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Gait State Transition by Gait Training Using Interactive Rhythmic Auditory Cue in Development Process of Gait Rhythm Generation Disorders

Leo Ota[1†], Hironori Hashiguchi[1], Ken-ichiro Ogawa[1], Satoshi Orimo[2] and Yoshihiro Miyake[2]

[1]Department of Computational Intelligence and Systems Science, Tokyo Institute of Technology, Kanagawa, Japan
(Tel : +81-45-924-5656; E-mail: ohta@myk.dis.titech.ac.jp, hashiguchi@dis.titech.ac.jp, ogawa@dis.titech.ac.jp, miyake@dis.titech.ac.jp)
[2]Department of Neurology, Kanto Central Hospital, Tokyo, Japan
(Tel : +81-3-3429-1171; E-mail: orimo@kanto-ctl-hsp.co.jp)

Abstract: We have developed Walk-Mate (WM) training using interactive rhythmic auditory cue, which is a new rehabilitation method concerning gait rhythm. Also, we have proposed the new evaluation method for gait rhythm generation disorders, which is often observed in Parkinson's disease (PD) patients. However, the recovery process by rehabilitation for gait rhythm was not yet evaluated from a viewpoint of gait rhythm generation disorders. In this paper, we aim to evaluate the recovery process by rehabilitation for gait rhythm by evaluation method for gait rhythm generation disorders in PD patients. For this purpose, we evaluated the effect of WM training compared to conventional Rhythmic Auditory Stimulation (RAS) training using fixed-tempo rhythmic auditory cue. To evaluate the rehabilitation effect, we hypothesized a transition probability model of discrete states in views of gait rhythm generation disorders. In detail, the state transition probability matrices of WM training, was compared with the probability matrices of RAS training. Thirty-one PD patients walked for approximately 2 minutes. We used the gait states constructed in previous study to evaluate the disease severity for gait rhythm generation disorders. Then we made state transition probability matrices from pre-WM training to post-WM training, and that from pre-RAS training to post-RAS training. The result showed the difference in effect between two training. Specifically, the WM training showed better gait state transition of the patients in severer states of gait rhythm generation disorders, compared to the RAS training. This suggests that this transition model is useful to identify the appropriate treatment of gait rhythm generation disorders.

Keywords: Walk-Mate, state transition probability, Parkinson's disease, walking rhythm generation disorders.

1. INTRODUCTION

Rhythm is important component in gait rehabilitation. We have proposed the Walk-Mate (WM) training, which is using gait rhythm interaction [1]. WM is realized by the interactive rhythmic auditory cue, which is mutually entrained with human gait rhythm. It was reported that WM reinstates the $1/f$ fluctuation property during and after the training in Parkinson's disease (PD) patients [2]. The white noise property of gait rhythm is often seen in PD patients [3]. In contrast, another group has proposed the methods using the auditory rhythmic cue based on the enforced entrainment. The method is called Rhythmic Auditory Stimulation (RAS) training, which is providing patients with the fixed-tempo metronome while walking based on the enforced entrainment [4]. Although RAS tended to decrease the gait rhythm variability in PD patients, it is likely to enhance the white noise property [3].

On the other hand, we have also proposed the evaluation method for gait rhythm generation disorders seen in PD patients [5]. In reference [5], the discrete three states were defined using gait rhythm variability and fluctuation property: no-disorder state, mild-disorder state, and obvious-disorder state. It is thought to be important to evaluate the rehabilitation concerning the gait rhythm.

However, conventionally, the recovery process by gait training for gait rhythm have not been evaluated from a viewpoint of a gait rhythm generation disorders. Therefore, the purpose of this study is to evaluate the effect of rehabilitation using rhythmic auditory cue from a viewpoint of gait rhythm generation disorders [5].

To evaluate the rehabilitation for gait rhythm, we compared the effect of WM with that of RAS. In previous studies, many kinds of progressive disease were taken account of the temporal development process between states [6]. In this study, we evaluated the utility of rehabilitation using state transition probability model from pre-training to post-training using finite-state Markov model. On the basis of reference [5], we defined three discrete states of gait rhythm generation disorders: no-disorder state, mild-disorder state, and disorder state. As an approach, we attempted to evaluate the effect of gait training using rhythmic auditory cue as the transition process between these states. In detail, we compared the state transition probability from pre-WM training to post-WM with the state transition probability from pre-RAS training to post-RAS.

2. MATERIALS AND METHODS

2.1 Experimental Settings of Rehabilitation for Gait Rhythm

To evaluate the gait rehabilitations for gait rhythm, we compared the two rehabilitations. One is Walk-Mate training (WM training) using interactive rhythmic auditory cue [1,7]. The other is fixed-tempo Rhythmic Auditory Cue training (RAS training) [4]. WM is composed of two modules described by (1) and (2).

$$\dot{\theta_m} = \omega_m + K_m \sin(\theta_h - \theta_m). \quad (1)$$

$$\dot{\omega_m} = -\mu \sin\{\Delta\theta_d - (\theta_h - \theta_m)\}, \quad (2)$$

where θ_m represents the phase variable of the auditory cue rhythm generated by WM system and θ_h is the natural frequency of the system. Here θ_m takes only a value between $-\pi/2$ and $\pi/2$. Also, θ_h represents the phase variable of the human gait rhythm. Here the phase difference between the human gait rhythm and the auditory cue rhythm can be updated only when the foot contacts to the ground ($\theta_h = 0$). These equations and the parameters were tuned empirically. In WM training, $K_m=0.5$, $\mu=0.3$, and $\Delta\theta_d=0.3$ were adjusted to synchronize the sound cue with human gait rhythm. To detect the foot contact timing online, peaks of trunk acceleration norm were used, and it is confirmed that the actual foot contact timing detected by foot switches were 0.2ms later than the peak of acceleration norm. In RAS training, K_m and μ were set to 0. The initial value of ω_m was determined by the average of first four steps.

2.1.1 Participants

Thirty-one PD patients were participated in this experiment (13 male and 18 female). Their stages of modified Hoehn-Yahr (mHY) scale was from 1 to 3. All participants were tested while "on" state of antiparkinsonian medication. The mean age was 68.8 years and the standard deviation was 10.0 years. The mean duration disease was 4.7 years and the standard deviation was 4.0 years. The procedure of this experiment was approved by Kanto Central Hospital Ethical Committee. Before the experiment, we obtained written informed consent from the participants.

2.1.2 Experimental Protocol and Devices

All participants walked six times. There are about 10 minutes' breaks between each trial. The rhythmic auditory cues based on entrainment of gait rhythm (WM and RAS) were provided using headphones during second walking trial and the fifth walking trial. Then, we analyzed the effect of training by the relationship between pre-training trial and post-training trial. The number of participants who are provided with WM first is the same as the number of the participants who are provided with RAS first.

To measure the real time estimation of foot contact timing and to provide auditory rhythmic cue, WM implemented in the smartphone (iPhone 5 or iPod touch 5th generation (Apple Ltd., U.S.)) was used [1,7]. The device was equipped in front of stomach. While walking, tri-axial acceleration of trunk was measured by each of devices every 10ms. Squared L2-norm of tri axial acceleration signal was calculated. By detecting the timing of the maximal acceleration after the norm falls below a certain threshold for 20 or more consecutive sample times, the foot contact timing were estimated in real time.

2.1.3 Analysis of Gait Rhythm

To analyze the gait rhythm, we measured the acceleration of trunk using smartphone (iPod touch 5th generation or iPhone 5 (Apple Ltd., U.S.)) was equipped with near L3 region. The norm of acceleration signal was smoothed by KZ filter [8]. The window size was 100ms and the cut-off frequency was 2.2 Hz. Then the stride intervals were calculated by the time duration between every other peaks of the smoothed norm.

2.2 Evaluation of Training for Gait Rhythm

We evaluate the training concerning the gait rhythm using transition probability matrices of state concerning gait rhythm generation disorders. We hypothesized that the effect of rehabilitation concerning the gait rhythm can be modeled by simple Markov chain defined by state concerned with gait rhythm generation disorders.

2.2.1 States of Gait Rhythm Generation Disorders

The states of gait rhythm generation disorders are defined by the combination of CV and α [5]. The indices are associated with the severity of the physical disabilities, such as postural reflex disorders. To classify the participants' state of gait rhythm generation disorders, we focused on mHY score. We used the same data set as in reference [5]. Fisher's linear discriminant analysis was used for classification. At first, we classified the presence or absence of postural reflex disorder (PRD). By the two linear discriminant function, no-PRD state s_1 can be differentiated from disorder state. Next, we differentiated participants with mild-PRD in state s_2 from patients with obvious-PRD in state s_3 in PRD groups.

The classification method of gait rhythm generation disorders was applied to the measured walking trial data. The population proportion in pre-WM and that in pre-RAS was not so different (State s_1: state s_2 : state s_3 = 16 : 6 : 9 in pre-WM. State s_1 : state s_2 : state s_3 = 22 : 2 : 7 in pre-RAS.). The age and the disease duration were not so different in each of the state in pre-training or the type of gait training (*ps* > 0.05, two way factorial analysis of variance).

2.2.2 State Transition Probability

To quantify the effect of WM or that of RAS on the individual gait dynamics, the state transition probability matrices from pre-training to post-training were calculated to evaluate the after effect of WM or RAS on the gait dynamics. In previous study, the short term after effect of WM was confirmed as improvement of gait rhythm fluctuation property [2]. Therefore, we set the cycle length about 30 minutes.

2.2.3 Stationary Distribution and Utility

We hypothesized the state transition process can be regarded as simple Markov chain. Under this hypothesis, we can estimate the stationary distribution $\pi^s = [p_1 \ p_2 \ p_3]$, which is represented by row vector, using equilibrium equation (3).

$$\pi^s = \pi^s P, \quad \text{s.t. } \textstyle\sum_{s=1}^{3} p_s = 1, \quad (3)$$

where P was the state transition probability matrix.

To estimate the utility of rehabilitation concerning gait rhythm, we determined the utility as referred to reference [6] ($u_1 = u_2 = 0.623$, $u_3 = 0.467$). Expected utility in stationary distribution for population was estimated by (4) [9].

$$U = \sum_{s=1}^{3} u_s \times p_s, \quad (4)$$

where u_s is utility when patients stay at state s_s, and the p_s is the steady state probability in state s_s.

3. RESULTS

3.1 Sample of Gait State Transition of Patients with State s_3 in Pre-training

Fig. 1 shows a sample result of gait rhythm. The CV in pre-WM was 4.0%, located in state s_3. In this case, this participant's gait rhythm variability decreased from 4.0% in pre-WM to 1.9% in post-WM. The α was increased from 0.46 in pre-WM to 0.95 in post-WM (see Figs. 1 (a), (b).). In another PD patient, the trajectory of gait state transition remained within the same level (state 3) between pre-RAS training and post-RAS training (see Figs. 1 (c) CV = 4.2%, α = 0.64, (d) CV = 6.0%, α = 0.84.).

3.2 State Transition from Pre-training to Post-training

Fig. 2 is the state transition diagram from pre-WM to post-WM, and the state transition diagram from pre-RAS to post-RAS. For instance, the transition probability from state s_3 in pre-WM to state s_2 in post-WM was estimated by the number (two) of people who transfer from state s_3 in pre-WM to state s_2 in post-WM divided by the number of participants who is classified to state s_3 in pre-WM (nine). The transition probability from state s_3 in pre-WM to state s_2 in post-WM was 22%. Comparing the result of the state transition probability (0.44) from state s_3 in pre-WM to other states in post-WM with that (0.29) from state s_3 in pre-RAS to other states in post-RAS, it is suggested that the participants of state s_3 in pre-WM improved their individual gait dynamics more than that of state s_3 in pre-RAS.

3.3 Estimation of Stationary Distribution and Utility

From the state transition probability matrices of WM, the stationary distribution was shown in (5).

$$\pi_{WM}{}^{s} = [p_1 \;\; p_2 \;\; p_3] = [0.84\ 0.03\ 0.13]. \quad (5)$$

From this result, we can estimate the general expected utility of WM in steady state by (6).

$$U = \sum_{s=1}^{3} u_i \times p_i \; =0.60. \quad (6)$$

On the other hand, the stationary distribution for the state transition matrices for RAS was shown in (7).

$$\pi_{RAS}{}^{s} = [p_1\, p_2\, p_3] = [0.57\ 0.03\ 0.41]. \quad (7)$$

From this result, we can estimate the general expected utility of RAS in steady state by (8).

$$U = \sum_{i=1}^{3} u_i \times p_i \; =0.57. \quad (8)$$

Compared Eqn. (6) with Eqn. (8), the utility of WM in steady state is slightly higher than that of RAS.

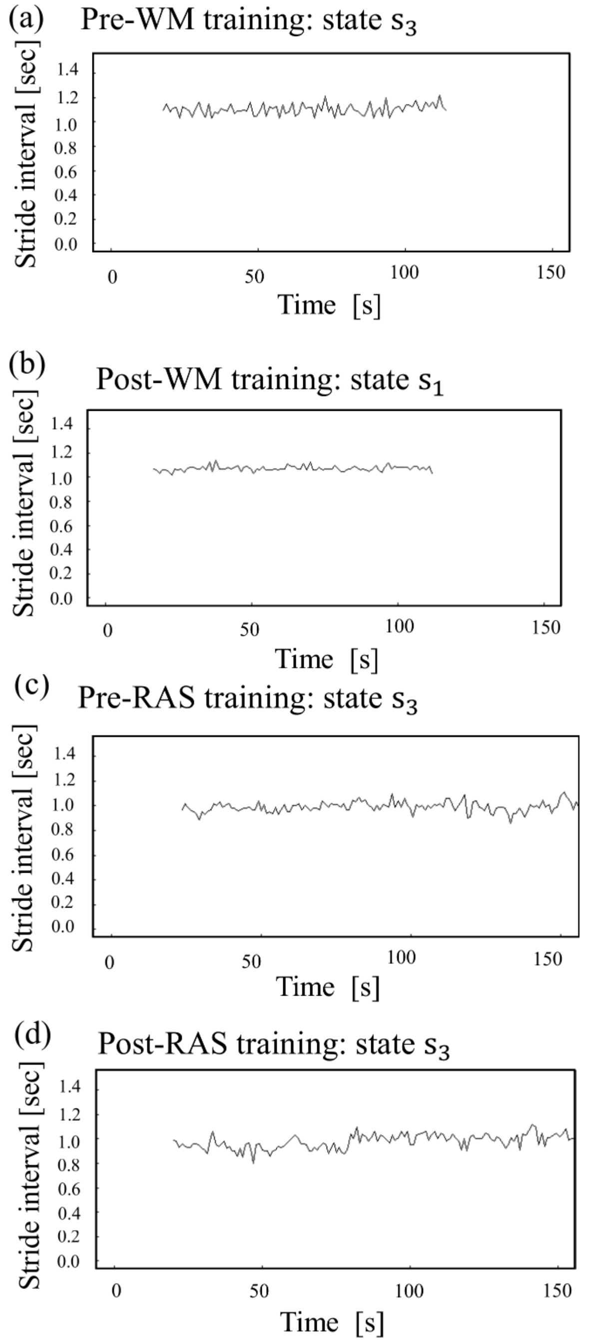

Fig.1 Sample results of gait rhythm data. (a) The data of pre-WM, (b) the data of post-WM, (c) the data of pre-RAS and (d) the data of post-RAS. These figures show stride interval time series. The data of pre-WM (a) is classified to state s_3, and the data of post-WM (b) is classified to milder state s_1 than that of pre-WM (a). On the other hand the data of pre-RAS (c) is the same state s_3 as the data of post-RAS (d).

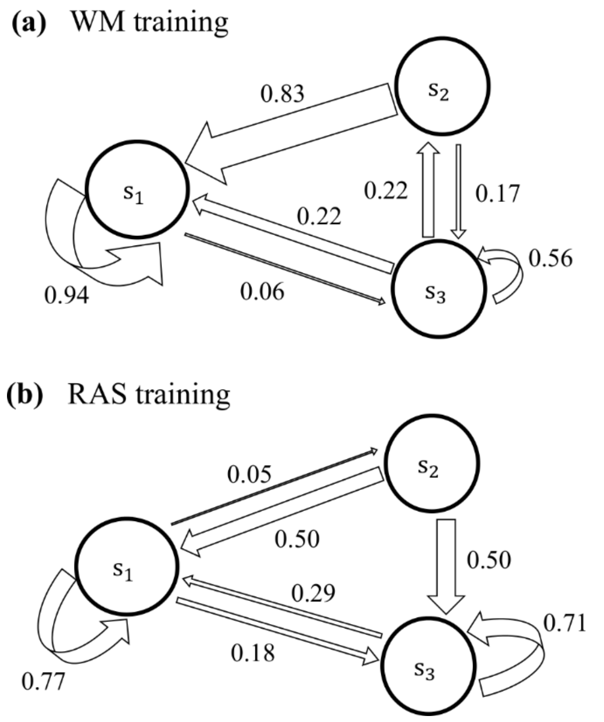

Fig.2 State transition diagram. (a) That from pre-WM to post-WM. (b) That from pre-RAS to post-RAS.

4. DISCUSSION

In this paper, we compared the effect of WM and RAS training by state transition probability, to evaluate rehabilitation concerning gait rhythm using state of gait rhythm generation disorders. We classified PD patients into no-disorder state s_1, mild disorder state s_2 and disorder state s_3, and regarded the recovery process by gait training using rhythmic auditory cue as a state transition process concerned with gait rhythm generation disorders.

As a result, the state transition probability (0.06) from state s_1 in pre-WM to other states in post-WM was lower than that (0.23) from state s_1 in pre-RAS to other states in post-RAS. In addition, the state transition probability (0.44) from state s_3 in pre-WM to other states in post-WM was higher than that (0.29) from state s_3 in pre-RAS to other states in post-RAS. These results suggested that WM training might be effective for patients to increase the state transition probability from any state to no-disorder state s_1. Actually, under the hypothesis of simple Markov chain, the stationary distribution for state transition probability of WM is biased to no-disorder state s_1. In addition, the expected utility of WM in steady state is also higher than that of RAS. These result suggested that WM has possibility to provide PD patients with the high quality of life.

In this study, we modeled the recovery process by rehabilitation concerning gait rhythm using stochastic state transition model. This method can quantify the temporal development of recovery process and this can be used to predict the effectiveness of rehabilitation method for gait rhythm [6,9].

For future study, the intra-individual variation of the state transition concerned with gait rhythm generation disorders in long period should be validated. Then the prediction of the progression of the disease and utility evaluation of longitudinal rehabilitation concerning gait rhythm is expected.

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