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Wavelet Entropy for Subband Segmentation of EEG During Injury and Recovery

HASAN A. AL-NASHASH,[1] JOSEPH S. PAUL,[2] WENDY C. ZIAI,[3] DANIEL F. HANLEY,[3] and NITISH V. THAKOR[2]

[1]School of Engineering, American University of Sharjah, Sharjah, United Arab Emirates; [2]Department of Biomedical Engineering, Johns Hopkins University School of Medicine, Baltimore, MD; and [3]Department of Neurology, Department of Anesthesiology, and Department of Critical Care Medicine, Johns Hopkins University School of Medicine, Baltimore, MD

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Abstract—In this paper, subband wavelet entropy (SWE) is used for the segmentation of electroencephalographic signals (EEG) recorded during injury and recovery following global cerebral ischemia. Wavelet analysis is used to decompose the EEG into standard clinical subbands followed by computation of the Shannon entropy. The EEG was measured from rodent brains in a controlled experimental brain injury model by hypoxic-ischemic cardiac arrest. Results show that while the relative EEG power failed to reveal the order of bursting activity associated with recovery, SWE was used to segment the EEG and delineate the initial bursting periods in each subband. Based on entropy variations obtained from a cohort of animals with graded levels of hypoxic-ischemic cardiac arrest, an intermittent pattern of bursting was observed in the high frequency bands. © *2003 Biomedical Engineering Society.*
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Keywords—Subband segmentation, Wavelet entropy, Burst patterns.

INTRODUCTION

The electroencephalograph (EEG) is a potential tool for the identification of cerebral injury and management of patients with neurological trauma in critical care units. EEG studies of cerebrovascular disease have mainly focused on the determinants of cerebral ischemia.[11,15,23] A sensitive and reliable way to study the effects of cerebral ischemia is to measure a combination of both power and frequency parameters,[11] although subtle changes caused by cerebral ischemia are best detected by measuring the peak and mean frequency of the alpha rhythm.[13,18,22] In patients with a nondisabling stroke, the peak frequency of the alpha rhythm appears to be decreased in the affected hemisphere and reveals significant variations in the complexity. In the present investigation of rodent models subject to a global ischemia, we have observed similar changes in the alpha rhythm patterns during the recovery period. Thus, in these circumstances, it would be useful to have *a priori* information about the changes in structural complexity of these rhythms.[16] Determination of relative changes in the subband entropy of each individual EEG frequency band would, therefore, be a clinically significant problem.

The monitoring of cerebral injury presently involves eyeballing long stretches of EEG. Previous research in this direction was mostly carried out using signatures of power and frequency.[5] One of the recent approaches to segmentation of EEG based on power and frequency uses a nonlinear energy operator.[1,2] In this method, the segmentation is performed in time domain and describes the dual variations in power and frequency over time. However, in situations where segmentation has to be performed in each frequency band, the above technique cannot be applied. For example, in models related to brain injury, it has been shown that the recovery of brain rhythms occurs in a highly selective fashion. The low frequency bands have been shown to recover faster than the higher frequency bands.[9] In this situation, it becomes important to monitor and quantify the variations within each clinical frequency band. Further, segmentation of EEG within each band helps to understand their relative role during recovery and may be used to predict the neurological outcome.

An important observation related to the process of neurological recovery is the presence of burst suppression pattern manifested in the EEG following global ischemic brain injury. Sherman *et al.*,[8,14,20] recently reported a high degree of bursting during the early period after injury was associated with a good neurological outcome. A typical bursting EEG is shown in Fig. 1. The idea of characterizing bursting EEG using subband wavelet entropy is to characterize the interactions and the sporadic nature of switching of the EEG microstates between the two distinguished phases of bursting and background rhythms. Though background rhythms are oscillatory, their amplitudes are often dictated by a nonstationary random process. Since the statistical distributions associated with bursting and accompanying background activity within each clinical band are time

Address correspondence to Professor N. V. Thakor, Department of Biomedical Engineering, 701, Traylor Building, 720 Rutland Avenue, Baltimore MD 21205. Electronic mail: nthakor@bme.jhu.edu

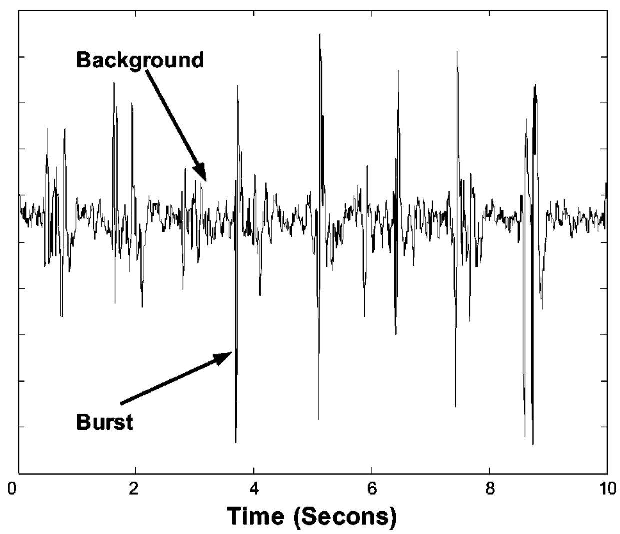

FIGURE 1. An EEG signal containing background and bursting activities.

varying, the entropy measure should be defined using a time-frequency formulation.[7,24] Using a time frequency description as described by the wavelet coefficients,[6,21] we anticipate that the high frequency bursting episodes are represented by the low entropy wavelet coefficients as opposed to the high entropy of the background oscillatory rhythms. Entropy is defined as a measure of uncertainty of information in a statistical description of a system.[10] If the frequency band is manifested as a peak then it has low entropy while if it is broadband then it has high entropy. Due to the combined presence of bursts and background activity, the signature used for segmentation should characterize the variations of entropy in each band as reflecting the sporadic nature of switching of the EEG microstates between bursting and rhythmic activities.

In this paper, we present a novel approach to segmentation of the fine changes in the subband EEG measured during the period of recovery following a short instance of cerebral injury created using hypoxic/asphyxic cardiac arrest in a rodent model. Distinct types of bursts have in general different types of frequency localizations and that the time-varying energies may be tracked by observing the temporal variations of the squares of the wavelet coefficients.

The wavelet transform is also useful for progressively and systematically ''decomposing'' the EEG into multiscaled components. For EEG sampled at 250 Hz, a five-level decomposition results in a good match to the standard clinical bands of interest.[17] There are no strict guidelines being followed as to the exact subdivision of the clinical bands. However, we follow the dyadic frequency scales that are closest to the standard definition of the clinical bands. Thus for the present discussion, the closest definition of the clinical bands are: gamma (31.2–62.5 Hz), beta (15.6–31.2 Hz), alpha (7.8–15.6 Hz), theta (3.9–7.8 Hz), and delta (1.9–3.9 Hz). In this paper, the entropy defined using the wavelet coefficients, referred to as subband wavelet entropy (SWE) is, hence, used for the segmentation of the different subbands of the EEG following injury.

THEORY

The entropy of a random variable reflects the degree of disorder that the variable possesses. The more uncertain the variable is, the greater its entropy. Entropy, H for discrete random variable X is defined as[3,4,10]

$$H(X) = -\sum_{i} P(X=a_i)\log P(X=a_i), \qquad (1)$$

where a_i are the possible values of X. The entropy is always greater than zero. The conventional definition of entropy (the Shannon entropy) is described in terms of the temporal distribution of signal energy in a given time window. The distribution of energy in a specified number of data values intervals is described in terms of the probabilities in signal space $\{p_i\}$ where p_i is the probability that $X = a_i$.

An efficient estimator for the density function usually requires either several samples of the process or strong assumptions about the process. To account for the nonstationarities in the EEG following resuscitation and gradual recovery, we consider the time–frequency distribution for the definition of entropy. In this approach, the probability density function is replaced by the coefficients of a given time–frequency representation (TFR) of the signal.[7,19,24]

The time–frequency representation based on Fourier analysis suffers from a significant problem because the spectral selection concept is based on a sinusoidal representation, which has an infinite extent in the basis function. As a result, activity with sharp variations in amplitude, phase and frequency such as the burst activities present in the EEG after injury cannot be well resolved. The transient features of the bursting activity are optimally represented using a continuous type wavelet transform. However, since we restrict the frequency levels to the discrete frequency bands of clinical interest, we resort to a simpler way of estimating the wavelet coefficients using a five level decomposition using the standard discrete wavelet transform. We used biorthogonal splines wavelets, for the purpose of matching the morphological features of the bursts in the presence of background oscillations.

It was found empirically that biorthogonal wavelet with order *(6,8)* resulted in the least oscillations at the coarse levels due to spiking. Furthermore, higher orders did not improve the accuracy of the filtered wave forms.

The wavelet decomposition for a given EEG signal $s(t)$ is obtained as

$$s(t)=\sum_{k=-\infty}^{\infty} a_N(k)\phi(2^{-N}t-k)+\sum_{j=1}^{N}\sum_{k=-\infty}^{\infty} C_j(k) \times\psi(2^{-j}t-k), \tag{2}$$

where $C_1(k),\ C_2(k),\ldots,C_N(k)$ are the wavelet coefficients and the sequence $\{a_N(k)\}$ represent the coarser resolution signal at resolution level N. Since $s(t)$ can be assumed to be zero mean and N is large, then the a_N term is nearly zero. Each subband contains the information of the signal $s(t)$ corresponding to the frequencies $2^{j-1}gq_s'\le|\omega'|\le 2^j\omega_s'$. The subband wavelet entropy is now defined in terms of the relative wavelet energy (RWE) of the wavelet coefficients.[17] Defining the energy at each resolution level $j=1,\ldots,N$, using the wavelet coefficients estimated for an EEG segment within a sliding temporal window with index n as

$$E_{n,j}=\sum_k |C_{n,j}(k)|^2, \tag{3}$$

the total energy of the wavelet coefficients will then be given by

$$E_{n,\text{total}}=\sum_j E_{n,j}. \tag{4}$$

Then, the normalized values, which represent the RWE are expressed as

$$p_{n,j}=E_{n,j}/E_{n,\text{total}}. \tag{5}$$

Since, for each time window n, $\Sigma_j p_{n,j}=1$, the subband wavelet entropy is defined using the probability distribution associated with the scale level j as

$$H(n)=-\sum_j p_{n,j}\log p_{n,j}. \tag{6}$$

METHODS

Protocol

The Animal Care and Use Committee of the Johns Hopkins Medical Institutions approved the experimental protocol used in this study. The asphyxic cardiac arrest and resuscitation protocol was performed as modified from Katz and colleagues.[12] Long-term EEG was recorded from awake behaving rats after being subjected to controlled periods of asphyxia and cardiac arrest. After preparation, the rats were anesthetized with Halothane and secured to a stereotaxic frame. Five small (2 mm diam) depressions were drilled in the skull. Electrodes were screwed into the depressions and cemented in place using cranioplastic grip cement. The asphyxia protocol was initiated by a period of anesthetic washout. Immediately after the 5 min anesthetic washout period, asphyxia was induced by stopping the ventilator and clamping the ventilator tubes for a controlled duration. After the airway obstruction period, resuscitation was initiated by resuming mechanical ventilation at 100% O_2 at 90 breaths/min and performing cardiopulmonary resuscitation (CPR). When a spontaneous mean arterial blood pressure (MABP) was more than 50 mm Hg and return of spontaneous circulation (ROSC) was achieved, then CPR was stopped. After 1 h of recovery, rats were extubated and allowed to breathe spontaneously.

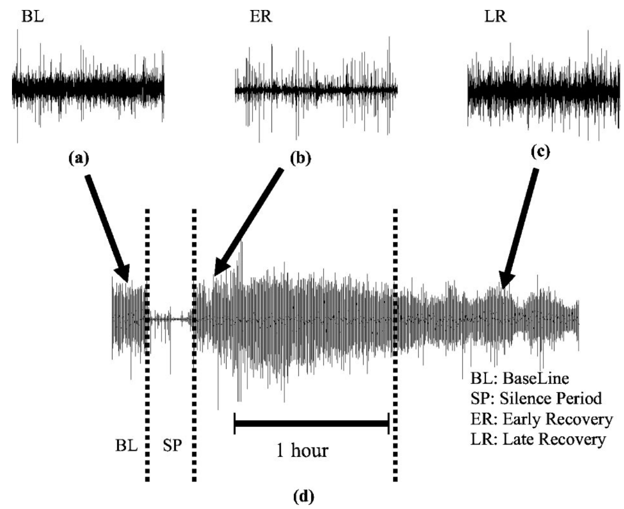

FIGURE 2. d) EEG signal record for a period of 200 min covering base line, asphyxia, and the evolving period. Figures in the inset represent typical EEG segments: (a) prior to injury (BL), (b) during early (ER), and (c) late periods of recovery (LR).

Data Collection and Preprocessing

The EEGs were recorded from two differential channels from the left and right frontoparietal regions of the rat's brain. Each channel was sampled at a frequency of 250 Hz using a 12 bit A/D converter. The signal was lowpass filtered at 100 Hz cutoff frequency prior to digitization. Figure 2 shows the EEG signal recorded for a period of 200 min. The EEG recording is divided in three parts: before asphyxia (base line), asphyxia, and evolving recovery period (the period when the EEG reaches 70% of the base-line amplitude). The division of the evolving EEG into subphases is related to the neurological outcome of the experiment.[12] The figures in the inset represent typical base-line (BL) EEG segments prior to injury, during early and late periods of recovery (ER, LR). The ER period is generally characterized by a very high level of burst or burst suppression activity while the LR period is characterized by general restoration of a continuous rhythm.

Computation of SWE

To compute the subband wavelet entropy of an EEG signal, it is first divided into windows each of 1 min duration. For each of these windows, the five-level wavelet decomposition is computed using the standard wavelet toolbox in MATLAB. The energy of each wavelet resolution is then calculated followed by calculating the total energy of the wavelet coefficients at all resolutions using Eq. (4). The relative wavelet energy is determined for each resolution according to Eq. (5), and finally, the entropy of each resolution level is computed using Eq. (6). The entropy values are smoothed using a median filter before displaying the subband entropy in the form of a ''checkerboard'' plot of gray levels. Each cell in the plot has a gray level resulting from bilinear interpolation of the neighboring four values of entropy. The smallest and largest elements of the resulting vector of entropy values are assigned the 0 and 1 values of the gray levels, respectively.

EXPERIMENTAL RESULTS AND DISCUSSION

A total of three EEG data records were segmented using the proposed method. The data records represent EEGs recorded using our experimental model for 3, 5, and 7 min asphyxia. Figures 3, 4, and 5 show the normalized gray level segments obtained using the SWE for the 3, 5, and 7 min asphyxic cardiac arrest, respectively. A gray level display has been developed to describe the entropy trends throughout the experiment. Black and white represents the lowest and the highest levels of entropy, respectively. The weight given to each gray level is as shown in the respective gray level bars. The injury and silence periods are represented by black. The recovery in different bands is judged by comparing the closeness between the gray level of the base line and the different phases of recovery. For the 3 min case, it is evident that the entropy in each band has reached a high value in about 10 min and it oscillates about this value during the acute stage of recovery. The oscillations between high and low values of entropy invariably points out the transitions between bursting and background activity. Bursting EEG has a relatively low value of entropy and background activity is characterized by relatively high values of entropy. The delta and theta bands recovered completely after resuscitation followed by intermittent periods of bursting in the presence of a strong

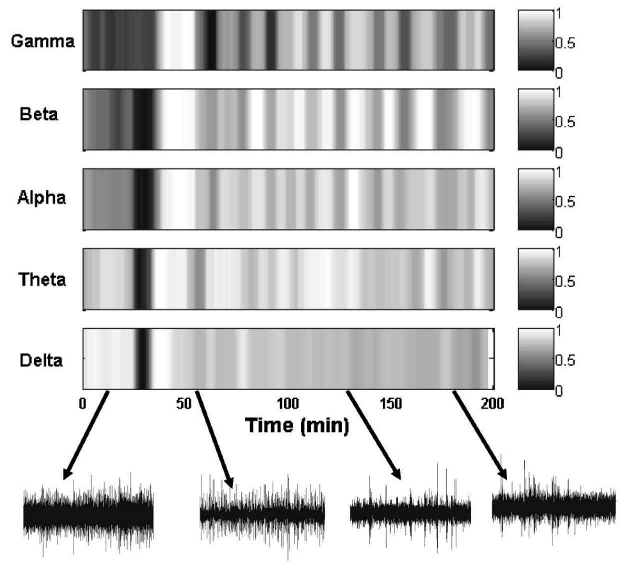

FIGURE 3. Normalized gray level segments based on SWE for the 3 min asphyxia. The weight given to each gray level is as shown in the respective gray level bars. The injury and silence periods are represented by black.

background rhythm. For the alpha band, the recovery was initiated by periodic bursting in the presence of a relatively weaker background rhythm. In contrast, the Beta and gamma bands revealed a highly varying structure. The neurological deficit scoring assessed for this animal after 6 and 24 h indicated a good outcome.[8] For the 5 min case, the entropy in each band exhibited a different gradation of recovery pattern as shown in Fig. 4. The delta band recovered within the first 10 min. The theta band took a little longer but again achieved a quick

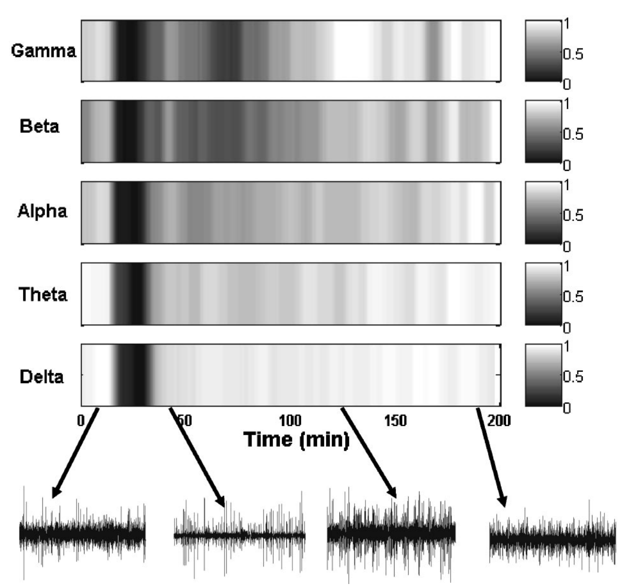

FIGURE 4. Normalized gray level segments based on SWE for the 5 min asphyxia.

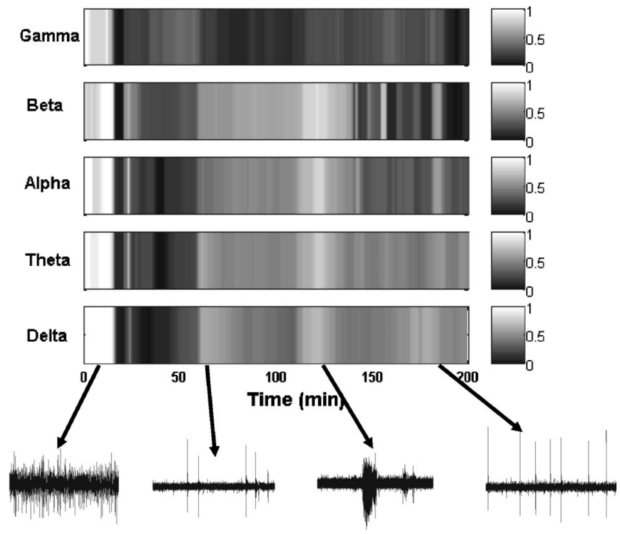

FIGURE 5. Normalized gray level segments based on SWE for the 7 min asphyxia.

recovery. In the alpha, beta and gamma bands, graded patterns of recovery were noticed. The neurological deficit scoring for this animal after 6 and 24 h also indicated a good outcome. In the 7 min case, the high level of entropy only appeared for a short period of time, almost after 2 hours as shown in Fig. 5. There were no graded and varying patterns of recovery similar to those noticed in the 3 and 5 min cases. In all the bands, there was a long period of silence lasting for 40 min, followed by sporadic (less frequent) episodes of bursting. The bursting activity was mainly present in all bands except for the gamma. A transient bursting pattern was observed in the beta, alpha, theta, and delta bands at 90 min after resuscitation. The entropy levels dropped drastically in the alpha, beta, and gamma bands following the short episode of transient bursting. The neurological deficit scoring performed at 6 and 24 h signaled a bad outcome.

From the above observations, it is clear that the early bursting activity associated with graded and varying entropy reaching levels close to the baseline during the first 90 min postresuscitation indicated a good outcome. This finding is in accordance with the observations made by Sherman *et al.*[20] Further, increase in SWE of low frequency bands was observed in both the 3 and 5 min cases. However, the early increase in SWE of high frequency bands indicated a good outcome. The varying structure of the coded patterns in each band reflected the variations in the order of bursting activity. In all the cases, such patterns were observed in the high frequency bands. The large variations in the order of bursting in the high frequency bands were also indicative of a good outcome and are in agreement with the observations made by other researchers.[14,20] The coded segments provide detailed information about the various phases of recovery.

To obtain a summary of the recovery trend using the SWE, we estimated the mean with 95% confidence level of the normalized entropy over consecutive segments of 1 h duration following resuscitation. For the three segments, the mean entropy values are summarized in Table 1. Maximum variance in SWE was observed in the gamma and beta bands during the early recovery period. It was noticed that for the 3 min animal, all bands revealed normalized entropy values higher than 0.7 ± 0.07

TABLE 1. Mean normalized entropy over segments of 1 h duration following resuscitation after 3, 5, and 7 min asphyxic cardiac arrest. ROSC: Return of spontaneous circulation.

Frequency band	Duration of asphyxia arrest (min)	Segment 1 (1 h post-ROSC)	Segment 2 (2 h post-ROSC)	Segment 3 (3 h post-ROSC)
Gamma	3	0.74±0.07	0.77±0.05	0.75±0.04
	5	0.45±0.04	0.75±0.03	0.76±0.03
	7	0.30±0.03	0.29±0.02	0.34±0.02
Beta	3	0.82±0.05	0.82±0.04	0.80±0.05
	5	0.48±0.03	0.68±0.03	0.74±0.03
	7	0.42±0.03	0.59±0.03	0.30±0.05
Alpha	3	0.86±0.03	0.84±0.03	0.82±0.03
	5	0.63±0.02	0.74±0.02	0.81±0.02
	7	0.35±0.04	0.53±0.04	0.36±0.03
Theta	3	0.82±0.02	0.84±0.02	0.80±0.02
	5	0.75±0.02	0.80±0.02	0.87±0.02
	7	0.40±0.05	0.57±0.03	0.49±0.02
Delta	3	0.84±0.02	0.84±0.02	0.80±0.02
	5	0.87±0.01	0.88±0.01	0.92±0.01
	7	0.42±0.05	0.50±0.03	0.52±0.02

in all segments. For the 7 min animal, all bands revealed normalized entropy values less than 0.6 ± 0.07 in all segments. Hence, we suggest the normalized entropy value of 0.65 ± 0.07 be used as a rule of thumb for global segmentation (see, also, Ref. 7).

CONCLUSION

In this paper, SWE was used to segment the EEG recorded during global hypoxic-ischemic injury and subsequent recovery stages. Wavelet decomposition was used to segment the EEG into standard clinical bands. The entropy of the wavelet coefficients in each level of decomposition reflects the underlying statistics and the degree of bursting activity associated with the recovery phenomenon. While segmentation based on power did not reveal the varying degrees of bursting activities, the gray level segmentation based on SWE was able to give additional information related to the frequency of the localized background activity and bursting. Results obtained from our injury model indicate that the phases of recovery as shown by SWE based segmentation conform to previous observations of the interrelationships between the nature and frequency of bursting activities and the outcome of the animal. The graded patterns of SWE reflect the background activity and the banded structure in the segmentation is indicative of the frequency of bursting present in different phases of recovery. Based on our observations of the entropy variations obtained from different levels of injury, the normalized mean entropy of 0.65 ± 0.07 was used to segment the recovering EEG.

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