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Gait phase analysis based on a Hidden Markov Model

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ABSTRACT

For effective gait rehabilitation treatments, the status of a patient's gait needs to be analyzed precisely. Since the gait motions are cyclic with several gait phases, the gait motions can be analyzed by gait phases. In this paper, a Hidden Markov Model (HMM) is applied to analyze the gait phases in the gait motions. Smart Shoes are utilized to obtain the ground reaction forces (GRFs) as observed data in the HMM. The posterior probabilities from the HMM are used to infer the gait phases, and the abnormal transition between gait phases are checked by the transition matrix. The proposed gait phase analysis methods have been applied to actual gait data, and the results show that the proposed methods have the potential of tools for diagnosing the status of a patient and evaluating a rehabilitation treatment.

1. Introduction

There is a steady rise in demand of gait rehabilitation treatments as the number of patients or elderly people who suffer from gait disorders is increasing [16,10,15]. For effective gait rehabilitation treatments, the status of a patient's gait needs to be analyzed precisely. Usually, the status of a patient's gait is analyzed by physical therapists with visual observations or verbal descriptions. Since these qualitative diagnostic methods depend on physical therapists' experience and knowledge, more objective methods to analyze patients' gaits are required.

Since the gait motions are cyclic with several gait phases, the gait motions can be analyzed by the gait phases [11]. The gait phases are observed by various gait data such as foot pressure distributions and joint angles. Due to the easiness and the practicality of measuring foot pressure distributions, shoe-type sensors have been devised by previous researchers. Also based on the measured foot pressure distributions, several methods for the detection of gait phases have been suggested. Morris and Paradiso developed a shoe-integrated sensor system for wireless gait analysis and real-time feedback [7]. Bamberg et al. developed a shoe-integrated wireless sensor system by applying four force sensitive resistors (FSRs) and a bend sensor [2]. Pappas et al. made a gait phase detection system with three FSRs and a gyroscope [9]. These researches, however, detected the gait phases as discrete events, which is not correct in actual gait motions.

In the previous works, a fuzzy logic was applied for the continuous detection of gait phases with the ground reaction forces (GRFs) measured by Smart Shoes [5,4]. Smart Shoes were developed to measure GRF embedded air-bladder type force sensors. By utilizing the GRF patterns in the fuzzy logic, the gait phases are detected continuously and smoothly. The fuzzy logic method uses fuzzy membership functions and fuzzy rule bases shown in Fig. 1. Due to the use of FMV and fuzzy rule bases, the fuzzy logic method can be considered as a pattern-based gait phase detection method. To determine "Large" and "Small" of the fuzzy rule bases in Fig. 1, the fuzzy member functions of (1) and (2) were applied.

$$f^{Large}(x) = \frac{1}{2}[tanh(s(x - x_0)) + 1] \quad (1)$$

$$f^{small}(x) = 1 - f^{small}(x) \quad (2)$$

where s, x and x_0 represent the sensitivity coefficient, the measured GRF and the threshold value. The threshold values are determined manually to distinguish the large value and the small value, and they are usually selected as small values such as about 5% of the body weight for the detection of the little contact to the ground and the fast response. But the small threshold values make it easy to have a large value in f^{Large}. For example, suppose that the threshold value for the heel is set to 30 N, and the actual GRF at the heel is measured 300 N for the heel strike. Then the f^{Large} is large enough even though actual GRF of the heel is not enough for the heel strike. Thus, if the sequence or the timing of each GRF are quite correct and the GRF values are larger than the threshold values for "Large" in the fuzzy rule bases, then the fuzzy rule bases in Fig. 1 can be satisfied regardless the actual GRF values. In other words, the fuzzy logic method may detect the gait phases wrong as normal gait phases if the GRF data have the similar patterns with a normal gait. The experimental results by the fuzzy logic and the proposed method are compared in Section 5.2. For the details about the fuzzy logic method, see [5,4].

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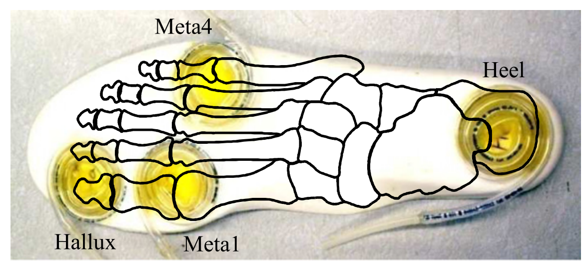
				Fuzzy Membership Value
Large	Small	Small	Small	$\mu_{Initial\ Contact} \to 1$
Large	Large	Small	Small	$\mu_{Loading\ \ Response} \to 1$
Large	Large	Large	N/A	$\mu_{Mid\ Stance} \to 1$
Small	Large	Large	N/A	$\mu_{Terminal\ Stance} \to 1$
Small	Small	Small	Large	$\mu_{Pre-Swing} \to 1$
Small	Small	Small	Small	$\mu_{Swing} \to 1$

Fig. 1. Fuzzy rule bases for gait phase analyses [5,4].

In this paper, a gait phases analysis method based on a Hidden Markov Model (HMM) is proposed. The proposed gait phase detection method uses the actual GRF values instead of GRF patterns which rely on threshold values, FMV, and fuzzy rule bases. Thus, it can be considered as a value-based gait phase detection method. In the HMM, six gait phases are considered as the hidden states, and they are inferred by the GRF observations measured by Smart Shoes. For the inference of the gait phases, the conditional probability of the observations with a given state is required. To calculate the conditional probability, the GRFs of normal gait are approximated as Gaussian distributions by collecting many GRF data of normal gait, and the GRFs are classified by gait phases. The transition matrix which shows the transition probabilities is used to check the abnormal transition between gait phases. The proposed method is verified by actual gait data.

This paper is organized as follows. In Section 2, gait phases and Smart Shoes are introduced. The proposed method for the detection of gait phases based on an HMM is discussed in Section 3. The method for the detection of abnormal transitions in gait phases is presented in Section 4. The proposed methods are evaluated by actual gait data and the results are shown in Section 5. Summary and conclusions are given in Section 6.

(a) Smart Shoes



(b) Location of air-bladders (Meta1/Meta4: first/forth metatarsophalangeal joint)

Fig. 2. Smart Shoes [5,4].

2. Gait phases and Smart Shoes

Walking motions are divided into two basic motions, stance and swing, and there are eight gait phases in those basic motions which were suggested by the Rancho Los Amigos gait analysis committee [11]. The stance motions include initial contact, loading response, mid-stance, terminal stance and pre-swing phases, and the swing motions include initial swing, mid-swing and terminal swing. Since the gait motions are cyclic, the gait phases are repeated in each stride. In normal gait, the gait phases appear sequentially from an initial contact phase to a terminal swing phase. In abnormal gait, however, the sequence of gait phases may be different from those of normal gait. Thus, the status of gait can be diagnosed by analyzing the gait phases, and the effectiveness of a rehabilitation treatment can be evaluated by analyzing the gait phases before and after the rehabilitation treatment.

The gait phases can be detected by the foot pressure distributions since there are unique and repetitive patterns of foot pressure distributions in each gait phase. In one stride of normal gait, the following pattern of foot pressure distributions appear sequentially. In the initial contact phase, pressure at the heel increases as the heel contacts the ground. The pressure at the forefoot increases in the loading response phase as the forefoot starts to contact the ground. In the mid-stance phase, foot pressure across the entire foot. In the terminal stance phase, there should be no heel pressure measured, since the heel does not touch the ground. In the pre-swing phase, there is foot pressure only at the forefoot around the hallux. Foot pressure is not observed in the swing phases, since the foot is in the air.

For the measurement of the foot pressure distribution, a force sensitive resistor (FSR) has been frequently used [2,9,7]. However, the FSR does not adequately reflect the actual foot pressure due to its small sensing area and limited sensing range. Smart Shoes shown in Fig. 2a is proposed for measuring the ground reaction force (GRF) in feet [5,4]. The GRFs are measured by a novel force sensor which consists of an air bladder made by winding a silicone tube and an air pressure sensor. Four air-bladder sensors are installed in Smart Shoes at the hallux, the first metatarsophalangeal joint (Meta1), the fourth metatarsophalangeal joint (Meta4) and the heel, as shown in Fig. 2b. For the detailed information of the air-bladder sensor and Smart Shoes such as linearity and repeatability, see the previous publication [5,4].

3. Detection of gait phases based on a Hidden Markov Model (HMM)

3.1. A Hidden Markov Model (HMM) for gait phase analysis

A Hidden Markov Model (HMM) is a statistical model which is appropriate for modeling sequential data [12,3]. Formally, the HMM is defined as a doubly embedded stochastic process with an underlying process that is not observable (it is hidden), but can only be observed through another set of stochastic processes that produce the sequence of observations [13]. This means that the states underlying the data generation process are hidden, and they can be inferred through observations. HMMs have been used successfully in many applications including speech recognition [13], gene detection [14], and gesture recognition [17,6].

Because three gait phases in the swing motion, initial swing, mid-swing and terminal swing, cannot be distinguished by GRFs, six gait phases (Initial Contact (IC), Loading Response (LR), Mid-Stance (MS), Terminal Stance (TS), Pre-Swing (PS), and Swing phases (SW)) are used to analyze gait motions in this paper. Now, there are six hidden states in gait motions, i.e., six gait phases, and they can be observed through the sequential GRF signals from the four air-bladder sensors installed in Smart Shoes (Hallux, Meta1, Meta4, Heel), the HMM is appropriate for gait phase analysis. A graphical representation of the HMM for gait

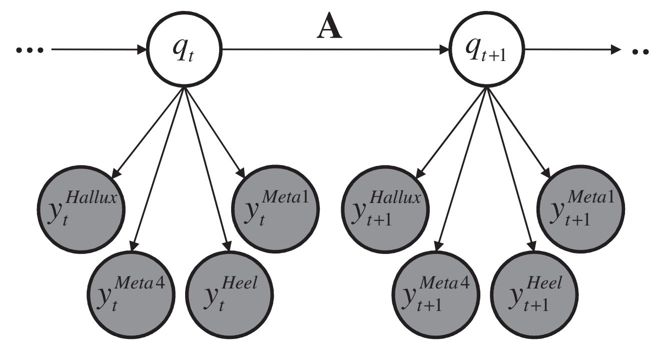


Fig. 3. A Hidden Markov Model (HMM) for gait phase analysis.

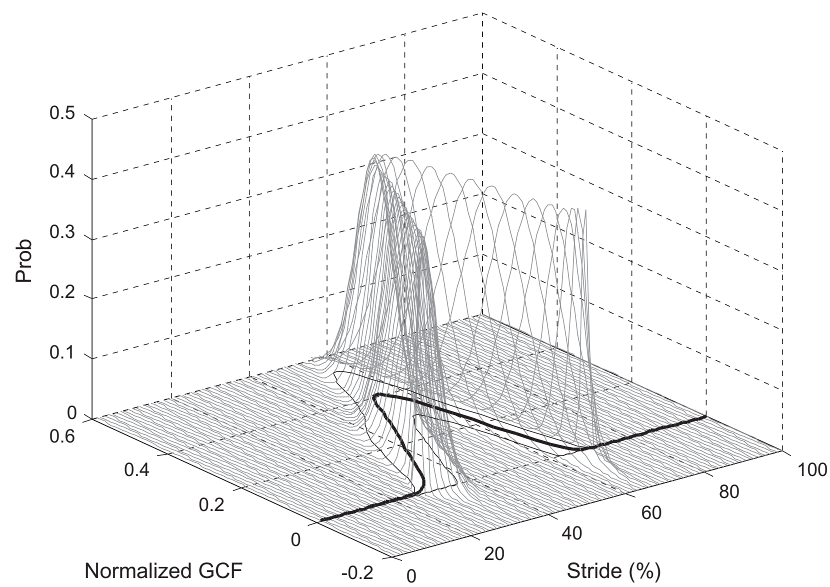


Fig. 4. Gaussian distribution at the hallux.

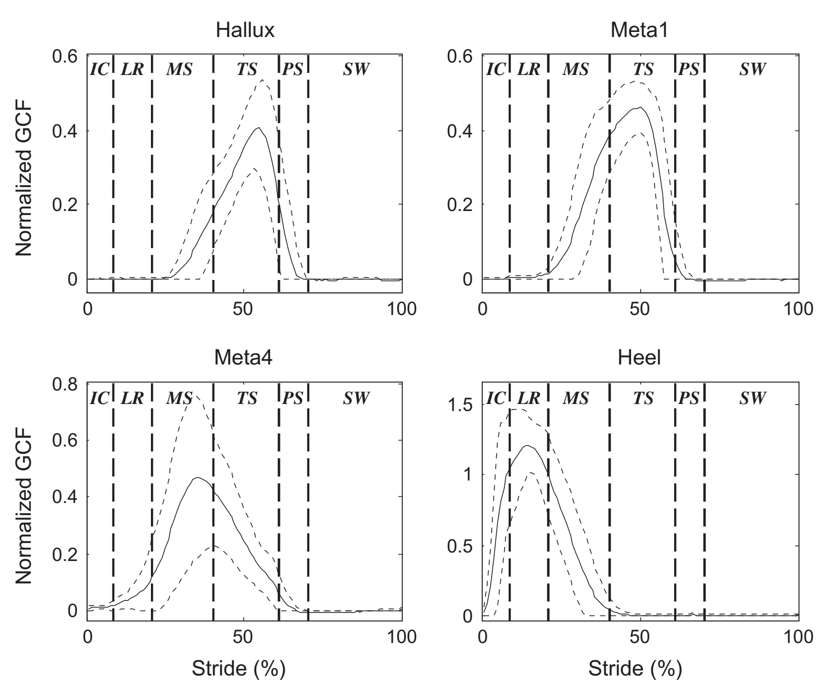


Fig. 5. Labeled GRF data of normal gait.

phase analysis is shown in Fig. 3. The state and the observations at time t are denoted as q_t and $\mathbf{y}_t$, respectively. The observations ($\mathbf{y}_t$'s) are in grey color. The six states at time t are expressed by a multinomial random variable q_t where $q_t = i$ (i = 1 for IC, 2 for LR, 3 for MS, 4 for TS, 5 for PS and 6 for SW). The four observation at time t are represented by y_t^j, where j = Hallux, Meta1, Meta4, Heel. $\mathbf{A}$ in Fig. 3 is a transition matrix, where the (i, j)th entry a_{ij} represents the transition probability $p(q_{t+1} = j | q_t = i)$, i.e., the transition probability from the ith state at a given step to the jth state at the following step.

3.2. Conditional probability with a given gait phase

Due to the unique and repetitive normal GRF patterns, the normal GRF at a certain time can be approximated as a Gaussian distribution by collecting many GRF data of normal gait. To obtain the mean and the variance of the Gaussian distribution, thirty GRF data of normal gait from five subjects without any known gait disorders were collected. Since the body weight is a main factor for the magnitude of the GRF, i.e., GRFs are proportional to the body weight, the magnitude of the GRF is normalized by the body weight. The time span of data is normalized by the stride percentage, which is distinguished by heel contact. Fig. 4 shows the Gaussian distribution at the hallux in one stride. The thick solid line in the bottom plane is the mean of the data, and the upper and the lower dashed lines in the bottom plane are ±1.96 standard deviation from the mean (95% confidence interval of a Gaussian distribution). Due to the large degree of freedom of the data, the t-distributions are approximated as a Gaussian distribution. The grey lines show the Gaussian distributions at each stride percentage.

Since four GRF signals are measured at the same time, the distribution is a multivariate Gaussian distribution as (3).

$$p(\mathbf{y}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{n/2}|\boldsymbol{\Sigma}|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{y}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\mathbf{y}-\boldsymbol{\mu})\right\} \tag{3}$$

where $\mathbf{y}$, $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are a GRF signal vector, a mean vector and a covariance matrix, respectively. In this case, since the number of observations at the given time is four, $n = 4$, $\mathbf{y}$ is a vector in $\Re^4$, $\boldsymbol{\mu}$ is a vector in $\Re^4$, and $\boldsymbol{\Sigma}$ is a 4×4, symmetric matrix.

For the inference of gait phases, which is discussed in the next section, the conditional probability of the observation with a given state, i.e., $p(\mathbf{y}_t|q_t)$, is required. To obtain the conditional probability, the values of $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ in (3) need to be classified by gait phases. When the normal gait data was obtained, the walking motions were recorded by a camcoder, and the joint angles of a lower extremity (hip, knee, and ankle) were measured by encoders and inclinometers. The gait phases were determined by recorded video and the joint angle data with skilled physical therapists. Also they were verified by the literatures [11]. Based on the gait phases from the data and the literature, the GCF data were labeled, i.e., 1–5% for IC, 6–10% for LR, 11–35% for MS, 36–55% for TS, 56–65% for PS, and 66–100% for SW. The normal GRF bands (solid lines and thin dashed lines) and the normal GRF data labeled by gait phases (thick dashed lines) at the four sensing areas in Smart Shoes are shown in Fig. 5.

There are several values of $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ in one labeled gait phase. For example, five different $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are in IC since 1–5% of normal GRF data are used for the classification. To find the most likely conditional probability with those $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$, the maximum probability is picked as the conditional probability after calculating the conditional probability in (3) with all $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ in the labeled gait phase as in (4).

$$p(\mathbf{y}_t|q_t = i) = \max_{\forall \boldsymbol{\mu}, \boldsymbol{\Sigma} in \{q_t = i\}} p(y_t|\boldsymbol{\mu}, \boldsymbol{\Sigma}) \tag{4}$$

where i is one of $1, \ldots, 6$ for IC, LR, MS, TS, PS, and SW.

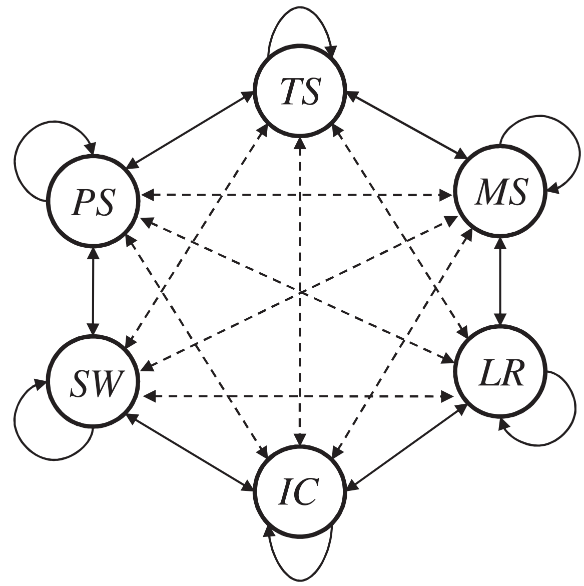


Fig. 6. Transitions between gait phases.

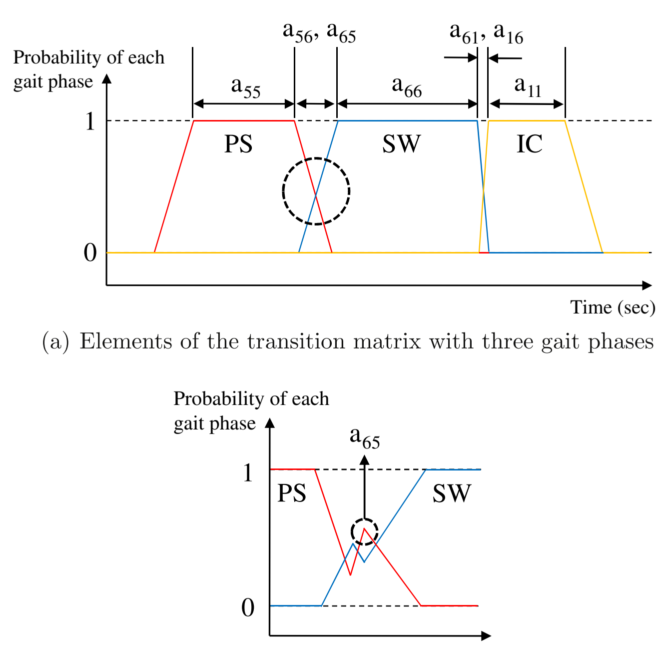
3.3. Detection of gait phases

The hidden states, i.e., gait phases, can be inferred as the posterior probability, $p(q_t|\mathbf{y})$. The inference problem for HMMs involves taking as input the sequence of observed data and yielding as output a probability distribution on the underlying states [12,3]. Due to the dependence between the states, this problem is substantially complex, but it can be readily solved by simple recursion equations guided by Bayes rule as follows:

$$p(q_t|\mathbf{y}) = \frac{p(\mathbf{y}|q_t)p(q_t)}{p(y)} \tag{5}$$

$$= \frac{p(\mathbf{y}_0, \cdots, \mathbf{y}_t|q_t)p(\mathbf{y}_{t+1}, \ldots, \mathbf{y}_T|q_t)p(q_t)}{p(\mathbf{y})} \tag{6}$$

$$= \frac{\alpha(q_t)\beta(q_t)}{p(\mathbf{y})} \tag{7}$$



(a) Elements of the transition matrix with three gait phases

(b) Gait phase transition with fluctuation

Fig. 7. Tridiagonal-like terms by detected gait phases.

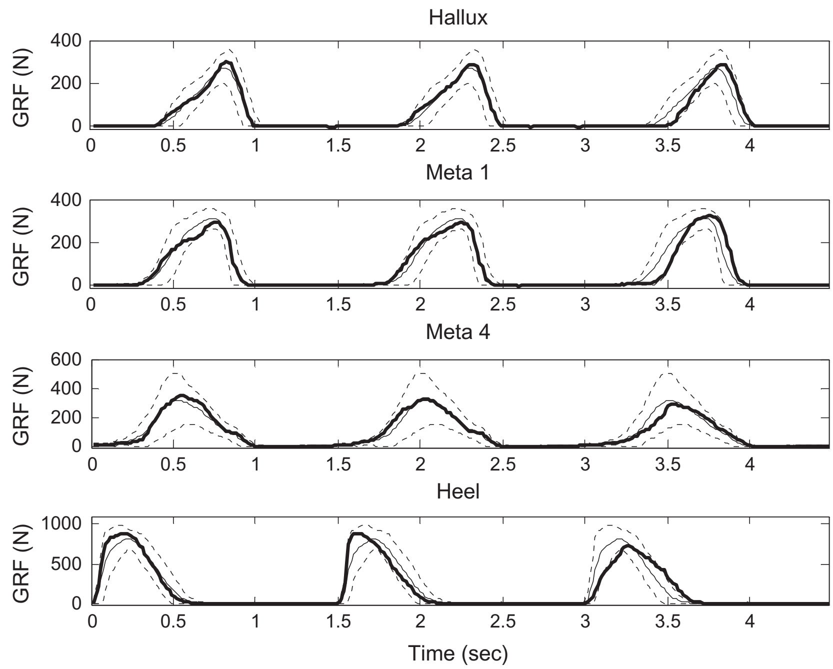


Fig. 8. GRF signals (normal gait).

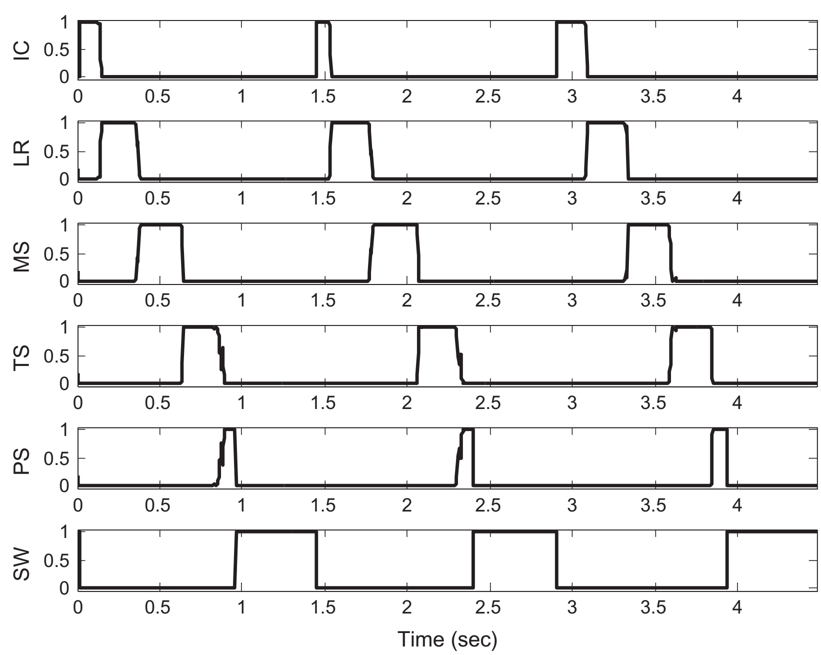


Fig. 9. Estimated gait phases (normal gait).

where

$$\alpha(q_t) = p(\mathbf{y}_0, \ldots, \mathbf{y}_t | q_t) \quad (8)$$

$$\beta(q_t) = p(\mathbf{y}_{t+1}, \ldots, \mathbf{y}_T | q_t) \quad (9)$$

and T is total experiment time. α and β of each time step can be found by the following recursion equations.

$$\alpha(q_{t+1}) = \sum_{q_t} \alpha(q_t) a_{q_t,q_{t+1}} p(\mathbf{y}_{t+1} | q_{t+1}) \quad (10)$$

$$\beta(q_t) = \sum_{q_{t+1}} \beta(q_{t+1}) a_{q_t,q_{t+1}} p(\mathbf{y}_{t+1} | q_{t+1}) \quad (11)$$

where $a_{q_t,q_{t+1}}$ denotes the (i, j) entry of the transition matrix $\mathbf{A}$ for $q_t = i$ $(i = 1, \ldots, 6)$ and $q_{t+1} = j$ $(j = 1, \ldots, 6)$. $p(\mathbf{y}_{t+1}|q_{t+1})$ is a conditional probability which is calculated by the method discussed in the previous chapter. For the details of the α–β recursion method, refer [12,3].

4. Detection of abnormal transitions in gait phases

Since there are six states in the HMM, the transition matrix has six rows and columns. In normal gait, the gait phases appear sequentially as the solid lines in Fig. 6. In other words, the state transitions in normal gait are only the transitions between adjacent gait phases, or self-transitions. Thus, the transition matrix of normal gait has the tridiagonal-like form as in (12).

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 & 0 & a_{16} \\ a_{21} & a_{22} & a_{23} & 0 & 0 & 0 \\ 0 & a_{32} & a_{33} & a_{34} & 0 & 0 \\ 0 & 0 & a_{43} & a_{44} & a_{45} & 0 \\ 0 & 0 & 0 & a_{54} & a_{55} & a_{56} \\ a_{61} & 0 & 0 & 0 & a_{65} & a_{66} \end{bmatrix} \tag{12}$$

The diagonal elements in (12) represent the probabilities of self-transitions in gait phases, and the other non-zero elements (a_{12}, a_{21}, a_{23}, a_{32}, etc.) mean the transition probabilities between adjacent gait phases. The diagonal elements are almost one since most of the state transitions are self-transitions. Also the 0's in (12) mean that there is no transition between non-adjacent gait phases.

This can be easily understood by Fig. 7. In Fig. 7a, three detected gait phases, PS, SW, and IC, are depicted as an example. As shown in the figure, the self-transitions are represented as diagonal terms (a_{55}, a_{66}, and a_{11}), and the transitions between them are represented as $a_{i+1,i}$ and $a_{i,i+1}$ (a_{56}, a_{65} and a_{61}, a_{16}). If the gait phases are changed as in the dashed circle of Fig. 7a, i.e., one monotonically decreases, and one monotonically increases, then there are not $a_{i+1,i}$ terms since $(i+1)$ state appears only after (i) state. However, if the gait phases are changed with fluctuation as in Fig. 7(b), i.e., (i) state (PS) appears after $(i+1)$ state (SW) as in the dashed circle, then this makes $a_{i+1,i}$. However, since these transitions rarely happen in normal gait, $a_{i+1,i}$ terms are usually smaller than $a_{i,i+1}$. Also a_{61} and a_{16} of normal gait are almost zero since the state transition from SW to IC is very sudden due to the heel strike. The experimental results of normal gait will be discussed in the next section.

The sequence of the gait phases may be changed in abnormal gait as the dashed lines in Fig. 6. If the gait phases are not changed sequentially, then non-zero probabilities appear between non-adjacent gait phases. Thus, by checking the self-transition probabilities and the transition probabilities between gait phases, abnormal gait phase sequence can be detected.

Table 1
Estimated transition matrix (normal gait).

	IC	LR	MS	TS	PS	SW
IC	0.9825	0.0174	0.0000	0.0000	0.0000	0.0000
LR	0.0004	0.9706	0.0288	0.0000	0.0000	0.0000
MS	0.0000	0.0074	0.9809	0.0116	0.0000	0.0000
TS	0.0000	0.0000	0.0040	0.8916	0.1043	0.0000
PS	0.0000	0.0000	0.0000	0.0220	0.9274	0.0504
SW	0.0000	0.0000	0.0000	0.0000	0.0000	0.9999

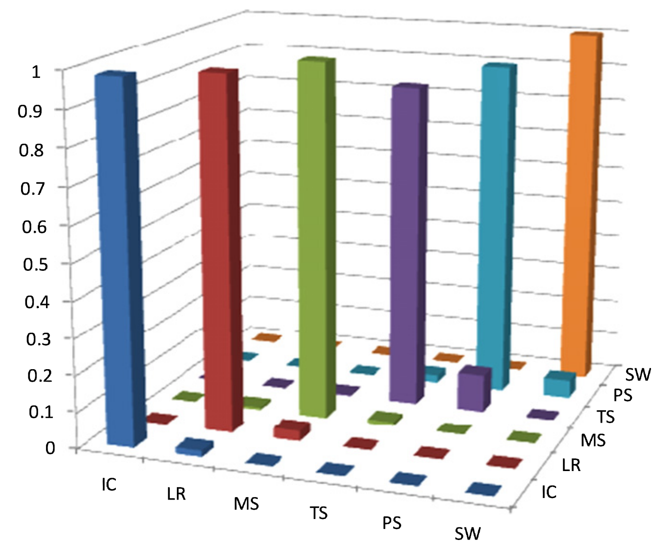


Fig. 10. Estimated transition matrix (normal gait).

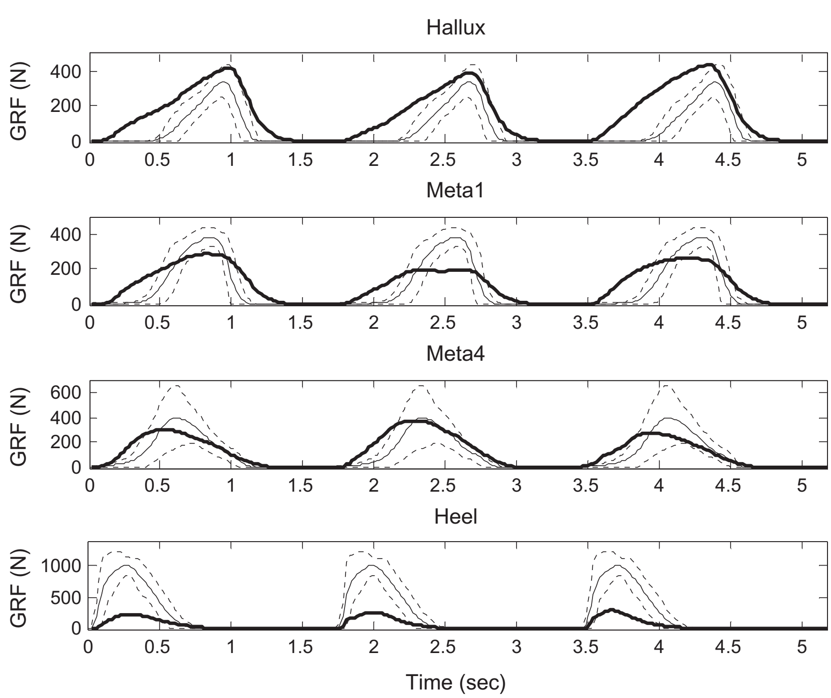


Fig. 11. GRF signals (abnormal gait, before a rehabilitation treatment).

The transition matrix can be estimated by the expectation–maximization (EM) algorithm as follows:

$$\hat{a}_{i,j} = \frac{\sum_{t=0}^{T} \xi_{t,t+1}^{i,j}}{\sum_{t=0}^{T} \gamma_t^i} \tag{13}$$

where γ_t^i denotes the posterior probability at time step t with the state i as in (5) and ξ is defined as follows:

$$\xi_{t,t+1} = \xi(q_t, q_{t+1}) \tag{14}$$

$$= p(q_t, q_{t+1}|\mathbf{y}) \tag{15}$$

$$= \frac{\alpha(q_t)p(\mathbf{y}_{t+1}|q_{t+1})\gamma(q_{t+1})a_{q_t,q_{t+1}}}{\alpha(q_{t+1})} \tag{16}$$

where $q_t = i$ ($i = 1, \ldots, 6$) and $q_{t+1} = j$ ($j = 1, \ldots, 6$), respectively. For the details of the EM algorithm with an HMM, see [12,3].

5. Experimental results

The proposed phase analysis methods have been applied to various GRF data. One normal GRF data and two abnormal GRF data were analyzed by the proposed methods. Two abnormal GRF data were from a Parkinson Disease patient before and after a rehabilitation treatment [1]. The proposed algorithm was implemented in Matlab. After obtaining the GRF data, they were analyzed by the Matlab program, which provides estimated gait phases and a state

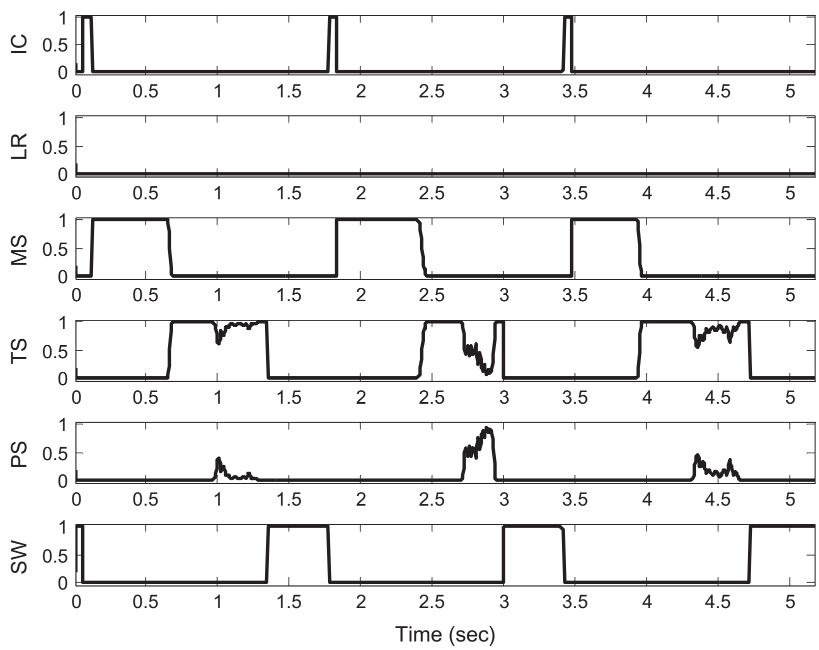


Fig. 12. Estimated gait phases (abnormal gait, before a rehabilitation treatment).

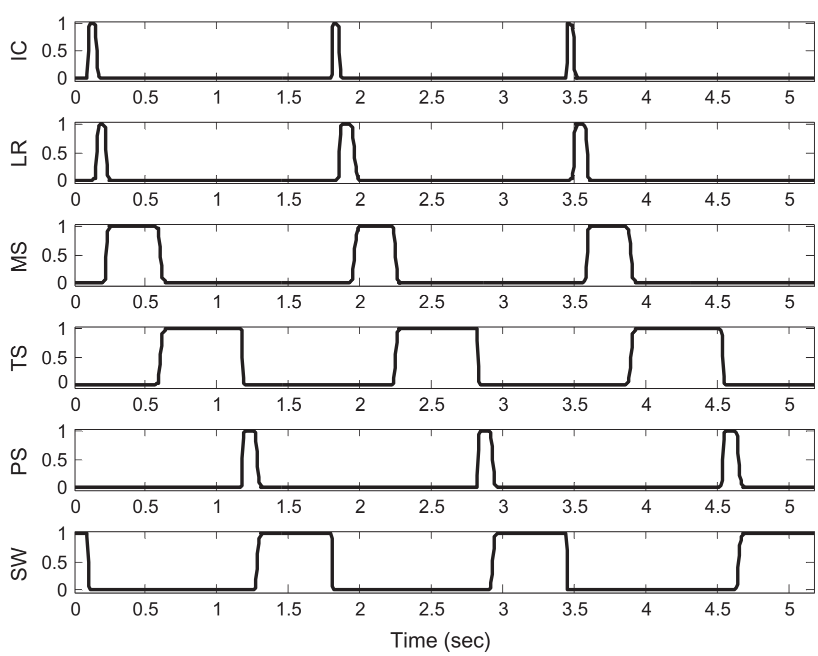


Fig. 13. Estimated gait phases by the fuzzy logic (abnormal gait, before a rehabilitation treatment).

transition matrix. By checking the gait phases and the transition matrix before and after the rehabilitation treatment, the status of the patient is diagnosed, and the effectiveness of the rehabilitation treatment is evaluated. The detected gait phases by the proposed method were checked by skilled physical therapists.

5.1. Normal gait

Fig. 8 shows the GRF data of normal gait with normal GRF bands. The thick line represents the normal GRF data, and thin solid and dashed lines are normal GRF bands. As shown in the figure, since all GRF signals are in the 95% confidence interval of normal GRF bands, it is expected that it would give the normal gait phase pattern. The gait phases, i.e., the posterior probabilities, are estimated by (5) with the data, and the result is shown in Fig. 9. As shown in the figure, the gait phases appear sequentially with the correct order. The estimated transition matrix is shown in Table 1 and plotted in Fig. 10. The self-transition probabilities, i.e., the diagonal elements, are almost one, and the state transition occurs only between adjacent states. Thus, it has tridiagonal-like form as shown in (12), which means that the gait phase are changed with the correct sequences.

5.2. Parkinson's Disease patient (before a rehabilitation treatment)

Parkinson's Disease is a degenerative disorder of the central nervous system that impairs ambulation, balance, speech, attention and other functions. It often associates with gait disorders, such as shuffling, freezing, decreased arm-swing, stooped posture and dyskinesia [8]. This patient suffered from Parkinson's Disease involving both sides of his body. The main problem in the patient's gait motions was shuffling. Due to the shuffling motion, the patient had a short step and insufficient foot clearance. This was followed by decreased heel strike and delayed shift from the lateral to the medial forefoot to achieve push off at the end of the stance phase.

Fig. 11 shows the patient's GRF signals before a rehabilitation treatment. It is observed that the GRF at the heel is much lower and the GRF at the hallux is higher than those of normal gait. Also the GRF at Meta1 is higher at the start and the end of each stride due to shuffling and the freezing gait motions.

These abnormal GRF signals make abnormal gait phases. Fig. 12 shows the estimated gait phases of the patient. Because of the low

Table 2
Estimated transition matrix (abnormal gait, before a rehabilitation treatment).

	IC	LR	MS	TS	PS	SW
IC	0.9321	0.0000	0.0019	0.0000	0.0001	0.0658
LR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MS	0.0000	0.0000	0.9989	0.0011	0.0000	0.0000
TS	0.0000	0.0000	0.0000	0.6380	0.2351	0.1268
PS	0.0000	0.0000	0.0000	0.5172	0.4798	0.0028
SW	0.0006	0.0000	0.0000	0.0000	0.0000	0.9993

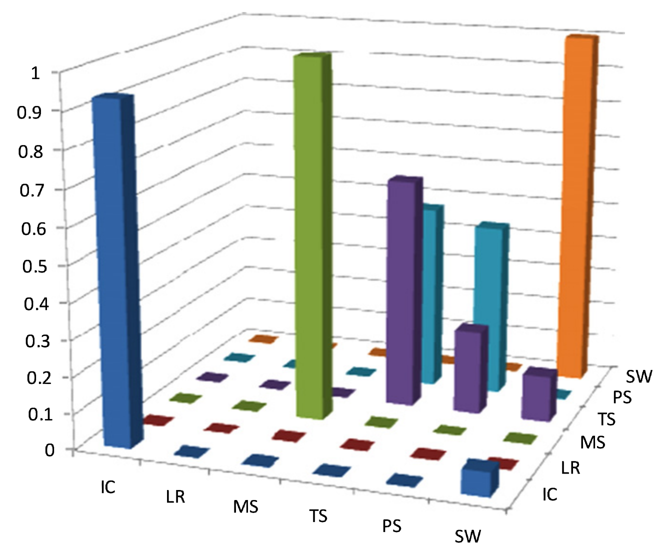


Fig. 14. Estimated transition matrix (abnormal gait, before a rehabilitation treatment).

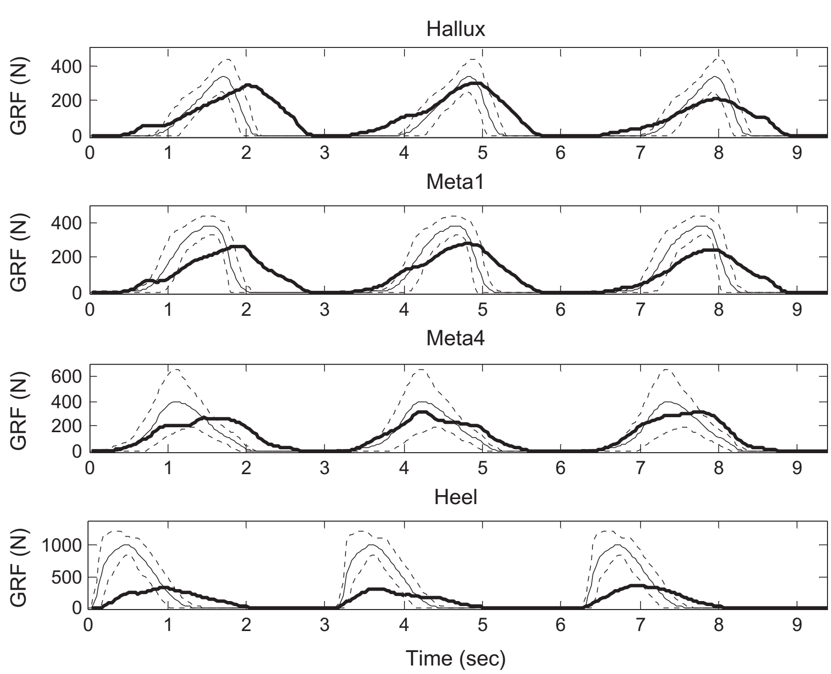


Fig. 15. GRF signals (abnormal gait, after a rehabilitation treatment).

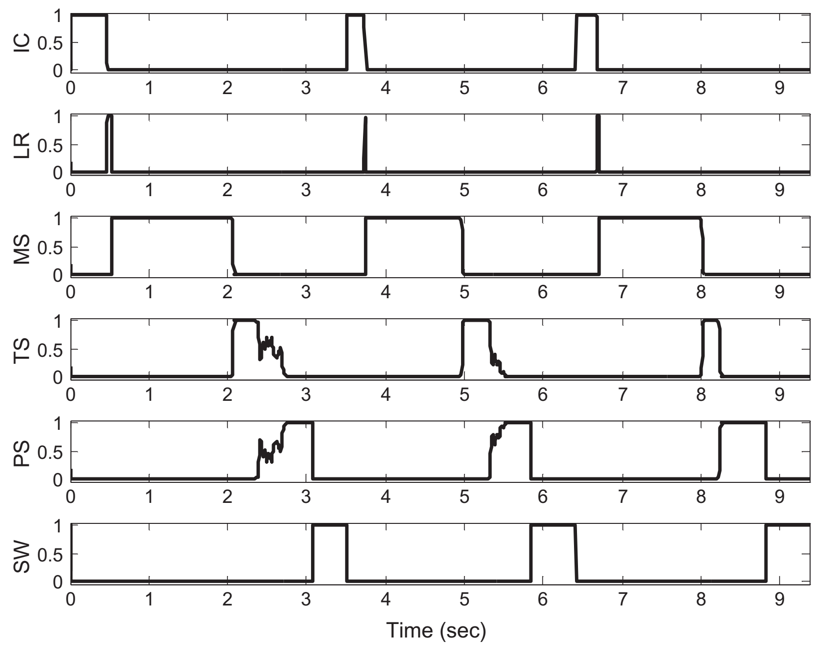


Fig. 16. Estimated gait phases (abnormal gait, after a rehabilitation treatment).

GRF at the heel and the high GRF at the hallux, IC lasts very shortly and LR is not observed at all. Also PS is mixed with TS due to the high GRF at Meta1 at the end of each stride. These results were coincident with the observation from the physical therapists; IC, LR and PS were not clearly observed.

The estimated gait phases were compared with those by the fuzzy logic described in Fig. 1, (1) and (2). Fig. 13 shows the estimated gait phases by the fuzzy logic. Although the actual GRFs of abnormal gait were quite different from those of normal gait, since the patterns of GRFs, i.e., the sequence or the timing of GRFs, were similar with those of normal gait, the gait phases were estimated as normal gait phases, which was not coincident with the observations from the experienced physical therapists.

The transition matrix of the patient is shown in Table 2. In a transition matrix, the probabilities in each row are normalized to make the sum of probabilities in each row be one. But, if one state does not appear at all, then the raw transition probabilities from the state to other states are very small, which makes the normalized transition probabilities do not make sense. Thus, in this algorithm, the transition probabilities in a certain row are not normalized if the sum of the raw probabilities in the row are too low. In this case, the transition probabilities from LR to other states are not normalized since LR does not appear at all, i.e., the raw transition probabilities from LR to other states are very small.

The transition probability from IC to MS is non-zero which means that there is an abnormal gait phase transition from IC to MS. Also as explained previously, the transition probabilities from LR to other states are all zero since LR is not observed at all. The self-transition probabilities of TS and PS are smaller, and the transition probabilities between them are larger than those of normal gait. It shows that TS and PS are mixed each other. As shown in Fig. 14, the pattern of transition probabilities are different from those of normal gait in Fig. 10.

5.3. Parkinson's Disease patient (after a rehabilitation treatment)

The patient took a rehabilitation treatment with a mobile gait monitoring system (MGMS) in the PT Health and Wellness Program, the Department of Physical Therapy and Rehabilitation Science, University of California, San Francisco. The patients' GRF signals were provided to the patient in the real-time as visual feedback information by the MGMS. For the details of the MGMS,

Table 3
Estimated transition matrix (abnormal gait, after a rehabilitation treatment).

	IC	LR	MS	TS	PS	SW
IC	0.9998	0.0001	0.0000	0.0000	0.0000	0.0000
LR	0.0174	0.9825	0.0000	0.0000	0.0000	0.0000
MS	0.0000	0.0000	0.9999	0.0000	0.0000	0.0000
TS	0.0000	0.0000	0.0000	0.7977	0.2022	0.0000
PS	0.0000	0.0000	0.0000	0.1579	0.6600	0.1820
SW	0.0000	0.0000	0.0000	0.0000	0.0000	0.9999

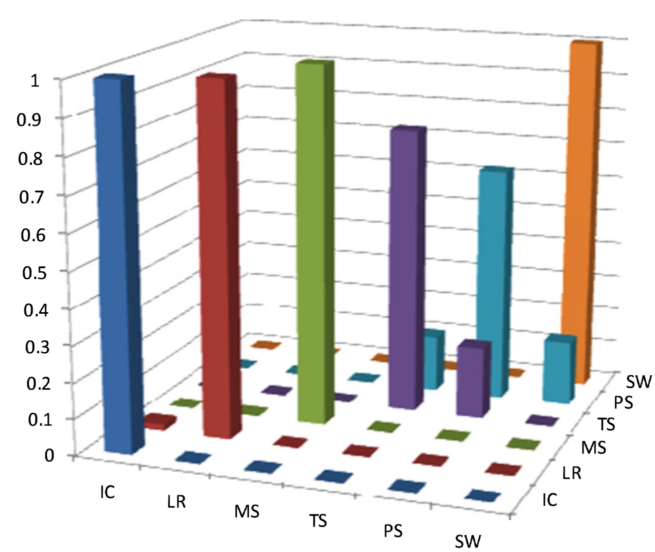


Fig. 17. Estimated transition matrix (abnormal gait, after a rehabilitation treatment).

see [1]. The effectiveness of the rehabilitation treatment with the MGMS is evaluated by checking the estimated gait phases and the transition matrix.

Fig. 15 shows the GRF data after the rehabilitation treatment with the MGMS. The GRF at the hallux is decreased, the GRF at the heel is increased, and the GRF at Meta1 is decreased at the start of each stride. Also the maximum values of GRFs at the hallux, Meta1 and Meta4 appear later due to the increased foot clearance. The GRF signals are still abnormal, but it is obvious that the shuffling motion is decreased.

The improved GRF signals make the gait phases changed as shown Fig. 16. The lasting time of IC is increased, and LR is observed even though it appears only in a short time. Also PS is observed more clearly than before.

As shown in Table 3 and Fig. 17, the transition matrix has been changed. The transition probabilities from LR to other states appear. The self-transition probabilities of TS and PS are increased, and the transition probabilities between them are decreased, which means that the sequence of gait phases is changed to that of normal gait.

6. Conclusion

In this paper, a Hidden Markov Model (HMM) was applied to analyze gait phases. Ground reaction forces (GRFs) data from Smart Shoes were used as observed data. For the detection of gait phases, the posterior probabilities from the HMM were utilized, and the transition matrix was analyzed to check the abnormal state transition between gait phases. The proposed method was verified by three GRF data sets; one normal GRF data, two data from a Parkinson Disease patient. The experimental results showed that the estimated gait phases and the transition matrix have the potential that can be used as tools for diagnosing the status of gait and checking the effectiveness of rehabilitation treatment.

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