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CHARACTERIZATION OF THE CHRONOBIOLOGICAL SIGNALS BASED ON THE CONTINUOUS WAVELET TRANSFORM

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Abstract — **Chronobiology, which studies periodic patterns or rhythms of the living beings, often needs to characterize the observed chronobiological time series (CTS) and to study the stability and adaptability of the periodic patterns in different environmental conditions. Fourier transform (FT) based methods and complex demodulation (CD) approach have been widely used in such study. However, the former lacks temporal resolution and the later needs to extract the temporal behaviors of individual frequencies. In this paper, we proposed a new approach to characterize the CTS based on the continuous wavelet transform (CWT). It allows us to investigate the time-frequency dynamics of different rhythmic-band activities in the CTS simultaneously. Two application results have been presented to illustrate the proposed method.**

Index Terms — **Continuous Wavelet Transform, Chronobiological Signals, Locomotion Activity.**

I. INTRODUCTION

In chronobiology study, it usually needs to characterize the behavioral and physiological changes over time. The chronobiological time series are complex signals, usually covering long duration with a broad range of periodic activities. Although the patterns of these periodic activities are relatively stable in normal conditions, they may exhibit some plasticity especially under varying experimental conditions. Regarding the temporal statistical characteristics, the CTS are non-stationary, thus, it is difficult to give accurate mathematical models to characterize the CTS. Nevertheless, in the past decades, a variety of approaches have been applied for the analysis of chronobiological signals. Fourier transform related methods [1-2] have been used extensively. But because of their assumption of stationary and global descriptive characteristics, these frequency-domain methods suffer from an inherent problem that it cannot provide information regarding the temporal dynamics of the rhythms. An improved technique, the complex demodulation (CD), was developed [3-4]. In contrast to the frequency-domain methods, the CD can extract information about temporal regularities (e.g. amplitude and phase) of individual frequencies. However, since the CD produces a smooth function (remodulate) for each frequency, this approach has the enormous difficulty in envisaging all demodulated frequencies, their respective peak amplitudes and their temporal relationships over the entire sampled time interval.

The time-frequency analysis is a very promising technique for time series analysis, which decomposes the signal into a time-frequency plane, and thus giving an overall view of the time-frequency behaviors of the signal. We selected the CWT as the tool to characterize the CTS. It uses a varying window adapted to the analyzed frequency, so that, the windows are narrow at high frequencies and wide at low frequencies. Thus, the CWT may provide much more accurate localization of the periodic activity patterns in the CTS than the SFFT, which uses a fixed length window. The CWT is specially suited for analyzing non-stationary signals such as the CTS. With the CWT representation we defined the functions of *band power spectral intensity (BPSI)* and *mean weight frequency (MWF)* and a feature parameter of *Activity Peak (AP)* to further characterize temporal behaviors of different band rhythmic activities.

In order to illustrate the efficiency of the proposed method, two experiments were carried out, with different intense changes to environmental conditions. In the first experiment, we study the effect of cage size on the locomotion activity of mice. In the second one, the synchronizing ability of mice to the shifting of lighting conditions was studied.

II. METHODS

A. Experimental Methods

1) Data Collection: Locomotion is one of the most important chronobiological behaviors. In our study, male mice C57 (8-10 weeks) were used. The locomotion activity of the mice was collected by the image-based system developed in our laboratory [5]. In each experimental session, one mouse was housed in a top-open perspex cage in a sound-shielded chamber with normal food and water provision. The animal displacement was obtained by summing the pixels in the difference image of two neighboring images two seconds apart, giving the index of the intensity of the locomotion

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activity over time. Two experiments were carried out, respectively.

2) Experimental 1:

To study the effect of cage size on the locomotion activity two experimental cages with the large four times larger than the small one were used. The standard lighting schedule with a uniform light-dark phase (12 hour : 12 hour) was adopted. Each experimental session consists of consecutive three days. Totally, the data of 8 mice were collected. Fig.1 shows a representative example of the locomotion activity of a mouse housed in the large cage.

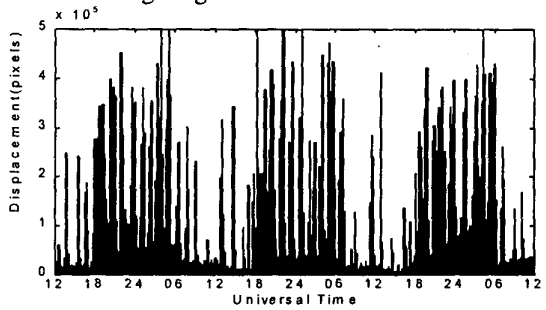

Fig. 1. A representative example of the locomotion activity signal over three days of a mouse housed in the large cage.

3)Experimental 2: In this experiment, the animal was housed in the large cage with the same size as in the experiment 1. To study the synchronizing ability of mice to changes to environmental lighting. We introduced either a light-light or dark-dark transition by changing the lighting phase during the procedure of experiment. The locomotion activity data of the mouse over consecutive eighteen days were collected. One example is given in Fig. 2 with the uniform dark-light lighting in the first four days followed by the light-dark lighting from the fifth day to produce a 12 hour light-light transition.

4) Preprocessing: Although the sampling rate allows us to analyze much higher frequency activity of the mice, in present study we have concentrated our analysis up to 30 cycles per day (cpd) activities. So a coarse resolution locomotion signal was extracted from the originally acquired data set by computing the root-mean-square value over a time window of 7.2 minutes. Thereafter, it was off-line analyzed using the CWT as described in the next session.

B. Continuous Wavelet Transform

The CWT of a time signal $x(t)$ is defined as:

$$CWT_x(\tau,a)=\frac{1}{a}\int_{-\infty}^{\infty}x(t)h^*(\frac{t-\tau}{a})dt \qquad (1)$$

While details of the WT can be referred to original sources (e.g., [6-7]), the CWT can be regarded as the computation of the cross-correlation between the mother wavelet $h(t)$ and the signal, and when the signal matches the mother function, it will give an optimal response. We chose the Mallet's WT [7]

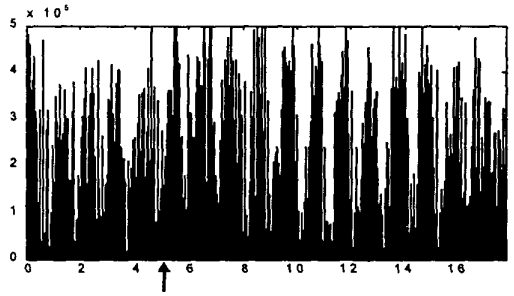

Fig. 2. An example of the locomotion activity over eighteen days of a mouse with the induction of the light-dark reversal at the fifth day as indicated by the arrow.

based on the following two reasons: 1) The Gaussian window gives a good compromise desirable for time-frequency concentration; 2) The Morlet WT uses the Gaussian window modulated sinusoid as the mother function, so for our signal these matched rhythmic activity frequencies will have maximum output. Thus it can be used to explore unknown endogenous rhythms in the CTS. Fig. 3 gives the CWT of the signal in Fig. 1. Besides the constant circadian activity (see the bottom), the daily activity of the mice C57 illustrates a double peak pattern, that is, there are two activity peaks around 15 cpd appearing in the early and late part of the dark phase. Fig.4 gives the CWT of the signal of Fig. 2. It can be seen that the high-frequency activities were increased (see the circle enclosed area) after the induction of the light-light transition. The circadian activity is also affected (see the bottom).

C. Characterization of the Locomotion Activity

The CWT provides a useful visualization tool to observe different rhythmic activities in the CTS simultaneously. But this is not enough. To have a quantitative evaluation on the locomotion activity of mice, we further characterized activity behaviors in different rhythmic bands based on the CWT representation. Using the categories suggested in Ref. [3], we first divided the CWT time-frequency spectrum into 6 bands: circadian (1 cpd); intermediate (2-5 cpd); subultradian (5-11 cpd); ultradian (12-20 cpd); supra-ultradian (21-29 cpd); and larger than 30 cpd. Then we defined two functions of *band power spectral intensity (BPSI)*, *mean weight frequency (MWF)* and a feature parameter of *activity peak (AP)* in the first five bands. The following gives the definition of the functions and the parameter.

1) Band power spectral intensity (BPSI): The time evolution of the *spectral frequency content (SFC)* in the i-band (i = 1, 2, 3, 4, 5) is defined as:

$$SFC^i(\omega,t)=\left|CWT(\omega,t)\right|^2 \qquad (2)$$
$$\forall\,\omega^i{}_{\min}\le\omega\le\omega^i{}_{\max}$$

where $\omega_{\min}$ and $\omega_{\max}$ represent the minimum and maximum frequency values that define the i-band. Thus, the

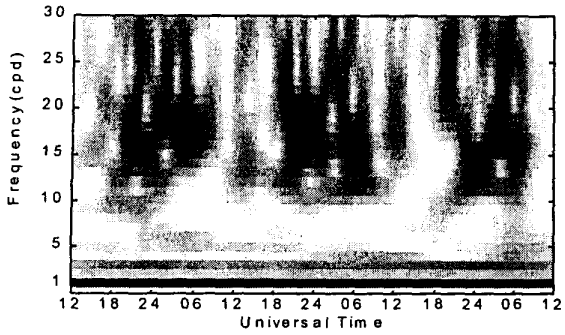

Fig. 3. The CWT representation of the signal shown in Fig. 1.

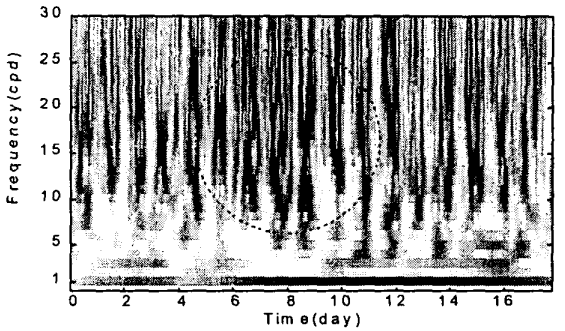

Fig. 4. The CWT representation of the signal shown in Fig. 2.

power spectral intensity of the *i*-band, we call it *band power spectral intensity (BPSI)* as a time function will be the sum of the spectral frequency content for each one of the frequencies included in the frequency interval ($\omega_{\min}$, $\omega_{\max}$), that is,

$$BPSI^i(t) = \sum_{\omega^i_{\min}}^{\omega^i_{\max}} SFC^i(\omega,t) . \qquad (3)$$

2) Mean Weight Frequency (MWF)

For the different bands, the *mean weight frequency (MWF)* $\bar{\omega}$ at time *t*, is defined as:

$$\bar{\omega}^i(t) = [\sum_{\omega^i_{\min}}^{\omega^i_{\max}} \omega \bullet SFC^i(\omega,t)] / [\sum_{\omega^i_{\min}}^{\omega^i_{\max}} SFC^i(\omega,t)] . \qquad (4)$$

3) Activity Peak (AP)

We further characterized feature points in the CWT plot. We first defined a function, *main peak frequency*($\omega^i{}_M$), in the *i*-band at time *t*. It is defined as the frequency value for which SFC^i takes its maximum value in the interval ($\omega_{\min}$, $\omega_{\max}$):

$$SFC^i(\omega_M,t) > FC^i(\omega,t) \quad \forall \omega \neq \omega_M \in (\omega^i{}_{\min}, \omega^i{}_{\max}) . \qquad (5)$$

Then we defined an *activity peak (AP)* ($t^i{}_M, \omega^i{}_M$) in the *i*-band as the position for which $BPSI^i$ takes the maximum value in its temporal neighborhood ($t^i{}_{M-1}, t^i{}_{M+1}$).

With the definition of these new series and parameter, the dynamic behaviors of activities in respective bands are completely characterized.

III. RESULTS

In this session, we show several analysis results in two experiments using the proposed method. Fig. 5 (A) gives the time-frequency plot of the average CWT results of the locomotion activity of 8 mice kept in the large cage and the corresponding small cage results in Fig. 5 (b). The ensemble average was used to enhance the activity peaks against inter-subject variations. By inspection, the activity pattern of the mice in the large and small cages is structurally similar. There are two activity peaks in the dark phase mainly locating in the ultradian band. We then extracted the frequency and time positions of the two peaks based on the definition of *AP* in the last session. The average peak values of 8 mice are listed in Table I. The results agree with our visual inspection. However, Fig. 5 shows that the ultradian activity is more intense and distinct when the mouse is kept inside the large cage. This suggests that the rhythmic activity may reflect more closely the inherited rhythms of these animals in an open field.

To study the synchroning ability of mice to the lighting transition we focused our study at the transition pattern of the large *APs*. We extracted these main *APs* in the eighteen days with *BPSI* larger than a threshold, and aligned them by day-to-day. The threshold was chosen equal to 10 percent of the maximum *BPSI* in a band. Fig. 6 gives the overlapped result of aligned peaks of two mice in the ultradian band in the light-light transition experiment, and shows a clear transition pattern corresponding to the light-light transition. It can also be seen that about 10 days after the induction of the light-dark lighting transition, the activity of mice synchronizes to the new lighting schedule. Moreover, we observed a phenomenon of split-merge-split of activity peaks after the induction of the light-light transition, Two activity peaks gradually merged into single peak, and about four days after that, the double-activity peaks reappeared.

We also studied the *BPSI* and *MWF* behaviors after the lighting transition. Fig. 7 gives the average *BPSI* of two mice in five bands. It is noted that after the induction of the light-light transition, the high-frequency activities first increased, and the circadian activity decreased. Thereafter, the circadian activity significantly increased. Finally, the all band activities gradually returned to a normal level as in the control period of the first four days. We could not observe apparent changes in the time courses of *MWF* in five bands. More data sets are being collected to confirm this new finding.

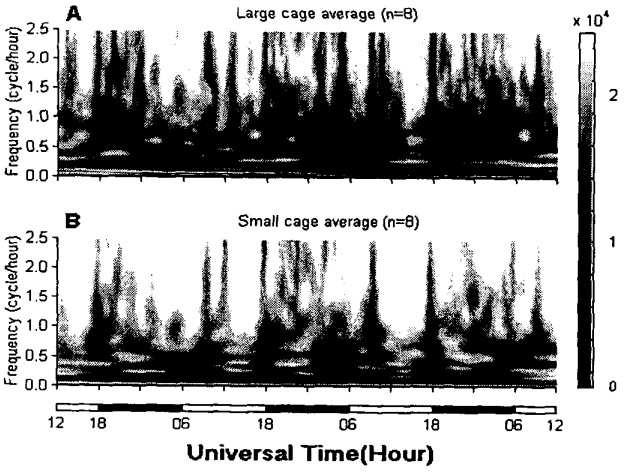

Fig. 5. The time-frequency spectrum of the average CWT results of 8 mice.

IV. CONCLUSION

A new approach based on the CWT to analyze the chronobiological signals has been proposed. The CWT gives us a visual inspection to the locomotion activity. The enormous difficulty, encountered by the CD method, in envisaging simultaneously all the demodulated frequencies, their respective peak amplitudes and their temporal relationships is made easier. Moreover, the *BPSI* and *MWF* functions give quantitative evaluation on the evolution of the activity intensity and periodicity in different rhythmic bands. The *APs* extract the most important features of the activity foci. All these allow us to study the behaviors of different rhythmic activities over time simultaneously and conveniently.

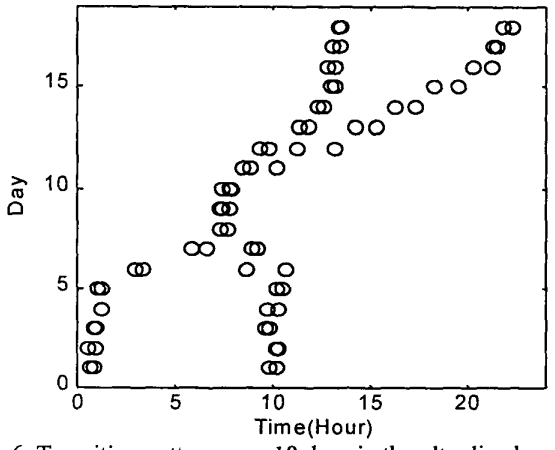

Fig. 6. Transition pattern over 18 days in the ultradian band to illustrate the transition pattern.

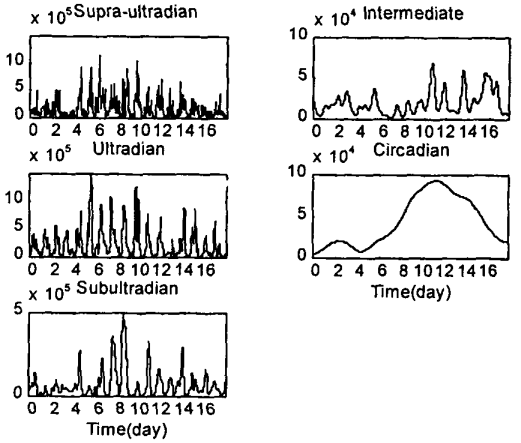

Fig 7. The average *BPSI* of two mice in five bands.

TABLE I. Average values of Peak clusters of 8 mice in the ultradian bands in three days.

	PEAK 1	PEAK 2
Large cage	(19.2±6.5, 1.6±1.2)	(12.4±4.6, 10.4±3.4)
Small cage	(18.6±5.8, 0.9±0.8)	(13.2±5.4, 11.2±3.2)

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