Emotion-induced Higher Wavelet Entropy in the EEG with Depression during a Cognitive Task

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Abstract—This paper presents a study about how emotion influences cognition. We used wavelet entropy as a tool to analyze event-related electroencephalograph during a cognitive task. Emotion and cognition are two major aspects of human mental life that are widely regarded as distinct but interacting. However, the mechanism of this interacting is still not well known. In our study, a recognition task with facial stimuli was utilized in order to address the influence of emotion on working memory. Three expressions of each face (happy-positive, sad-negative, and neutral) were chosen for the experiments. Since depression is characterized as a typical mental disease with emotion processing deficits, sixteen patients with depression and sixteen normal controls were chosen to participate in the experiment. The repeated measure analysis of variance (ANOVA) revealed that the patients with depression had a significantly higher entropies than the normal control overall the brain regions. Although behavior results did not indicate any emotion effect, wavelet entropy told more about it. The emotion effect was found in the right anterior and right center of the brain by the analysis of entropy. We concluded that patients with depression showed much higher emotion-induced disorder than normal persons after about 300ms after stimulus onset. In methodology Wavelet entropy can help us to understand the interaction between emotion and cognition.

I. INTRODUCTION

I N the past two decades, a growing body of work has pointed to the interdependence or interaction between cognition and emotion. Depressed patients have been conceptualized as a disorder of emotion dysregulation, in other words, who have emotionally biased perceptual processing. And studies investigating the interaction of cognition and emotion have a long tradition in depression research [1]. However, the time course of this interaction is not well known. Event-related potentials (ERP)

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Jijun Wang is with the Laboratory of Neuro-electrophysiology, Shanghai Mental Health Center, Shanghai 200030 China (cocorresponding author to provide e-mail: oukeigun@yahoo.com.cn). measurements have been frequently utilized to investigate the information processing time courses due to its high temporal resolution of milliseconds. Some ERP studies showed that depressed patients have higher frontal amplitudes in the 250-500ms temporal range for negative valenced words. Other research found a negative emotion effect in the 110-150ms after stimulus onset. Unfortunately, there was no consistent conclusion about emotion-specific time course. New methods may give new view of the problem.

Classical ERP analysis focuses more on the amplitude and latency of the components. Recent years, event-related EEG analysis is drawing increasing attention from the researchers, which has been thought to provide more insights into the pathophysiological processes underlying cognitive deficits and clinical symptoms in neuropsychiatric disorders [2]. There are many methods in so-called event-related brain dynamics, one of which is entropy analysis.

The processing of information by the brain results in dynamical changes of its neuronal activities. After [3] introduced the method of wavelet entropy (WE) into ERP study, many researches have proved the robustness of the method. WE reflects the degree of order–disorder associated with a multi-frequency signal response [4]. The information obtained with the WE proved to be not trivially related to the energy and consequently to the amplitude of the signal.

In the present study, emotional faces were used as stimuli to study basic emotion cognition. The paper is organized into three sections. The materials and methods are introduced first. Results are described based on the materials and methods. Following the results, the discussions are presented to conclude the study.

II. MATERIALS AND METHODS

A. Participants

Sixteen human subjects diagnosed with depressive disorder (11 female, 5 male) and sixteen normal subjects (10 female, 6 male) with no history of psychiatric disorder participated in this study. All subjects had no personal neurological history, no drug or alcohol abuse, no current medication, and had normal or corrected-tonormal vision. Participants with depression were recruited from Shanghai Mental Health Center's psychiatric outpatient clinics according to CCMD-3 (Chinese Classification of Mental Disorders, Version 3) and the control subjects were students and workers there. All the subjects signed an informed consent according to the guidelines of the Human Research Ethics Committee at shanghai mental health center, and were paid for participation after the experiment.

B. Stimuli and procedure

The stimuli consisted of 36 photographs of human faces (18 female, 18 male) selected from a standardized set of stimuli [5]. Each face has positive, negative and neutral expressions, and no face contained hair, glasses, beard or other facial accessories. Additionally, photographs were all software-edited using Adobe Photoshop and converted to grey scale. The experiment had two blocks, each including 36(faces) ×2(repeated) =72 trials (half matched). Each trial had two faces (S1, S2). Since each face was presented twice and there were 2 blocks, 2(block) ×72(trial) ×2(for judge task) =286 stimuli in total were presented.

These stimuli were presented on a 17-inch LCD monitor. Subjects were seated at 80cm distance from the screen. They were instructed to sit quietly and to look at the cross in the centre of the screen. Each trial began with a fixation cross appearing alone for 1500ms in the center of the display. A face stimulus for study then appeared for 1s. After 500ms ISI (interstimulus interval), the second stimulus for recognition appeared for 2s, during which time participants responded. Another trial began after 1500ms ITI (intertrial interval) (see Fig.1). Two blocks were presented with a rest period of 1 minute in between blocks. All 286 stimuli order was randomized and with equal probability for each block. Each participant was informed about the experiment course before the trial. During the stimulus onset asynchrony (SOA), participants were asked to judge if S2 were the same as S1 as soon and accurate as possible by pressing buttons with their hands. If they found the identical stimuli, press '1' button, otherwise, press button '5'. When the participant pressed a selected response key, reaction time (RT) and correct response were stored. The whole experiment took about 15min for each subject. The experiment was run in an acoustically treated and electrically isolated room. Following the mounting of the electrode-cap the participants were seated in a comfortable reclining chair.

Prior to EEG testing, all participants took the Self-Rating Anxiety Scale (SAS) and Self-Rating Depression Scale (SDS) by themselves. Then the physician asked them some questions to complete the Hamilton Depression Scale (HAMD) and a simple scale include gender, age, years of education, marital and left/right-handed status.

C. EEG recording

The electroencephalogram (EEG) was recorded using a sixty-four-channel EEG system with 60 surface electrodes mounted in an electrode cap (electrode impedance <10 $k\Omega$, 0.05-100Hz band pass, 1000 samples/s). Vertical and horizontal EOGs were simultaneously recorded to monitor eyes movement and blinks. The data were referenced to one electrode placed on nose. The raw EEG data were pre-processed using Vision Analyzer 1.1(Brain Product, Germany) offline. Trials with ocular, saccades



Fig. 1. Sequence of events in a typical trial from the task

artifacts and artifacts $>\pm 100\mu V$ were rejected before exporting. Artifact-free data were then segmented ranging from -200ms before to 1000ms after stimulus onset for all conditions.

D. Wavelet Entropy

The wavelet analysis is a method which relies on the introduction of an appropriate basis and a characterization of the signal by the distribution of amplitude in the basis. The correlated decimated discrete wa6elet transform (DWT) provides a nonredundant representation of the signal and its values constitute the coefficients in a wavelet series. These wavelet coefficients provide full information in a simple way and a direct estimation of local energies at the different scales [6]. The wavelet expansion for a discrete time series S(t) of length M can be represented by a wavelet family $\psi_{i,k}(t)$ that is generated by dilations and translations of a unique admissible mother wavelet $\psi(t)$, and coefficient $C_i(t)$. The wavelet coefficients contain full information of the signal S(t) in a simple way and a direct estimation of local energies at the different scales. The number of $C_i(t)$ at each level is $N_i=2^iM.$

In the following, the signal was decomposed into scale levels by wavelet multi-resolution decomposition in accordance with the traditional frequency bands in EEG analysis, i.e., Band 1: 31.25–62.5Hz (gamma), Band 2: 15.63–31.25Hz (beta), Band 3: 7.81–15.63Hz (alpha), Band 4: 3.9–7.81Hz (theta), Band 5: 0.1–3.9Hz (delta). In the present work, the 'db5' mother wavelet which was better to reconstruct the original EEG signals from our prior study was employed with 7 levels decomposition.

The concept of energy is linked with the usual notions derived from the Fourier theory. Here, the energy at each resolution level j can be defined as

$$E_{j} = \left\| r_{j} \right\|^{2} = \sum_{k} \left| C_{j}(k) \right|^{2}$$
(1)

Then the normalized values p_j , which represent the relative wavelet energy, will be

$$p_j = \frac{E_j}{\sum_j E_j} E_j \tag{2}$$

So the total wavelet entropy (WE) was defined as

$$WE = -\sum_{j} P_{j} \ln P_{j} \tag{3}$$

The WE is a natural measure of the frequency stabilization of different EEG oscillations. Disordered (broad-band) signals had higher entropy than those corresponding to ordered (narrow-band) behaviors. For



Fig. 2. The demarcation of the 9 regions. The regions were leftanterior, medial-anterior, right-anterior, left-center, medial-center, right-center, left-posterior, medial-posterior and right-posterior.



Fig 3. The mean value of accuracy(%,the left one) and reaction time (ms, the right one) to three stimulus (positive, neutral and negative) in patients and normal controls .

instance, the WE of a periodic signal like sinusoidal wave will be 0; and the WE of a random signal will be almost 1. Therefore, the WE appears as a measure of the degree of order/disorder of the time series.

Moreover, when we focus on the time-evolution of brain signal, we could divide up a given signal and their corresponding wavelet coefficients series into nonoverlapping temporal windows of length L_w [4], and for each interval with *i* (*i*=1,2,..., *NT*) we evaluated the total wavelet entropy WE, indicated by windowed WE. The minimum length of the temporal window will be 128 (namely 128 ms in this paper) in order to get a meaningful wavelet coefficient in accordance with EEG rhythm [6]. Since then, we applied the WE to our EEG data with non-overlapping time windows of length L=128. We analyzed seven windows (128*7=896ms) in this study because we want to investigate the changing trends of entropy on facial emotion recognition.

Furthermore, we demarcated the 64 sites from where EEG was recorded to 9 regions, our analysis compared left, midline, and right clusters at anterior, center, and posterior regions (see Fig.2). The gray labeled sites were included in the statistical analysis.

E. Statistical analyses

Considering the accuracy in the task, we chose the data of matched task to analyze. For the primary analyses, repeated measures ANOVAs were performed with one between-subject factor, Group (control, depressed), and three within subjects factors: 3 Emotion (as stated above), 9 Regions (see also figure 2) and 7 Time (time windows). The simple effect analysis was followed if any interaction between factors was found. All analysis was conducted at the 0.05 level of significance.

III. RESULTS

A. Behavior results

We compared the response accuracy (ACC) and reaction time (RT) of two groups (see Fig.3). Only correct answers were included in the RT analysis. Group difference (F (1, 30) =3.737, P=0.063) were found in the ACC, but not in the RT. The ACC of depressed people is lower than that controls performed. There was no any significant effect of emotion in neither the ACC nor the RT (P>0.05).

B. Wavelet entropy topography

The repeated measures analysis of variance (ANOVA) revealed a main effect of group (F(1,30)=5.203,P=0.030), (F(2,60)=3.298, P=0.044), emotion Region (F(8,240)=9.259, P<0.001), Time (F(6,180)=86.899, P<0.001) and significant interaction of Group×Emotion (F(2,60)=6.002, P=0.004). Then, 2 group×3 emotion×7 time repeated measures ANOVA was performed to the 9 regions. The group differences between entropy of depressed patients and controls were significant in the right-center (F(1,30)=9.385, P=0.005), medial-posterior (F(1,30)=4.417,and right-posterior P=0.044) (F(1,30)=6.734, P=0.014) derivations. The entropy value in the patients was higher than that of the normal controls (see Fig.4). Furthermore, a main effect of emotion was found in the right-anterior (F(2,60)=3.959, P=0.024), right-center (F(2,60)=3.342, P=0.044) regions (see Fig.5) and there was significant interaction of Group×Emotion in the medial-anterior (F(2,60)=5.148, P=0.009), right-(F(2,60)=5.166,P=0.009), left-center anterior (F(2,60)=7.592,P=0.001) and medialcenter (F(2,60)=4.431, P=0.016) regions. The subsequent simple effect analyses identified that depressed participants had a significantly greater value of entropy to negative faces compared with normal controls in the right-center. Findings indicated that there were significant group differences under the positive emotion conditions in the anterior and center regions and depressed patients exhibited higher entropy value than healthy participants. To the normal controls, difference of emotion was significantly in the right-anterior (F (2, 30) = 4.67, P=0.013) and the entropy value to positive stimulus was greatest. While to the depressed people, this difference was significantly in anterior and center derivations. Both 'positive & neutral' and 'positive & negative' stimulus showed significant statistical difference. The mean value of positive stimuli was higher than other emotions. However, the difference between positive and negative stimuli was not significant.

We also analyzed the time effect among wavelet entropy in the cognition processing in the two groups. There was an overall decreased trend of entropy for all the subjects. From the 3rd time window (about after 256ms), this decrease became flat and the value had an upward trend (see Fig.6), especially in the results of depression. The change was significant for all the emotion stimuli and regions.

IV. CONCLUSION

This paper introduced the wavelet entropy analysis of emotion-induced EEG signals. The WE helped us to



Fig. 4. Topographical plots of mean entropy value in two groups



Fig. 5. Topographical plots of mean entropy value of three emotions in two groups

notice the interaction between emotion and cognition that behavior results could not tell.

In conclusion, we proved that 1) depression and normal controls had different WE during a recognition task with emotional faces; 2) WE is sensitive to the emotion influence on cognition; 3) WE could provide evidence for right-hemisphere disorganization in major depression.

According to our results and meanings of WE, human subjects with depression would mobilize more neurons to perform a cognitive task than normal persons, which found in our previous study [7]. Meanwhile, the effect of emotion on cognition could occur at about 250ms latency after stimulus onset.

Compared with the time course study, research of emotion-specific region gets consistent results. Many works suggest that the prefrontal cortex (PFC) is an important component of a circuit critical to emotion regulation. Researches proved that depressive patients revealed abnormal brain activities in PFC [1]. In this study, we also found similar higher entropy in the EEG with depression in prefrontal region. Moreover, we found an interesting entropy distribution while negative stimuli were shown in front of the depression group (see Fig.5), in PFC especially right side higher entropy. Right PFC is associated with withdrawn and depressive [8]. Therefore, we inferred that emotional cognitive activity could be characterized by WE. The WE proved right hemisphere disorganization in the depression.

REFERENCES

 J. Joormann, Cognitive aspects of depression. in: G.I.H.H.C. L., (Ed.), handbook of depression (second edition), Guilford Press, 2009, pp. 298-317.



Fig. 6. The group differences (normal/depression) on scalp distribution of nine regions in seven time windows.

[2] B.J. Roach, and D.H. Mathalon, "Event-related EEG time-frequency analysis: An overview of measures and an analysis of early gamma band phase locking in schizophrenia," *Schizophrenia Bulletin*, vol. 34, no. 5, pp. 907-926, Aug. 2008.

[3] R. Quian Quiroga, O.W. Sakowitz, E. Basar, and M. Schurmann, "Wavelet Transform in the analysis of the frequency composition of evoked potentials," *Brain Res Protoc*, vol. 8,no. 1,pp. 16-24, Aug. 2001.
[4] O.A. Rosso, "Entropy changes in brain function," *Int J*

Psychophysiol, vol. 64,no. 1,pp. 75-80, Apr. 2007.

[5] F.W. Ekman P, Pictures of Facial Affect, Consulting Psychologists Press, Palo Alto, CA, 1975.

[6] O.A. 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 Neurosci Methods*, vol.105,no. 1,pp. 65-75, 2001.

[7] Y.J. Li, S.B. Tong, D. Liu, Y. Gai, X.Y. Wang, J.J. Wang, Y.H. Qiu, and Y.S. Zhu, "Abnormal EEG complexity in patients with schizophrenia and depression," *Clinical Neurophysiology*, vol. 119, no. 6, pp. 1232-1241, Jun. 2008.

[8] R.J. Davidson, K.M. Putnam, and C.L. Larson, "Dysfunction in the neural circuitry of emotion regulation - A possible prelude to violence," *Science*, vol. 289, no. 5479,pp. 591-594,Jul. 2000.