Quantitative Brain Recovery Assessment Using EEG After Cardiac Arrest

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Abstract – This paper presents a study of measures that enable diagnosis of brain recovery after cardiac arrest by using subband-based Information Quantity (SIQ). By using Discrete Wavelet Transform (DWT) and Shannon Entropy (SE), brain signals after cardiac arrest are converted into quantitative IQ and this is put into subband-based IQ. By using IQ and SIQ, a comparison and analysis on correlation between measures suggested in this paper and Neural Deficit Score (NDS) is developed. This goes further by collecting the features in each subband and analyzing the changes in brain signals from the biological prospective. Experiment data is collected from 26 rats. Based on correlation between suggested measures and NDS, this study will allow early assessment of brain recovery after cardiac arrest. Furthermore, it is expected that proposed measures could be an assistant index of NDS.

Key words – ***BMI***; ***EEG***; ***IQ***; ***SIQ***; ***brain injury***

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1 Introduction

Sudden deaths (also called sudden cardiac deaths) occur within minutes after symptoms appear. Brain deaths and permanent deaths start to occur in just 4 to 6 minutes after someone experiences cardiac arrest. Cardiac arrest can be reversed if it is treated within a few minutes with an electric shock to the heart to restore a normal heartbeat. A victim's chances of survival are reduced by 7 to 10 percent with every minute that passes without Cardiopulmonary Resuscitation (CPR) and defibrillation. Few attempts at resuscitation succeed after 10 minutes[1-2].

To non-invasively monitor and predict critical brain injury after cardiac arrest, quantitative Electroencephalogram (EEG) analysis has developed and showed promising results. Most quantitative EEG measures are based on the hypothesis that information about brain injury and recovery is embedded in neurological activities, the EEG signals. The Time Dependent Entropy (TDE) measure has been used to study EEG during recovery from asphyxic cardiac arrest injury[3-8]. Also a quantitative metric called Information Quantity (IQ) has been introduced to measure the effects of temperature manipulation on brain recovery. As an alternative measure, Subband IQ (SIQ) has been developed to account for the behavior of the clinical EEG bands such as delta, theta, alpha, beta and gamma.

In this paper, by using very early EEG signals, quantitative EEG measures are proposed to monitor and predict the neurological recovery without baseline EEG information before cardiac arrest. The proposed measures are based on SIQ time evolution, which separately calculates the Shannon Entropy (SE) in five different EEG bands.

Finally, the subband-based study discoveres new features that have not been found in fullband-based studies. This work goes further by collecting the features in each subband and analyzing the changes in brain signals from a biological point of view[9-12].

2 Proposed measures

In this experiment, cardiac arrest is induced with asphyxia to the rats, and the EEG data recorded after CPR is defined into IQ by DWT and SE transformations. This paper compares the correlation between the suggested measures and NDS in subband-based EEGs and based on this outcome, the characteristics of each subband-based EEG is farther analyzed.

2.1 Information Quantity (IQ)

EEG signals as physical signals can be divided into predictable parts and uncertain parts. By using Wavelet Transform (WT) to divide signals into predictable parts and uncertain parts, the measure calculates the entropy from the uncertain parts. This measure is called Information Quantity (IQ). IQ is a

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measure defined in the existing paper, referring to the raw data converted into new information quantity by using DWT and SE.

$$IQ(n) = -\sum_{m=1}^{M} P_n^{wc}(m)\log_2 P_n^{wc}(m). \qquad (1)$$

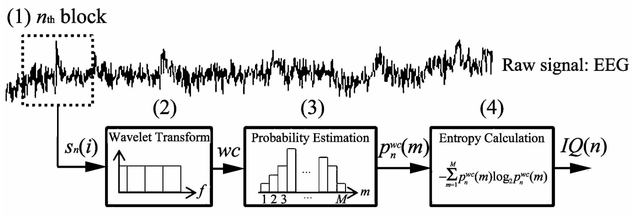

Fig. 1 Architecture of the IQ

2.2 Subband Information Quantity (SIQ)

Even though IQ is effective in analyzing EEG signals, there is a limit in examining characteristic of recovery in each subband-based EEG. SIQ refers to IQ in each subband EEG, or each subband IQ obtained from subband-based EEG which is extracted from raw data by using band-pass filter. The formula is as following, where k refers to subband frequency (delta, theta, alpha, beta, gamma)

$$SIQ(n) = -\sum_{m=1}^{M} p_n^{(wc)_k}(m)\log_2 P_n^{(wc)_k}(m). \qquad (2)$$

2.3 Measures

SIQ patterns during the recovery period after CPR (Cardiopulmonary Resuscitation) can be divided into 3 parts as shown in Fig. 2. IQ remains low after CPR during the Period 1, and IQ increases rapidly during the Period 2 (Fast Progression). At last, IQ remains high without any fluctuation in Period 3 (Slow Progression).

In order to extract the characteristics of SIQ the patterns, we set up 3 measures that distinguish 3 periods (Period 1~3), as shown in Fig. 2.

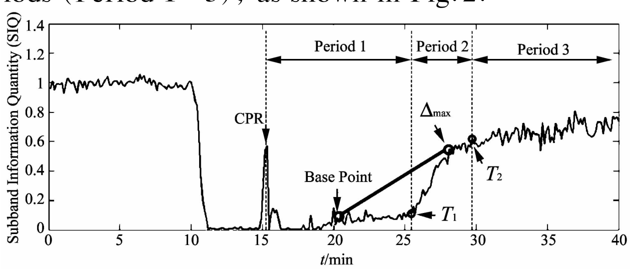

Fig. 2 Measures

First of all, T_1 is the point when the rat induced to cardiac arrest starts to revive after CPR, which bears biological significance in that the brain and the autonomic nervous system start to operate again. As shown in Fig. 2, T_2 refers to the point when the steeply increasing IQ starts to remain stable, or the start point of the steady-state period. Δ_{max} shows the point when the gradient of IQ reaches its maximum from its base point. Δ_{max}, as well as T_2, can be used as a criterion to show how rapidly the recovery is occurring.

μ_{IQ} is the mean value in period A ~ B after recovery, and similar to the method used in existing papers. How much the brain recovers can be analysed by comparing μ_{IQ} and the brain signal before cardiac arrest.

$$\mu_{IQ}(A,B) = \frac{1}{(B-A)}\sum_{t=A}^{B} IQ(t). \qquad (3)$$

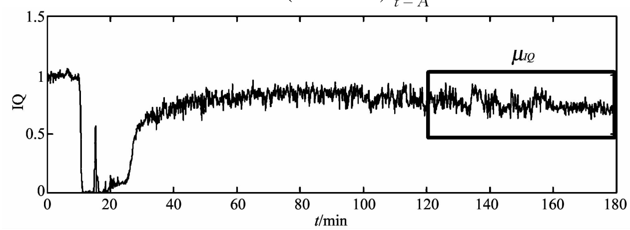

Fig. 3 Selection

T_1 is the point when the brain which temporarily stops working starts to work again as CPR revives the autonomic nervous system and the brain. This bears a great significance in regard to the purpose of this paper when the possibility of early diagnosis is examined. As given in Fig. 4, T_1 is the point when the amplitude and IQ start to increase in the time domain. T_1 can be put as follows by using the mean value of IQ in the $A_1 \sim B_1$ period around the base point and the mean value of IQ in the steady-state, $A_2 \sim B_2$. This value is derived from setting the CPR time to '0'.

$$T_1 = \arg_t\{\alpha\mu_{IQ}(A_2,B_2) + \beta\mu_{IQ}(A_1,B_1)\}$$
$$(\alpha + \beta = 1,\ \alpha < \beta). \qquad (4)$$

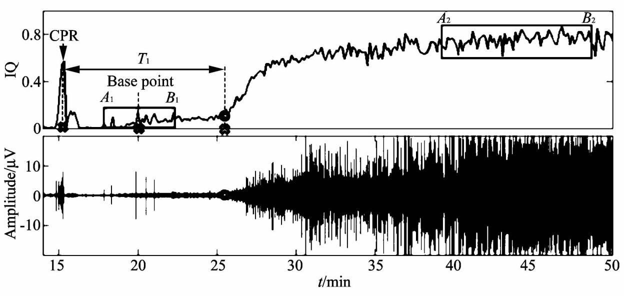

Fig. 4 Selection

T_2 corresponds to the point when the increasing rate of IQ diminishes after IQ shows a rapid increase right after T_1. Even though this does not exactly match the normal state in a biological sense, it still means that the recovery is in advance. T_2 can be put in the same formula as Formula 4, as long as each parameter is set up differently. Here α is put far higher than β so that T_2 approximates to the mean value of IQ in the steady-state. This is also calculated by setting CPR time into '0'.

$$T_2 = \arg_t\{\alpha\mu_{IQ}(A_2,B_2) + \beta\mu_{IQ}(A_1,B_1)\}$$
$$(\alpha + \beta = 1,\ \alpha > \beta). \qquad (5)$$

Δ_{max} presents the point of time when the gradient of the IQ, or $\Delta_s(t)$ is the highest after the base point.

$$\Delta_s(t) = \frac{IQ(t) - IQ(t_0)}{t - t_0}, \quad (6)$$

$$\Delta_{max} = \arg_t\{\max(\Delta_s(t))\}. \quad (7)$$

This Δ_{max} helps to measure how rapidly the recovery is in progress, which is derived from a hypothesis that the faster the rate of progress is, the shorter the time of Δ_{max} takes.

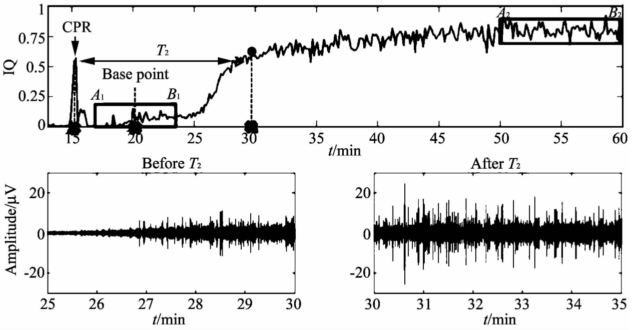

Fig. 5 Selection : The figure left below shows the raw data before T_2, while the one right below shows the change in the raw data afterwards

3 Experimental methods

By inducing rats into cardiac arrest with asphyxia, 26 samples of EEG data are obtained from the brain responses after CPR. Two channels of EEG using implanted screw electrodes (Plastics One, Roanoke, VA) in right and left parietal areas, one channel of ECG (subdermal electrode, Grass Instruments, Quincy, MA) and one channel of arterial pressure are recorded continuously before insult, during the insult and about 24 hours recovery. The signals are digitized using the data acquisition package CODAS (DATAQ Instruments INC., Akron, OH). Sampling frequency of 250 Hz and 12 bits A/D conversion are used. The experiment is conducted in two different ways. Firstly, by controlling the temperature of the test subjects during the recovery stage after cardiac arrest, the degrees of recovery in normothermia and hypothermia are compared. Secondly, CPR time is controlled after inducing cardiac arrest with asphyxia. In this respect, an analysis is developed regarding the differences in progression of recovery among the occurrences of CPR respectively, 5, 7 and 9 minutes after the cardiac arrest. Based on subband-based EEG, what suggested measures mean for the whole recovery process in correlation with NDS is examined.

4 Results

4.1 μ_{IQ}

Considering IQ in a period, where the progression reaches a certain point, μ_{IQ} can be referred to as an indirect measurement in assessing the degree of recovery. For the size of EEG data adopted in the experiment is 3 hours, the EEG data collected during the time period 120 min(A)~180 min(B) is used where the progression of recovery is the most rapid. 26 figures from EEG data are categorized into 3 groups by CPR time (5min, 7min, 9min).

As described in Tab. 1, the correlation coefficient of NDS in beta band is the highest (0.76). Considering that the measure uses the brain signals in full recovery of μ_{IQ}, especially in regard to the biological fact that the beta band is the most significant when the brain is active. This result can be very meaningful.

4.2 T_1 time

T_1 is the first measure suggested in this paper and has significance that it points to where the recovery starts. In T_1, the parameters in Formula 3 need to be specified. Tab. 1 demonstrates that there is a negative correlation between T_1 and NDS regarding 26 data, which means that NDS gets better when T_1 is faster.

T_1, or the point when the subject is just about to revive after CPR, figuratively in coma or in REM sleep(or deep sleep) can also be identified in Tab. 1. A very interesting outcome can be derived when the fact that the delta band (δ) and the theta band (θ) are the most dominant during the deep sleep stage is related to the high correlation coefficients of the delta band and the theta band, in contrast to μ_{IQ}.

4.3 T_2 time

T_2 is the base point of the steady-state stage after T_1. Even though T_1 and T_2 use basically the same parameters(Base point, A_1, B_1, A_2, B_2), α and β are set to 0.8 and 0.2 respectively in contrast to A_1, in order to set a similar level to averaged IQ between A_2 and B_2.

T_2 refers to the starting point of the steady-state stage, or the point where the change in T_2 time according to β starts to decrease ($\beta = 0.2$).

The correlation between T_2 and NDS allows to derive that the quicker the recovery takes, the bettes NDS gets. This is a good example that shows the necessity of subband-based analysis because this type of result cannot be obtained from the full-band. This table also results in an interesting finding that the correlation coefficient is the highest in the theta band. In the biological point of view, T_2 can be interpreted as a point when the subject is going through a recovery phase, not yet to a full degree. T_2 is compared to the light sleep stage, while T_1 can be compared to the deep sleep stage. This corresponds to the fact that the theta band dominates during the light sleep stage.

4.4 Δ_{max} time

Δ_{max} is the point when the gradient of IQ reaches its maximum since the base point (5 minutes after CPR) and can also serve as a measure like T_2 in accessing how fast the recovery occurs. Tab. 1 shows the scores of Δ_{max} .

4.5 $T_1 + T_2 + \Delta_{max}$

As above mentioned, T_1, T_2 and Δ_{max} have negative correlation with NDS. Assume that it will result in the same outcome when these measures are added up, is set up a new measure ($T_1 + T_2 + \Delta_{max}$).

Tab. 1 Correlation between measures and NDS

Measures	Full	δ	θ	α	β	γ
T_1	−0.51	−0.54	−0.58	−0.61	−0.52	0.42
T_2	−0.35	−0.44	−0.48	−0.45	−0.42	−0.10
Δ_{max}	−0.45	−0.42	−0.39	−0.40	−0.48	−0.61
$T_1 + T_2 + \Delta_{max}$	−0.46	−0.47	−0.49	−0.50	−0.47	−0.63

5 Conclusions

The delta band and theta band are dominant respectively during the REM sleep stage and light sleep stage. The alpha band is prominent when subject is taking a rest while the beta band is generated mainly in active phase. When the change in the brain signals after cardiac arrest, the measures suggested in this paper and NDS are taken together, the conclusion is reached: the correlation coefficient of delta band is the highest in T_1 because the brain is about to be active, or in coma or in deep sleep stage. Likewise, the correlation coefficient of the theta band is the highest in T_2 when the brain is about to wake, or in the light sleep stage. This is related to the fact that T_2 refers to the point where the recovery reaches 80% of the full degree, or when the subject starts to revive but not yet to be fully active. And also, the correlation coefficient of the beta band is the highest in μ_{IQ} because the brain returns to the normal condition and be active again. Even though the human brain signals, according to biorhythm, might not show exactly the same biological properties as that of rats', similar outcomes can be deducted on the basis of the subband-based EEG analysis.

This subband-based study of EEG after cardiac arrest until recovery discovers new features that have not been found in fullband-based studies, which testifies the necessity of further study based on subband analysis. This study also examines the possibility of early diagnosis which enables to infer the condition after the subject's recovery, by adopting EEG in the early stage after CPR. Furthermore, this study can allow using EEG as an assistant index of NDS as well.

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