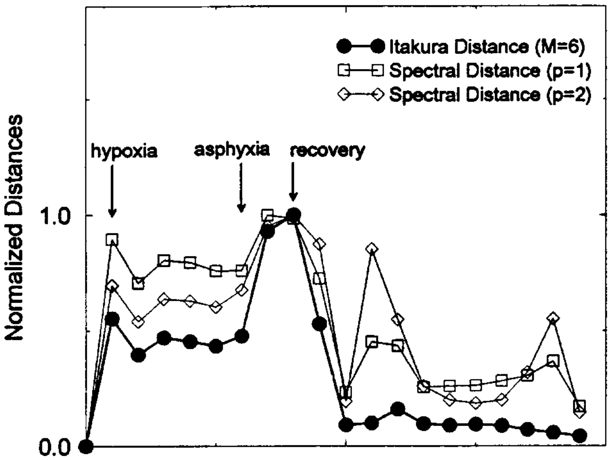

Figure 3: Comparison between spectral distance measure and Itakura distance measure. Arrow indicates the first data segment processed for that period.

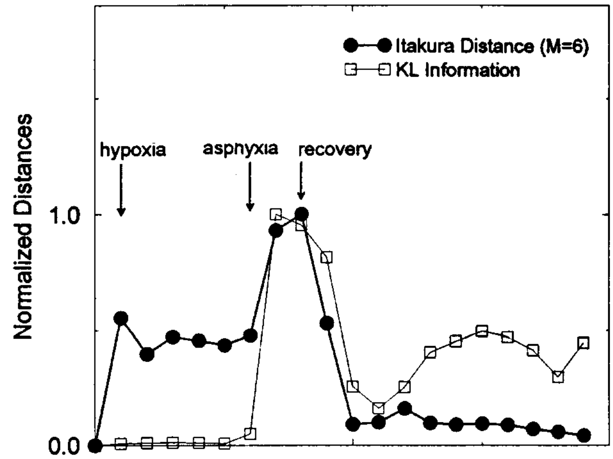

Figure 4: Comparison between KL information and Itakura distance measure. Arrow indicates the first data segment processed for that period.

covery progresses, the Itakura distance between current EEG and normal EEG gradually approaches zero. This coincides with the fact that the animal recovered from the injury based on follow-up observations.

Using Akaike information criterion[8], the optimum AR model order is found to be $M = 6$ for the reference EEG. Itakura distance with $M = 6$ is used in the following comparison study. Figure 3 compares the Itakura distance and the spectral distance measure of various norms ($p = 1$ and 2). Finally, both Itakura distance and KL information are plotted in Figure 4 as a function of different stages of experiment.

5. CONCLUSIONS

From the data analysis results we conclude that the Itakura distance responds reliably to the changes of the neurological system due to injury. It can also distinguishes the two types of insults to the brain (hypoxia/asphyxia) under study. Spectral distance measure is effective in signaling changes in EEG due to injury but the ambiguity is greater in distinguishing hypoxia and asphyxia. The KL information is not very sensitive to hypoxia but it responds quickly to asphyxia. Overall, we determine that the Itakura distance measure is an effective indicator of the neurological system condition. Development of this type of tool may be very useful in monitoring patients in operation room or intensive care unit.

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