30th Annual International IEEE EMBS Conference
Vancouver, British Columbia, Canada, August 20-24, 2008

Monitoring of Global Cerebral Ischemia Using Instantaneous Phase Variation Plots

A. S. Elwakil, H. Al-Nashash** and N. V. Thakor***

* Dept. of Electrical & Computer Engineering, University of Sharjah, UAE (email: elwakil@ieee.org)

** College of Engineering, American University of Sharjah, UAE

*** Dept. of Biomedical Eng., Johns Hopkins School of Medicine, Baltimore MD 21215

Abstract— **In this paper, the derivative of the instantaneous phase of electroencephalographic (EEG) signals is used as a basis for monitoring of global cerebral ischemia. Visual and quantitative results were obtained from six rodents that were subject to 3, 5 and 7 minutes of global ischemic brain injury by asphyxic cardiac arrest. Results show that the variations in the instantaneous phase are capable of amplifying the variations during the various stages of the recovery process and may serve as a novel analytical approach to grade and classify brain rhythms during global ischemic brain injury and recovery.**

I. INTRODUCTION

Accurate detection and quantification of brain injury severity and progression in cardiac arrest (CA) victims can provide an enormous improvement in objective assessment of therapeutic methods [1]-[6]. The EEG is a standard clinical tool for the recognition of cerebral injury. Quantitative EEG analysis methods are of great value to neurologists in guiding therapy. These methods include the Fourier transform, the wavelet transform, entropy and subband wavelet entropy methods [7]-[10]. Wavelet analysis was previously used to decompose the EEG into standard clinical subbands followed by computation of the Shannon entropy [11]. The method used for segmentation of EEG during different recovery periods relied on the variations of entropy in each band.

On the other hand, several analysis techniques based on chaos theory have been introduced in the literature [12]-[14]. These techniques exploit the inherent determinism of chaos generating engines assuming that an EEG signal can be treated as high-dimensional chaotic signal. Most of these techniques rely on quantified measures such as Lyapunov exponents, fractal dimension and recurrence which are derived from the EEG data.

Some time ago, a few articles have pointed out the relationship between chaos and phase turbulence [15], [16]. In particular, it was conjectured in [15] that "the fluctuations of the phase from that of a uniform rotation are a fractional Brownian-type of random process" and that "the fractional Brownian-type random phase dynamics are general". This direction of thought inspires us to investigate the phase dynamics of an EEG signal, derived from the recorded data samples using the Instantaneous Phase function, as explained below.

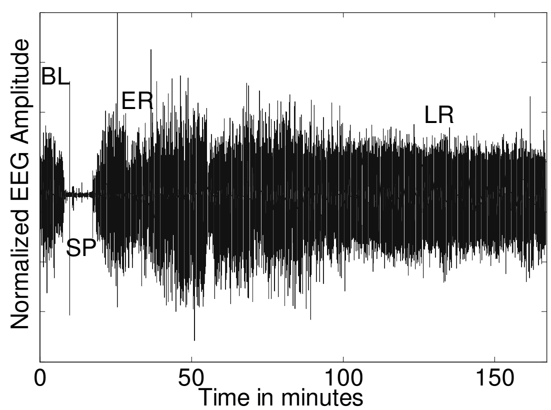


Figure 1: Highly compressed EEG signal record for a period of 167 minutes. The EEG recording is divided in four parts: Base line (BL), Silent period (SP) following arrest and resuscitation, Early recovery (ER), and Late recovery (LR) .

II. BACKGROUND

A. Data

The EEG signals used in this work were recorded from rats after being subjected to controlled periods of asphyxic cardiac arrest and resuscitation protocol [17]. The electrodes were screwed in place after the rats were anesthetized with Halothane. The asphyxic cardiac arrest was initiated with a 5-minute anesthetic washout period. Asphyxia was first induced by stopping the ventilator and clamping the ventilator tubes for controlled time duration. Resuscitation was initiated by resuming mechanical ventilation of 100% O_2 at 90 breaths/minute and performing Cardio Pulmonary Resuscitation (CPR). After one hour of recovery, the rats were extubated and allowed to breathe normally. The EEG signals were recorded using two differential channels from the left and right fronto-parietal regions of the rats' brains [11]. The signals were lowpass filtered with 100Hz cut-off frequency prior to sampling at 250 samples per second and digitization using a 12bit A/D converter. Figure 1 shows 167 minutes of an EEG signal recorded following 5 minutes asphyxic cardiac arrest injury. The EEG recording is divided into four parts: before asphyxic arrest (BaseLine, BL), asphyxic cardiac arrest (Silence Period, SP), Early Recovery (ER) and Late Recovery (LR) periods. The division of the evolving EEG into sub-phases is related to the neurological outcome of the experiment.

B. Instantaneous Phase

Given a scalar data set $x(t)$ and applying the Hilbert transform, a vector $\tilde{x}(t)$ is obtained and is given by

$$\tilde{x}(t) = \frac{a}{\pi} \int_{-\infty}^{\infty} \frac{x(t^{'})}{t - t^{'}} dt^{'} \tag{1}$$

where a is the Cauchy principal value for the integral. The complex signal

$$\chi(t) = x(t) + j\tilde{x}(t) = A(t)e^{j\phi(t)} \tag{2}$$

is obtained where the instantaneous phase is $\phi(t)$. It was shown in [15] that $\phi(t)$ can be generally written as

$$\phi(t) = \omega t + F(A(t)) \tag{3}$$

where $F(\cdot)$ is some nonlinear amplitude to phase transformation function. For a chaotic or random signal, $A(t)$ and hence $F(A(t))$ are chaotic or random and it is conjectured that the distribution of $F(A(t))$ is fractional Brownian-type.

In this work, we follow up in this direction and indeed show that the distribution of the instantaneous phase in various segments of the EEG recorded signal is best captured through Gaussian distribution functions. Since $\phi(t)$ is a smooth monotonically increasing function (due to the linear time dependent term ωt), the derivative $d\phi(t)/dt$ can be used to show the phase variations only. In particular,

$$d\phi(t)/dt = \omega + dF(A(t))/dt \tag{4}$$

constitutes a fixed angular rotation frequency (ω) modulated by a stochastic term $(dF(A(t))/dt)$. The DC term ω can be easily filtered out leaving only $dF(A(t))/dt$.

III. Proposed Technique

The data set used here consists of recordings following 3, 5 and 7 minutes asphyxic cardiac arrest injuries respectively (2 recordings for each case). The recorded data was then split into four segments corresponding to the BL, SP, ER and LR periods mentioned above; each segment 10^5 data points. For each segment, the instantanous phase $\phi(t)$ was computed. The upper trace of Fig. 2 shows a sample BL segment for one of the 5 minutes recordings; the corresponding $\phi(t)$ and $d\phi(t)/dt$ (3, 4) are shown respectively in the middle and lower traces of the same figure.

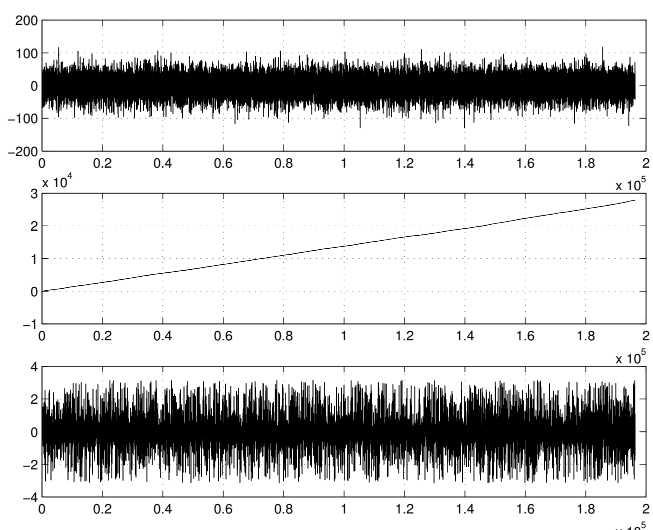


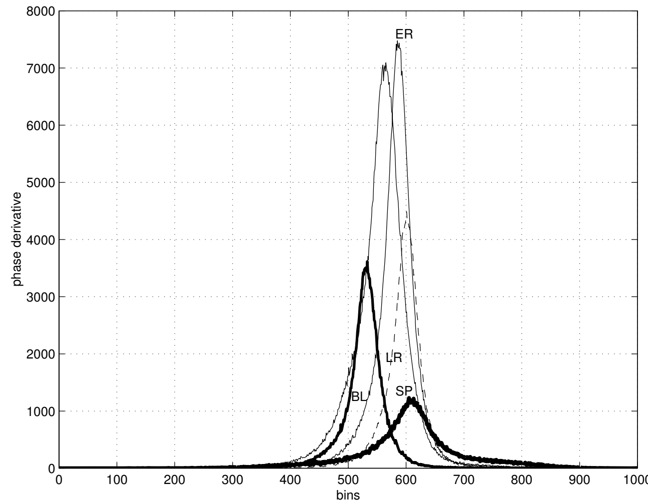
Figure 2: Sample EEG segment recording (upper trace), derived phase $\phi(t)$ (middle trace) and $d\phi(t)/dt$ (lower trace).

According to the conjecture of [15], the distribution of $d\phi(t)/dt$ should follow a random-like distribution. We have thus plotted the distribution of $d\phi(t)/dt$ for each recorded EEG during its different segments. Figure 3(a) shows the distribution for a 3-minute cardiac arrest while Fig. 3(b) shows the distribution following a 5-minute arrest. In each figure, the BL, SP and LR segments are marked. The distribution of the ER segment and a following segment of equal length is also marked (toral two ER plots). The following is noted from the figures:

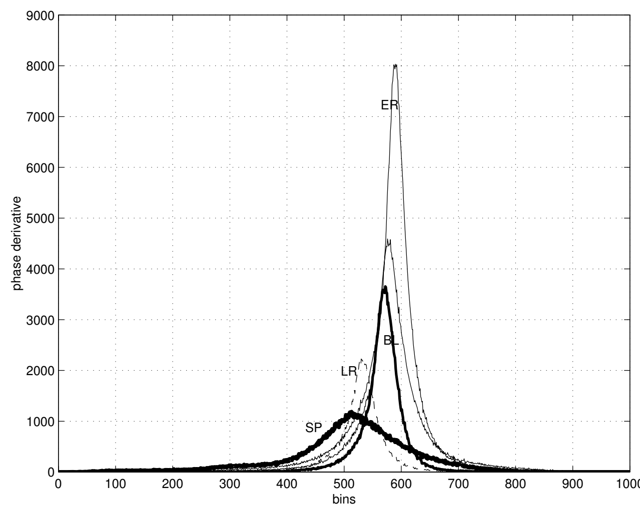
1) During the arrest period, the distribution of $d\phi(t)/dt$ has the lowest peaking with a clear flatness. Measuring the kurtosis of the distribution in this period indeed shows that it is very close to that of a random distribution with ideal kurtosis $= 3$. The SP plot of Fig. 3(a) has kurtosis $= 4.6169$ while that of Fig. 3(b) has kurtosis $= 4.8248$.
2) During the ER period, the distribution of $d\phi(t)/dt$ has the highest peaking, indicating the existence of severe and sharp phase changes during this period (spikes). As recovery goes on, the peaking of the distribution gradually lessens approaching that of the normal (BL) distribution at final recovery (LR).
3) The best fit curve for all distributions is based on Gaussian fitting of the form $f(x) = \sum_{i=1}^{i=n} a_i e^{-[(x-b_i)/c_i]^2}$. For all cases, 95% confidence in the fitting is obtained sufficiently with three terms; i.e. $n = 3$. For example, the values of the coefficients a_i, b_i and c_i for the 3-minute arrest are given in Table 1. Figure 4 shows the fitted curves during the SP period and LR period.

	(a_1, b_1, c_1)	(a_2, b_2, c_2)	(a_3, b_3, c_3)
BL	(1494,531,17.6)	(513,517,75)	(1518,533,34)
SP	(522.7,605,64)	(488,611,27.8)	(159,579,181)
LR	(2876,601,21)	(1027,614,32)	(774,572,30.3)

Table 1: Coefficients for the best fitting curves corresponding to Fig. 3(a) and shown in Fig. 4.



(a)



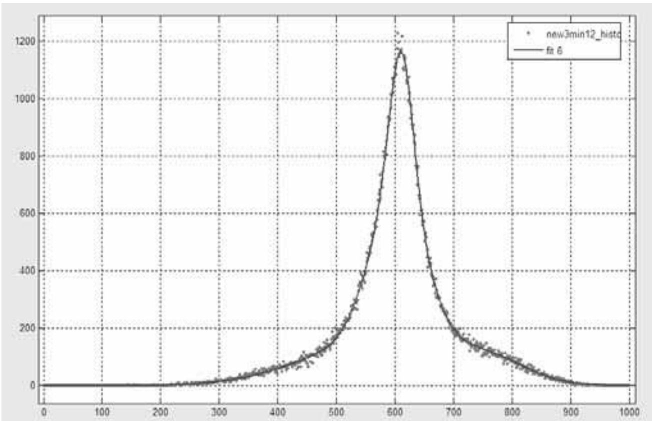
. (b)

Figure 3: Distribution of $d\phi(t)/dt$ for (a) 3-minute arrest and (b) 5-minute arrest.

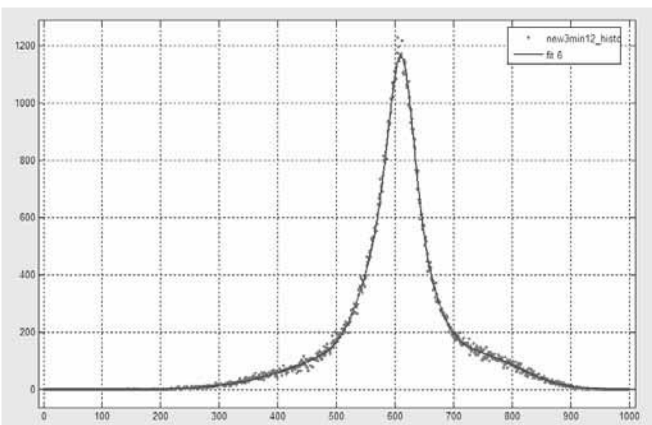
IV. CONCLUSION

We have shown that the distribution of the derivative of the instantaneous phase derived from a recorded EEG signal changes significantly during the different modes BL, SP, ER and LR.

The distribution is best fitted through a function of the form $f(x) = \sum_{i=1}^{i=n} a_i e^{-[(x-b_i)/c_i]^2}$ where the difference between modes lies in the coefficients a_i, b_i and c_i.



(a)



. (b)

Figure 4: Example curve fitting using Gaussian functions for $d\phi(t)/dt$ during (a) dead period and (b) final recovery.

REFERENCES

[1] P. Safar, "Mild resuscitative hypothermia and outcome after cardiopulmonary resuscitation," *J. Neurosurg. Anesthesiol.*, vol. 8, pp. 88-96, 1996.

[2] R. Thatcher, R. Walker, I. Greson, and F. Geisler, "EEG discrimination of mild head injury," *Electroencephalogr. Clin. Neurophysiol.*, vol. 73, pp. 94-106, 1989.

[3] M. Thiel and C. O'Connor, "Cardiopulmonary resuscitation: Historical perspective to recent investigations," *Amer. Heart J.*, vol. 137, pp. 39-48, 1999.

[4] I. Toner, K. Taylor, G. Lockwood, S. Newman, and P. Smith, "EEG changes during cardiopulmonary bypass surgery and postoperative neuropsychological deficit: The effect of bubble and membrane oxygenators," *Eur. J. Cardiothorac. Surg.*, vol. 11, pp. 312-319, 1997.

[5] D. L. Sherman, A. Bambrink, R. Ichord, V. Dasika, R. Koehler, R. Traystman, D. F. Hanley and N. V. Thakor, "Quantitative EEG during early recovery from hypoxic-ischemic injury in immature piglets: burst occurrence and duration", *Clinical Electroenceph.*, vol. 30, no. 4, pp. 175-183, 1999.

[6] Z. Xu-Sheng, R. Roy and E. Jensen, "EEG complexity as a measure of depth of anesthesia for patients," *IEEE Trans. Biomed.Eng.*, vol. 48, no. 12, pp. 1424-1433, 2001.

[7] V. Goel, A. Bambrink, A. Baykal, R. Koehler, D. Hanley and N. Thakor, "Dominant Frequency Analysis of EEG Reveals Brain's Response during Injury and Recovery," *IEEE Trans. Biomed. Eng.*, vol. 43, no. 11, pp. 1083-1092, 1996.

[8] E. Niedermeyer, D. Sherman, R. Geocadin, H. Hansen and D. Hanley, "The Burst-Suppression Electroencephalogram," *Clin. Electroenceph.*, vol. 30, no. 3, pp. 99-105, 1999.

[9] R. Geocadin, R. Ghodadra, T. Kimura, H. Lei, D. Sherman, D. Hanley and N. Thakor, "A Novel Quantitative EEG injury measure of global cerebral Ischemia", *Clinical Neurophysiol.*, vol. 111, pp. 1779-1787, 2000.

[10] O. Rosso, S. Blanco, J. Yordanova, V. Kolev, A. Figliola, M. Schurmann and E. Basar, "Wavelet Entropy: A new tool for analysis of short duration Brain Electrical signals," *J. of Neuroscience Methods*, vol. 105, pp. 65-75, 2001.

[11] H. Al-Nashash, J. Paul, W. Ziai, D. Hanley and N. Thakor, "Wavelet entropy for subband segmentation of EEG during injury and recovery," *Annals Biomed. Eng.*, vol. 31, pp. 653-658, 2003.

[12] W. J. Freeman, "Strange attractors that govern mammalian brain dynamics shown by trajectories of electroencephalographic (EEG) potential," *IEEE Trans. Circuits & Syst.-I*, vol. 35, pp. 781-783, 1988.

[13] L. Iasemidis, J. Sackellares and R. Savit, "Quantification of hidden time dependencies in the EEG within the framework of nonlinear dynamics", in *Nonlinear Dynamical Analysis of the EEG*, pp. 30-47, World Scientific, Singapore, 1993.

[14] J. Jaeseung, C. Jeong-Ho, S. Kim and H. Seol-Heui, "Nonlinear dynamical analysis of the EEG in patients with Alzheimer's disease and vascular dementia," *Clin. Neurophysiol.*, vol. 18, pp. 58-67, 2001.

[15] T. Yalcinkaya and Y. Lai, "Phase characterization of chaos," *Physical Review Letters*, vol. 79, pp. 3885-3888, 1997.

[16] M. Steyn-Ross, D. Steyn-Ross, J. Sleigh and D. Liley, "Theoretical electroencephalogram stationary spectrum for a white-noise-driven cortex: evidence for a general anesthetic-induced phase transition," *Phys. Rev. E* , vol. 60, pp. 7299-7311, 1999.

[17] L. Katz, U. Ebmeyer, P. Safar and A. Radovsky, "Outcome model of asphyxial cardiac arrest in rats," *J. Cereb. Blood Flow Metab.*, vol. 15, pp. 1032-1039, 1995.