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

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***Abstract* – We have developed Walk-Mate (WM) training using interactive rhythmic auditory cue, which is a new rehabilitation method focused on gait rhythm. Also, we have proposed the new evaluation method for gait rhythm generation disorders, which is occasionally observed in Parkinson's disease (PD) patients. However, the recovery process by rehabilitation focused on 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 focused on gait rhythm by evaluation method for gait rhythm generation disorders seen 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 concerning WM training, was compared with the probability matrices concerning RAS training. Thirty-one PD patients walked for approximately 2 minutes. We defined the three states concerning gait rhythm generation disorders using 62 gait data in previous study. Then we made state transition 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 these trainings. Specifically, the WM training showed the 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.**

Index Terms – Walk-Mate, gait rhythm generation disorders, state transition probability, Markov chain.

I. Introduction

Rhythm is important component in gait rehabilitation. We have proposed the Walk-Mate (WM) training, which is focused on 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 [2,3]. The white noise property of gait rhythm is occasionally seen in PD patients [4,5]. 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 [6]. Although RAS tended to decrease the gait rhythm variability in PD patients [7], it is likely to enhance the white noise property [5].

On the other hand, we have also proposed the evaluation method for gait rhythm generation disorders seen in PD patients [8]. In reference [8], 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 focused on the gait rhythm.

However, conventionally, the recovery process by gait training focused on gait rhythm have not been evaluated from a viewpoint of a gait rhythm generation disorders. In this study. Therefore, the purpose of this study is to evaluate the effect of rehabilitation using rhythmic auditory cue by integrating the aforementioned previous studies from a viewpoint of gait rhythm generation disorders [8].

To evaluate the rehabilitation focused on 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 [9-11]. 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 [8], we defined three discrete states of gait rhythm generation disorders: asymptomatic 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.

II. Methods

A. Experimental Design of Rehabilitation focused on Gait Rhythm

To evaluate the gait rehabilitations focused on gait rhythm, we compared the two rehabilitations. One is interactive rhythmic auditory cue Walk-Mate training (WM training) [1,12]. The other is fixed-tempo Rhythmic Auditory Cue training (RAS training) [6]. WM is composed of two modules. Module-1 was described by

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

This is based on the mutual entrainment mechanism [13].

Module-2 was described by

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

This module controls the phase difference between human-foot-contact timing and the auditory-cue-providing timing.

These equations and the parameters were tuned empirically. In WM training, K_m, μ, and $\Delta\theta_d$ were set to synchronize the sound cue with human gait rhythm. In RAS training, K_m and μ were set to 0. The initial value of ω_m was determined by the average stride interval of first four steps.

1) Participants

Thirty-one PD patients were participated in this experiment (13 male and 18 female). Their stages of modified Hoehn-Yahr (mH-Y) 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. All participants were provided written informed consent in accordance with the Declaration of Helsinki. The procedure of this experiment was approved by Kanto Central Hospital Ethical Committee.

2) Experimental Protocol and Apparatus

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 [1,12]. 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.

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, which is believed to be close to the center of mass during quiet standing [14,15].

The norm of acceleration signal was smoothed by a moving average method twice [16]. 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.

Stride interval time series was analyzed by two indicators. One is coefficient of variation (CV). CV is calculated by the standard deviation normalized by the mean value. CV is one of the indicator of the variability. CV of healthy people's stride interval is near 2%, and the CV of PD patients' stride interval is around 3%.

The other is scaling exponent α, which can be calculated by detrended fluctuation analysis (DFA) [17]. This method can be used for relatively short data [18]. The α is one of the indicator of the fluctuation property. If α is near 0.5, the time series is white noise. If α is near 1.0, the time series is *1/f* noise. *1/f* fluctuation property is observed in stride interval of healthy young people [19-22]. However, white noise property is observed in stride interval of PD patients or some kind of neurological disorders [23].

B. Evaluation of Rehabilitation Focused on Gait Rhythm

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

1) Markov States Concerned with Gait Rhythm Generation Disorders

The states of gait rhythm generation disorders are defined by the combination of CV and α [8]. 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 mH-Y score [24]. We used the same data set as in reference [8], and the binary tree structure to equalize the prior probability of each group in classification into two groups (see Fig. 1).

Fisher's linear discriminant analysis [25] was used for classification as shown in Fig. 2. At first, we classified the presence or absence of postural reflex disorder (PRD). By the two linear discriminant function, asymptomatic state s_1 can be differentiated from disorder state (case 1 in Fig. 1). The boundary between presence and absence of PRD is described by

$$\alpha = 50 + 16 \times CV. \quad (3)$$

Next, we differentiated participants with mild-PRD in state s_2 from patients with obvious-PRD in state s_3 in PRD groups (case 2 in Fig. 1). The boundary between mild-PRD and obvious-PRD was described by

$$\alpha = 0.72 - 0.02 \times CV. \quad (4)$$

The classification method of gait rhythm generation disorders was applied to the measured walking trial data. The participants' characteristics of the state in pre-WM were shown in Table I. The participants' characteristics of the state in pre-RAS were shown in Table II. The population proportion in pre-WM and that in pre-RAS was not significantly different (State s_1: state s_2 : state s_3 = 15 : 7 : 9 in pre-WM. State s_1 : state s_2 : state s_3 = 16 : 8 : 7 in pre-RAS.). The age and the disease duration were not so different in each of the state in pre-training (*ps* > 0.05).

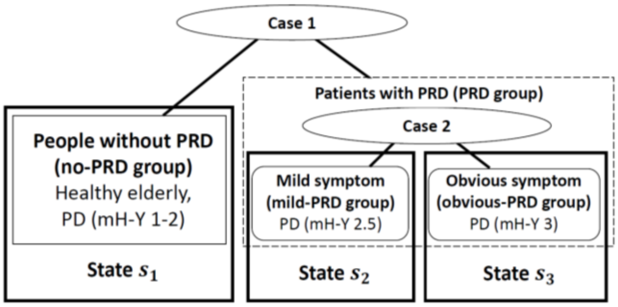

Fig. 1. Definition of the states of gait rhythm generation disorders.

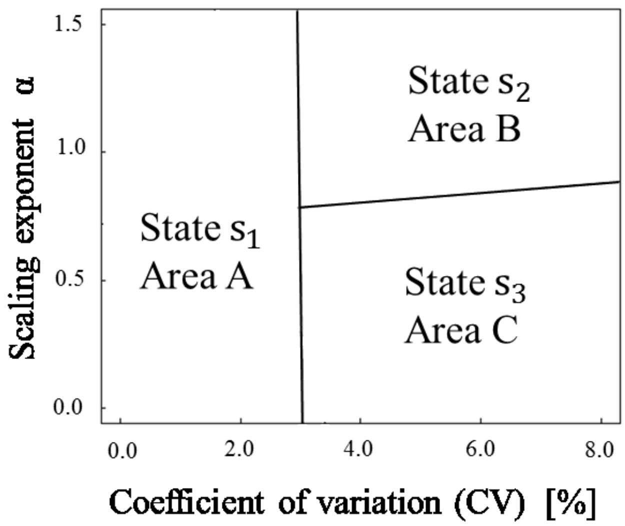

Fig. 2. Boundary among the states of gait rhythm generation disorders in (CV, α) plane.

TABLE I
PARTICIPANTS CHARACTERISTICS OF STATE IN PRE-WM

State	Age [year]	Sex (Male : Female)	Disease Duration [year]	mHY (min, median, max)
s_1	65 ± 7.0	7:8	4.2 ± 4.0	1, 2, 3
s_2	71 ± 11	2:5	6.8 ± 4.1	1, 2, 3
s_3	72 ± 12	4:5	4.0 ± 3.8	2, 2.5, 3

TABLE II
PARTICIPANTS CHARACTERISTICS OF STATE IN PRE-RAS

State	Age [year]	Sex (Male : Female)	Disease Duration [year]	mHY (min, median, max)
s_1	69 ± 10	5:11	4.5 ± 3.8	1, 2, 3
s_2	68 ± 11	5:3	3.6 ± 3.1	1, 2, 3
s_3	69 ± 9.8	3:4	6.7 ± 5.1	1.5, 2, 3

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.

TABLE III
DEFINITION OF UTILITY FOR PARKINSON'S DISEASE PATIENTS [11]

State	Stage	Utility
s_1, s_2	mH-Y 1 and mH-Y 2	$u_1 = u_2 = 0.623$
s_3	mH-Y 3 and mH-Y 4	$u_3 = 0.467$

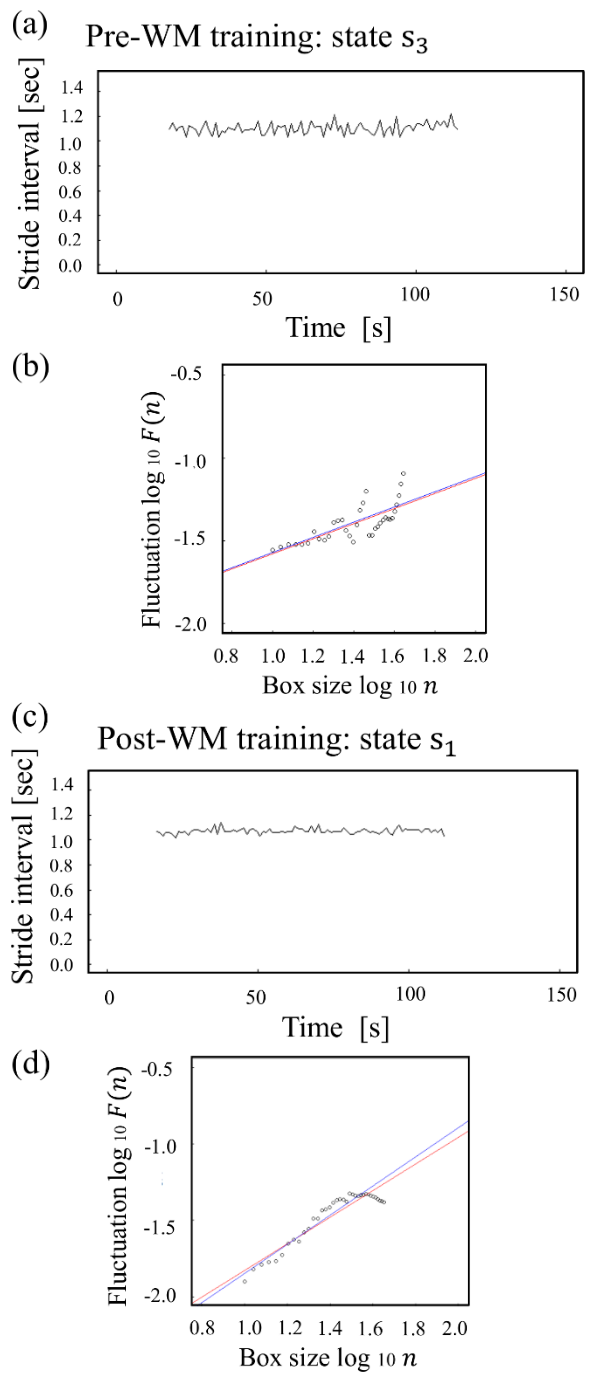

Fig. 3. A Sample result of gait rhythm data of pre-WM (a, b) and post-WM(c, d). The figures (a) and (c) show stride interval time series, and the figures (b) and (d) show the diffusion plots of stride time. In each of diffusion plot, the red line is the original linear regression line of fluctuation to box size, and the slope of blue line is the scaling exponent α, the result after cutting from the data with larger box size while R^2 is less than 0.95.

3) Estimation of 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 $\pi^s = [\mathrm{P}(\mathrm{s}_1)\ \ \mathrm{P}(\mathrm{s}_2)\ \ \mathrm{P}(\mathrm{s}_3)]$, which is represented by row vector, using equilibrium equation (5).

$$\pi^s = \pi^s P,\ \text{ s.t. } \textstyle\sum_{i=1}^{3} P(s_i) = 1, \tag{5}$$

where P was the state transition probability matrix. When t(・) represent the transposed matrix, we can calculate the result of $\mathrm{t}(\pi^s) = t(P) \cdot \mathrm{t}(\pi^s)$. The eigen vector of $t(P)$ corresponding to eigenvalue "1" was calculated by R version 2.15.2.

To estimate the utility of rehabilitation focused on gait rhythm, we determined the utility as referred to reference [11]. The utility was determined by the Table III [11]. Expected utility in stationary distribution for population was estimated by (6) [26].

$$U = \textstyle\sum_{s=1}^{3} u_s \times p_s \tag{6}$$

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

III. Results

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

Fig. 3 shows a sample result of gait rhythm in before the WM training (pre-WM, upper panels) or after the WM training (post-WM, lower panels). The left panels show the stride interval time series. 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 right panels show the diffusion plots, which is the results of DFA. The slope of fluctuation to box number corresponds to the scaling exponent α. The α was increased from 0.74 in pre-WM to 0.95 in post-WM.

Fig. 4 shows a sample result set of gait rhythm in before the RAS gait training (pre-RAS) and after the RAS gait training (post-RAS). The variability was the same level among them.

B. State Transition from pre-training to post-training

The state transition probability matrices of WM and that of RAS were shown in Table IV and Table V, respectively. For instance, the transition probability from state s_1 in pre-WM to state s_2 in post-WM was estimated by the number of people who transfer from state s_3 in pre-WM to state s_1 in post-WM (five) divided by the number of participants who is classified to state s_1 in pre-WM (nine). The transition probability from state s_1 in pre-WM to state s_2 in post-WM was 22%.

Fig. 5 is the state transition diagram from pre-WM to post-WM, and Fig. 6 is the state transition diagram from pre-RAS to post-RAS. 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 (0.28) 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.

C. Estimation of Stationary Distribution and Utility

From the state transition probability matrices of WM, the stationary distribution was shown in (6).

$$\pi_{WM}{}^{s} = [P(\mathrm{s}_1)\ \ P(\mathrm{s}_2)\ \ P(\mathrm{s}_3)] = [0.83\ \ 0.03\ \ 0.14]. \tag{6}$$

From this result, we can estimate the general expected utility in steady state by (7).

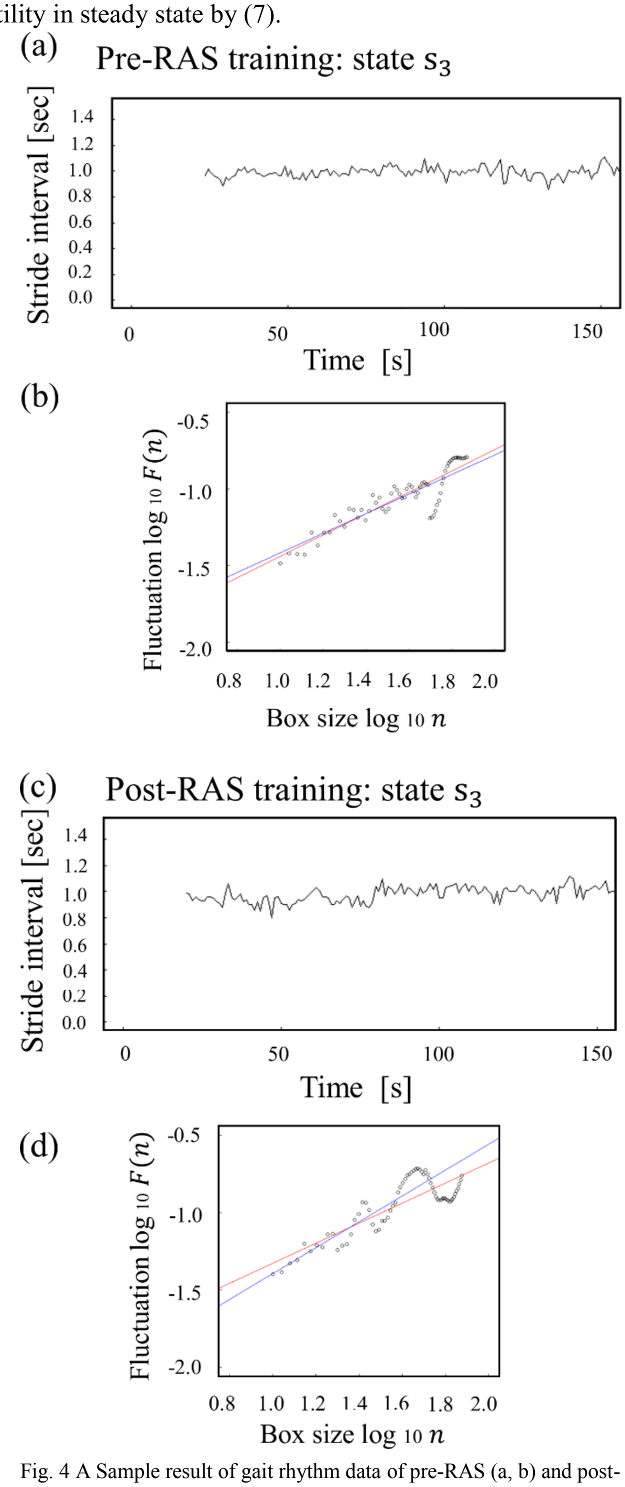

Fig. 4 A Sample result of gait rhythm data of pre-RAS (a, b) and post-RAS (c, d). The figures (a) and (c) show stride interval time series, and the figures (b) and (d) show the diffusion plots of stride time. In each of diffusion plot, the red line is the original linear regression line of fluctuation to box size, and the slope of blue line is the scaling exponent α, the result after cutting from the data with larger box size while R^2 is less than 0.95.

$$U = \sum_{s=1}^{3} u_i \times P(s_i)$$
$$= 0.623 \times 0.83 + 0.623 \times 0.03 + 0.467 \times 0.14$$
$$= 0.60. \quad (7)$$

On the other hand, the stationary distribution for the state transition matrices for RAS was shown in (8).

$$\pi_{RAS}{}^{s} = [P(s_1) \;\; P(s_2) \;\; P(s_3)] = [0.49 \;\; 0.09 \;\; 0.42]. \quad (8)$$

From this result, we can estimate the general expected utility in steady state by (9).

$$U = \sum_{i=1}^{3} u_i \times P(s_i)$$
$$= 0.623 \times 0.49 + 0.623 \times 0.09 + 0.467 \times 0.42$$
$$= 0.56. \quad (9)$$

Compared Eqn. (7) with Eqn. (9), the expected utility of WM in steady state is slightly higher than that of RAS.

TABLE IV
STATE TRANSITION PROBABILITY MATRIX FROM PRE-WM TO POST-WM

		To		
		s_1	s_2	s_3
From	s_1	0.93	0.00	0.07
	s_2	0.88	0.00	0.13
	s_3	0.22	0.22	0.56

TABLE V
STATE TRANSITION PROBABILITY MATRIX FROM PRE-RAS TO POST-RAS

		To		
		s_1	s_2	s_3
From	s_1	0.77	0.05	0.18
	s_2	0.50	0.00	0.50
	s_3	0.14	0.14	0.71

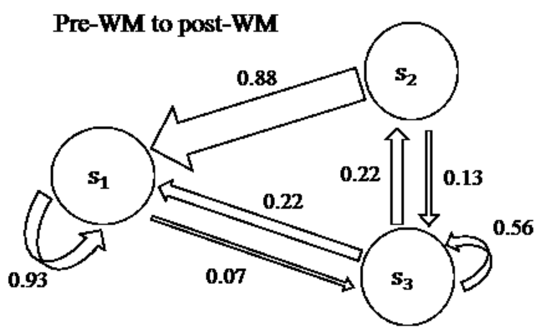

Fig. 5 State transition probability diagram from pre-WM to post-WM.

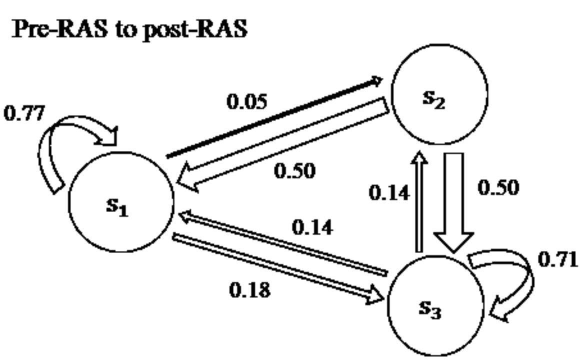

Fig. 6 State transition probability diagram from pre-RAS to post-RAS.

IV. DISCUSSION

In this paper, we compared the effect of WM and RAS training by state transition probability, to evaluate rehabilitation focused on gait rhythm using state of gait rhythm generation disorders. We classified PD patients into asymptomatic 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 (0.08) from state s_1 in pre-WM to other states in post-WM was lower than that (0.08) 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 (0.28) from state s_3 in pre-RAS to other states in post-RAS. These results suggested that WM training might be effective for patients increase the state transition probability from any state to asymptomatic state s_1. Actually, under the hypothesis of simple Markov chain, the stationary distribution for state transition probability of WM is biased to asymptomatic 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 life.

In this study, we modeled the recovery process by rehabilitation focused on 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 focused on gait rhythm [10,11,26].

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 focused on gait rhythm is expected.

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