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Human Level Walking Gait Modeling and Analysis based on Semi-Markov Process

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Abstract — **Evaluation of individual gait pattern is important for both abnormal gait diagnosis and gait rehabilitation in mobility impaired people. In this paper, semi-Markov process (SMP) is applied to model and analyze human gait in level walking. Gait states are detected from ground reaction forces (GRFs), and gait cycles are described as state transitions in a gait Markov chain (GMC) with sojourn times. Several gait features are defined and online estimated based on the SMP model. With this model, abnormal gait patterns are further analyzed and indexes for gait abnormality assessment are proposed. Experiments of gait analyses with proposed method are conducted on subjects with different health conditions. Results show that individual gait pattern can be successfully obtained and evaluated. Potential applications in gait diagnosis and powered lower limb orthosis (PLLO) control for gait assistance are also discussed.**

I. Introduction

As the number of elderly people and patients suffering from impaired mobility increases, there is a growing demand for abnormal gait diagnosis and gait rehabilitation. Clinical gait diagnostic methods depend on standard gait analysis in gait lab. It usually takes a lot of time to process huge amount of gait data and characterize abnormal gait, and experienced physical therapists are needed to provide rehabilitation suggestions based on these data. Recently, assistive devices like powered lower limb orthoses (PLLO) were designed to help people with abnormal gait. In order to provide effective gait assistance, PLLO control is also based on real-time analysis of the wearer's gait information. Therefore, gait analysis is important for gait diagnosis and rehabilitation.

Different gait analysis methods have been developed by researchers in various applications. Two types of gait data commonly used for gait analysis are joint kinematics and ground reaction forces (GRFs). In applications like PLLO control, gait analysis was done online with gait data collected from wearable sensors. Here gait cycle is usually divided into several simple stages, and different control objectives can be set for each stage to achieve better bionic functions. For example, in HAL [1,2] and Vanderbilt Exoskeleton [3] control for paralytic assistance, walking was divided into three to four stages and gait data like GRFs or joint angles were monitored for state transitions. Some other methods focused more on gait modeling and abnormal diagnosis, and these are often offline processes where gait models were trained with gait data. Chen [4], Alvarez [5] and Tilmanne [6] used Hidden Markov Model (HMM) or Finite State Machine (FSM) to model the gait states in their models, but they do not have clear physical meaning to be mapped to foot events or joint functions. Bae and Tomizuka proposed a HMM model with state defined on foot-ground contact conditions for abnormal gait diagnosis [7]. Abnormal state transitions were checked by state transition matrix. However, their model was only based on gait data associated with single leg, and gait abnormality was assessed through state transition probabilities without modeling the timing.

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Considering the limitations of the above gait analysis methods, we would like to develop a novel gait modeling and analysis method that can model both state transitions and their timing based on GRF information. This method is desired to estimate individual gait pattern of level walking in an ideal environment, like in gait experiment and rehabilitation. And obtained gait model is expected to be further applied in abnormal gait diagnosis and PLLO control for gait assistance. In our previous work [8], states representing foot-ground contact forms of both legs were defined and estimated from GRFs. Gait cycle was described in a FSM, but the gait modeling was rough and incomplete. In this paper, we will introduce the well-defined gait model based on semi-Markov process, and then apply it in gait pattern evaluation and abnormality diagnosis.

The content of this paper is arranged as follows. Section II gives out human gait model based on semi-Markov process. Section III introduces the gait analysis methods for online estimation of individual gait pattern. Section IV proposes the indexes for evaluating gait abnormality. Section V presents the experimental results of level walking on subjects with different health conditions and some further discussion. Section VI summarizes the work.

II. Gait Modeling with Semi-Markov Process

Human gait has cyclical nature with sequential movements in both legs. Since human body configuration and lower limb joint functions keep changing during walking, we can define states to represent specific foot-ground contact condition or joint kinematics within gait cycle. Then gait cycle is described as a series of states with transitions at specific timing. In order to model individual gait pattern, both state transitions and their timing should be considered. Besides, human gait is a stochastic process, that means for each person state sequence and state durations may be different in each gait cycle [7]. Based on the above considerations, we model human gait as a semi-Markov process, and gait cycles are described as state transitions in a gait Markov chain (GMC) with sojourn times.

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TABLE I. STATE DEFINITIONS OF HUMAN GAIT IN LEVEL GROUND

Right \ Left	HC	FC	TC	SW
HC		2	3	4
FC	5	6r | 6l	7 | 7a	8
TC	9	10 | 10a	11l | 11r	12
SW	13	14	15	

A. Gait State Transition Graph

In this research, we focus on studying gait information from GRFs. A pair of pressure shoe pads are designed to measure GRFs at specific locations, so that foot-ground contact of a single leg can be divided into: Heel Contact (HC), Full Contact (FC), Toe Contact (TC), and Swing (SW). Then we define state as specific combination of contact forms in both legs, and it can be detected from GRFs through fuzzy inference as described in our previous paper [8]. Table I shows the state definitions for possible contact combinations of both legs in level ground walking. Four combinations are further separated according to relative positions of two legs.

Then based on physical process of human gait, the general state transition graph for level walking is proposed in Fig. 1. It is directed, connected, and circular with 18 nodes for defined states, and 30 directed connections for possible state transitions during level walking. A gait cycle always contains 8 states based on this graph, so that we divide the graph into 8 stages, with state 14 as the 1st stage.

This state transition graph considers both heel-to-toe and toe-to-heel walking, where single leg full contact (state 14 and 8) always exist in the gait cycle. But special cases like toe-walking and heel-walking are not discussed in this paper. In actual walking, two situations may cause different state transitions that violate our model. For measurement errors, like skipping a state which is too short, we add the expected missing state according to reasonable state sequence. For reciprocating motion between two states, like state sequence 14→2→3→2→3→4, we simplify it into no reciprocating motion gait. After processing, we can describe the actual gait into the state transition graph in the form of Fig. 1.

B. Semi-Markov Process

Based on gait state transition graph, state can transfer to different descendants to form different state sequence. These variations in gait pattern can be found in different person, or even different gait cycles of a person. Thus, we introduce state transition probabilities into gait model to describe the stochastic characteristics of individual gait pattern.

Discrete-time Markov chain is a powerful tool to model stochastic process with Markov property on a finite state space [9]. The Markov property means that the state transition probability depends only on the current state of the system, not on the states of the system at previous steps. Human gait could be approximately considered to have Markov property, so that we could model state transitions of human gait as a discrete-time Markov chain, namely gait

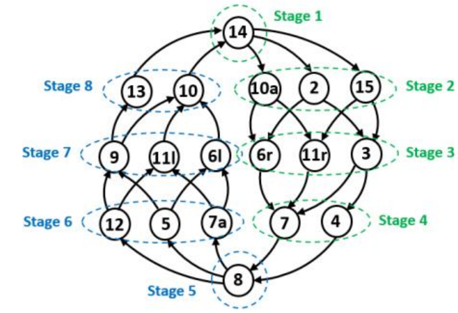

Figure 1. General level walking state transition graph

Markov chain (GMC). The state diagram of GMC is just the state transition graph in Fig. 1. A complete GMC should also include the state transition probabilities, which mean the weight of each connection in the state diagram. For gait analysis purpose, it is reasonable to assume human gait in gait experiment is in ideal environment without external assistance or disturbance. In this case, GMC should be time-homogeneous with a stationary gait pattern.

However, GMC can only model state transitions without considering their timing. In order to add state durations into the model, a discrete-state continuous-time semi-Markov process (SMP) is further considered for human gait modeling. SMP is one kind of Markov process, in which the time interval of each state has an arbitrary distribution [10]. It consists of an embedded Markov chain, GMC in our case, and a sequence of sojourn times between state transitions. The basic idea of SMP is shown in Fig. 2. Besides Markov property of GMC, the Markov assumptions in human gait SMP also include that sojourn time of a state just depends on current and the last states. Mean of sojourn time $U(n)$ in state j after transition from state i is denoted as $\bar{U}_{i,j}$, and we further define the sojourn time conditional only on current state as $\bar{U}_j$ for later calculations.

$$\bar{U}_{i,j} \coloneqq \mathbb{E}[U(n)|S(n-1)=i, S(n)=j] \tag{1}$$

$$\bar{U}_j \coloneqq \mathbb{E}[U(n)|S(n)=j] \tag{2}$$

C. Gait Features in Semi-Markov Process

Based on the SMP model of human gait, several gait features are defined for characterizing individual gait pattern. These features represent both state transitions and their timing in the gait cycle. The first two features are used to describe the GMC, including weights of connections and limiting probability of each state derived from these weights. And the latter two features are used to estimate the average duration of each state in the SMP.

In later analysis, the finite state set of SMP is denoted as $S = \{s_2, s_3 \dots, s_{15}\}$. For any state $i \in S$, its ancestor set is denoted as A_i, and this contains all states that have direct connection pointed to i in GMC. Similarly, the descendant set is denoted as D_i. Z_k is the state set of stage k.

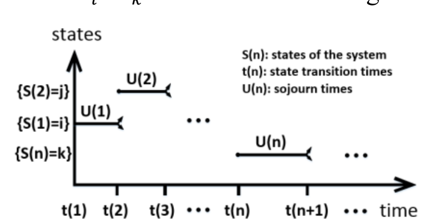

Figure 2. Sample path of a semi-Markov process

1) State Transition Probability (STP): State transition probability $P_{ij} := \Pr[S(n) = j | S(n-1) = i]$ stands for the probability of the transition from i to j. It can be used to predict the next state based on current one during walking. Then transition matrix of GMC is defined with 1-step state transition probability P_{ij}. Since only transitions from i to its descendent state $j \in D_i$ may have $P_{ij} > 0$, transition matrix is actually a sparse matrix. From the definition of state transition probability, we can obtain (3). Especially, if $j = D_i$ we will have $P_{ij} = 1$.

$$\sum_{j \in S} P_{ij} = \sum_{j \in D_i} P_{ij} = 1 \tag{3}$$

2) State Probability (SP): State probability is defined as the limiting probability of each state $\pi_j := \lim_{n\to\infty} p_{i,j}^{(n)}$, where lower case $p_{i,j}^{(n)}$ denotes n steps probability from state i to j [9]. It stands for the probability of a state appearing in gait cycle. Since GMC is periodic with 8 stages, state probability is actually related to the specific stage. For state i and j in stage k' and k, let $n = 8m + (k-1) + (9-k')$ where m is number of gait cycles within these two states. Since state 14 is the only state in stage 1, all states will go to state 14 after several steps. So for any state i, we have $p_{i,14} \equiv 1$ and $\pi_{14} = 1$. Then from Chapman-Kolmogov equation, we will obtain (4) and (5). Actually we can derive all the state probabilities from state transition probabilities and within each stage the state probabilities add together equal to 1.

$$\pi_j = \lim_{n\to\infty} p_{i,j}^{(n)} = \lim_{m\to\infty} p_{i,14}^{(9-k\prime)} p_{14,14}^{(8m)} p_{14,j}^{(k-1)} = \lim_{m\to\infty} p_{14,j}^{(k-1)} \tag{4}$$

$$\pi_j = \sum_i \pi_i P_{ij} = \sum_{i \in A_j} \pi_i P_{ij} \tag{5}$$

3) Mean Intrinsical Percentage of State (IPS): Conditional mean intrinsical percentage of state (CIPS) $\eta_{i,j} := \frac{\bar{U}_{i,j}}{\bar{T}}$ is defined as the mean sojourn time of state j transferred from i over mean gait cycle duration. It can be used to predict the sojourn time of current state during walking. And similarly $\eta_j := \frac{\bar{U}_j}{\bar{T}}$ is further defined as the mean sojourn time of state j over mean gait cycle duration. From the definition of mean sojourn time in (1) and (2), we can obtain relationship (6) and (7) based on Bayes' theorem.

$$\begin{aligned}\bar{U}_j &= \mathbb{E}[U(n)|S(n) = j] \\ &= \textstyle\sum_i (\mathbb{E}[U(n)|S(n) = j, S(n-1) = i] P_{ij} \frac{\pi_i}{\pi_j}) = \frac{1}{\pi_j} \sum_i P_{ij} \pi_i \bar{U}_{i,j}\end{aligned} \tag{6}$$

$$\eta_j = \frac{\bar{U}_j}{\bar{T}} = \frac{1}{\pi_j \bar{T}} \sum_i P_{ij} \pi_i \bar{U}_{i,j} = \frac{1}{\pi_j} \sum_i P_{ij} \pi_i \eta_{i,j} \tag{7}$$

4) Mean Percentage of State (PS): The average percentage of state λ_j stands for the limiting percentage of time spend in state j in the gait cycle. It represents the overall time distribution of each state in the gait cycle. Based on previous defined features, it is clear that the time spent in state j should be proportional to $\pi_j \bar{U}_j$. Then we can obtain expression (8). Of course, the mean percentages of all the states add together should be 1.

$$\lambda_j = \frac{\pi_j \bar{U}_j}{\bar{T}} = \pi_j \eta_j = \sum_i P_{ij} \pi_i \eta_{i,j} \tag{8}$$

Overall, these four gait features defined above can be summarized in Table II. With SMP model individual gait can be described as a sequence of state with specific GMC and timing. As the result, individual gait pattern is presented as state transition graph with 4 groups of gait features.

TABLE II. GAIT FEATURES IN SEMI-MARKOV PROCESS

	State Transition	**State**
GMC	STP (P_{ij})	SP (π_j)
Timing	CIPS ($\eta_{i,j}$)	PS (λ_j)

D. Gait Pattern Online Estimation

The features derived from SMP are designed to characterize individual gait pattern in both abnormal gait diagnosis and PLLO control. In order to be integrated with PLLO control, gait features should be estimated online based on gait data from wearable sensors like pressure shoe pads in this research.

Considering the assumption of gait in ideal environment, individual gait pattern should have constant parameters in the gait model. And the estimations are updated at the end of each gait cycle and gradually converged to the actual values. As to the gait pattern variations in each gait cycle, we will consider and try to model them in the next section. Assume now we have an observation of SMP censored at fixed program cycle, and recorded the gait Markov chain $\{S(n), U(n)\}_{n\in\mathbb{N}^+}$ with $S(1) = 14$. We introduce the following variables for estimation of gait features.

- $N := \sum_{k=1}^{n} \mathbf{1}_{\{S(k)=14\}}$ the number of gait cycles up to now;
- $N_j := \sum_{k=1}^{n} \mathbf{1}_{\{S(k)=j\}}$ the number of visits to state j in the GMC up to now;
- $M_{i,j} := \sum_{k=1}^{n} \mathbf{1}_{\{S(k-1)=i, S(k)=j\}}$ the number of state transitions from i to j up to now;
- $\tau := \sum_{k=1}^{n} U(k)$ the total time up to now;
- $\tau_{i,j} := \sum_{k=1}^{n} U(k)_{\{S(k-1)=i, S(k)=j\}}$ the sojourn time in state j with last state in i up to now;
- $\tau_j := \sum_{k=1}^{n} U(k)_{\{S(k)=j\}}$ the total sojourn time in state j up to now;
- $\hat{T} := \tau/N$ the estimated mean gait cycle duration time.

Referring to the definitions, SMP parameters estimations are summarized as (9) to (13). These values are updated per gait cycle, and they will finally converge to actual gait pattern parameters after large gait cycles [11].

$$P_{ij} = \frac{M_{i,j}}{N_i} \tag{9}$$

$$\pi_j = \frac{N_j}{N} \tag{10}$$

$$\eta_{i,j} = \frac{\bar{U}_{i,j}}{\hat{T}} = \frac{\tau_{i,j}/M_{i,j}}{\hat{T}} = \frac{\tau_{i,j}}{M_{i,j}\hat{T}} = \frac{\tau_{i,j} N}{M_{i,j} \tau} \tag{11}$$

$$\eta_j = \frac{\bar{U}_j}{\hat{T}} = \frac{\tau_j/N_j}{\hat{T}} = \frac{\tau_j}{N_j \hat{T}} = \frac{\tau_j N}{N_j \tau} \tag{12}$$

$$\lambda_j = \frac{\pi_j \bar{U}_j}{\hat{T}} = \frac{(\tau_j/N_j)\cdot(N_j/N)}{\hat{T}} = \frac{\tau_j}{N\hat{T}} = \frac{\tau_j}{\tau} \tag{13}$$

In the actual gait of a specific person, usually only part of states defined in SMP will occur. Therefore, as a result individual SMP can be simplified by removing the states and state transitions that have zero probabilities in general SMP.

III. EVALUATION OF GAIT ABNORMALITY

After individual gait pattern is obtained based on gait SMP model, we can further analyze the gait abnormality. This section introduces the abnormal diagnosis derived from state transition graph, and further proposes a few indexes for the overall gait abnormality assessment.

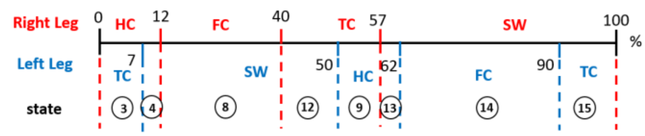

Figure 3. Standard gait pattern within a gait cycle.

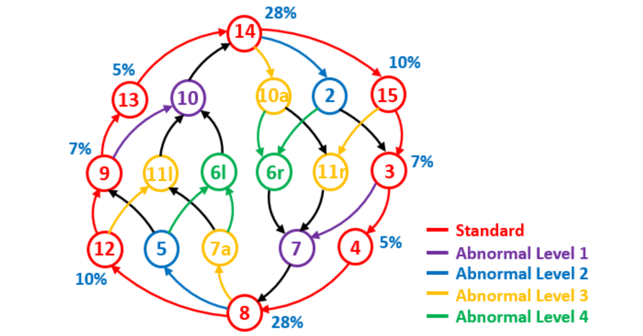

Figure 4. Level walking state diagram with abnormal states/state transitions.

A. Standard & Abnormal Gait Patterns

Standard gait pattern of healthy people has symmetric motions of both legs with specific foot events and timing [12]. This is summarized in Fig. 3 with the standard state sequence (14→15→3→4→8→12→9→13) and percentages of state in gait cycle according to our definitions. In the general state diagram shown in Fig. 4, the standard state sequence is marked red with associated percentage of state in gait cycle. Then based on the deviations from the standard pattern in the state diagram, we then classify all the other states and state transitions into four abnormal levels (ALs). Here, an abnormal state transition means a transition from state with lower AL to state with higher AL. Different abnormal levels are shown in different colors in Fig. 4. Actual states and state transitions in AL 1 exist in normal gait, so we still consider them as part of normal pattern.

B. Abnormal Evaluation Indexes

In order to quantify the abnormality of individual gait pattern for gait diagnosis purpose, a series of Abnormality Evaluation Indexes (AEIs) are proposed in this research. Generally, there are three main criteria to determine the derivation between individual gait pattern and the standard one as listed below. Accordingly, three AEIs based on gait SMP model are defined.

(1) Consistency of gait pattern in different gait cycles;

(2) Whether abnormal states occur in gait cycles;

(3) Derivation of stance/swing percentages in the gait cycle from standard pattern.

1) AEI 1: Gait Pattern Consistency

AEI1 is used to describe the consistency of gait pattern among all gait cycles. It is defined as one subtract the probability of the major state sequence. The more state sequence in each gait cycle varies, the larger AEI1 will be. And the range of AEI1 will be (0, 2).

$$AEI1 = 2(1 - P_{SS_{maj}}) \tag{14}$$

A state sequence (SS) is defined as a cycle in GMC such that $SS = \{s_{SS,1}, \dots, s_{SS,k}, \dots, s_{SS,8}\}$ with each state $s_{SS,k} \in Z_k$. There are in total 64 possible SSs within a gait cycle according to general GMC, however, individual GMC may have only a few of them. The actual SS set for specific gait pattern is denoted as $W = \{SS_l | \text{all } l \text{ s.t.} P_{SS_l} > 0\}$. Probability of a specific SS P_{SS} is calculated as the product of all state transition probabilities along this SS as (15). Obviously, P_{SS} of all possible SSs add together should equal to 1. If the SS with maximal probability does not belong to normal SSs (contain only normal and AL1 states), then it is defined as major state sequence SS_{maj}. Otherwise, SS_{maj} should also include other normal SSs with large probabilities.

$$P_{SS} = \left(\prod_{k=1}^{7} P_{s_{SS,k}, s_{SS,k+1}}\right) \cdot P_{s_{SS,8}, s_{SS,1}} \tag{15}$$

2) AEI 2: Abnormal States

AEI2 is used to describe the abnormal states and state transitions occur in the individual GMC. The probability of abnormal states from abnormal state transitions in each level could be calculated as a vector shown in (16). Then AEI2 is considered as the weighted sum of abnormal state probabilities in all levels as (17). The weight vector gives larger values for higher abnormal levels, and the range of AEI2 is designed to be (0, 6).

$$\begin{aligned}\pi_{abn} = [\, &\pi_3 P_{3,7} + \pi_9 P_{9,10}, \pi_2 + \pi_5, \pi_{10a} + \pi_{15} P_{15,11r} + \pi_{7a} \\ &+ \pi_{12} P_{12,11l}, \pi_{6r} + \pi_{6l} \,]\end{aligned} \tag{16}$$

$$AEI2 = [0.3\ 0.6\ 1.2\ 1.8] \cdot {\pi_{abn}}^T \tag{17}$$

3) AEI 3: Stance/Swing Percentages

AEI3 is used to describe the derivation of the current stance/swing percentages in the gait cycle from the standard pattern. In order to evaluate the percentages of stance/swing in the gait cycle, we divide the gait cycle into four support phases: Left Single Support (LSS), Double Support I (DSI), Right Single Support (RSS), and Double Support II (DSII). Then states are mapped to these support phases as shown in Fig. 5. The support phase percentage vector is defined as a vector of percentages for each support phase in the gait cycle. In standard pattern the support phase percentage vector ξ_{std} is calculated as (18), and this is actually related to walking speed. For a specific SS, ξ_{SS} is calculated from the mean percentage of state of the SS according to Fig. 4 by (19).

$$\begin{aligned}\xi_{std} &= [\lambda_{13} + \lambda_{14} + \lambda_{15}, \lambda_3, \lambda_4 + \lambda_8 + \lambda_{12}, \lambda_9] \\ &= [0.43, 0.07, 0.43, 0.07]\end{aligned} \tag{18}$$

$$\begin{aligned}\xi_{SS} = [&\textstyle\sum_{s_{SS,k} \in LSS} \lambda_{s_{SS,k}}, \sum_{s_{SS,k} \in DSI} \lambda_{s_{SS,k}}, \\ &\textstyle\sum_{s_{SS,k} \in RSS} \lambda_{s_{SS,k}}, \sum_{s_{SS,k} \in DSII} \lambda_{s_{SS,k}}]\end{aligned} \tag{19}$$

Then AEI3 is defined as the sum of error between support phase percentage vector and the standard one in (20). The estimated range of AEI3 will be within about (0, 2).

$$AEI3 = 2 \sum_{ss_j \in W} \left[\left(\sum_{i=1}^{4} \left| \xi_{ss_j}(i) - \xi_{std}(i) \right| \right) \cdot P_{ss_j} \right] \tag{20}$$

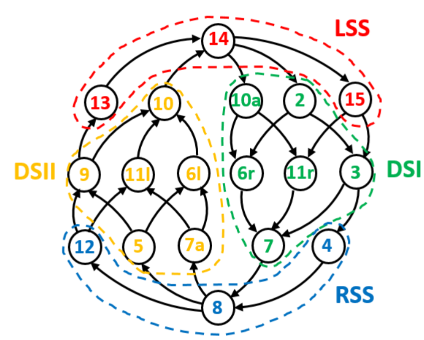

Figure 5. Support phase division in state diagram

Thus, the first two indexes are used to assess the abnormality in GMC, and the third one is used to evaluate the gait timing. Finally, the total AEI is calculated as the sum of each AEI. By allocating different coefficients for each AEI, the contribution of each term is well designed and balanced.

IV. Gait Experiments and Discussions

In this section, we apply the previously developed gait analysis method in the gait experiments of several subjects with different health conditions. Individual gait patterns are described as SMPs with specific gait features, and AEIs are further calculated. Discussions and comparisons are made to verify the feasibility of the proposed method in gait pattern estimation and abnormal gait diagnosis.

A. Experimental Setup and Subjects

In the experiment part, subjects with different health conditions are recruited. Gait patterns of healthy subjects are used to verify the gait model and study the variation of normal gait. And subjects with abnormal gait like the elderly and patient are also studied for verifying the abnormal gait diagnosis part. In total 11 subjects participated in the testing, and according to different age and health conditions, they are divided into 4 groups: young healthy (Y), middle-aged healthy (M), elderly (E), and patient (P). The average age for young healthy group (subject A~C) is 24, the middle-aged group (subject D~H) is 55, and the elderly group (subject I & J) is 75. A patient (subject K) with hemiplegia in the left side due to spine cord injury also enrolled in the testing.

In the gait experiments, attachable shoe pads with 8 Force Sensing Resistors (FSRs) at specific locations are stuck to the bottom of the subjects' shoes to measure GRFs during walking. Each subject was asked to walk on the level ground for 10 gait cycles, and individual gait pattern was estimated based on the GRF data during walking. Especially, the patient participated in the experiment twice, so as to check the consistency of the gait analysis results for abnormal gait.

B. Gait Analysis Results

As the result, gait patterns of each subject are shown in Fig. 6. These graphs represent the SMP models of individual gait pattern. In these graphs, the solid cycles stand for the major state sequences, red and brown values are the STPs and CIPSs of state transitions, green and blue values are the SPs and PSs of states. Some gait feature values that can be directly obtained from the state diagrams are omitted. In addition, abnormality evaluation results are summarized in Table III, and average values of each group are calculated.

For young healthy group, the major state sequences are all standard state sequence, and sometimes AL 1 states (7 & 10) may occur with small probabilities. This is in accordance with the previous analysis of normal pattern. The average AEI1 and AEI2 of this group are very small. AEI3 is a little larger since it is more susceptible to walking speed. The middle-aged healthy group also have normal state sequences as major pattern. But since they usually have smaller stride length, they are more likely to have AL 1 states instead of states 4 & 13. Generally, although this group still belongs to normal cases, they have more variations in state diagrams, and larger AEI values compared to the young healthy group.

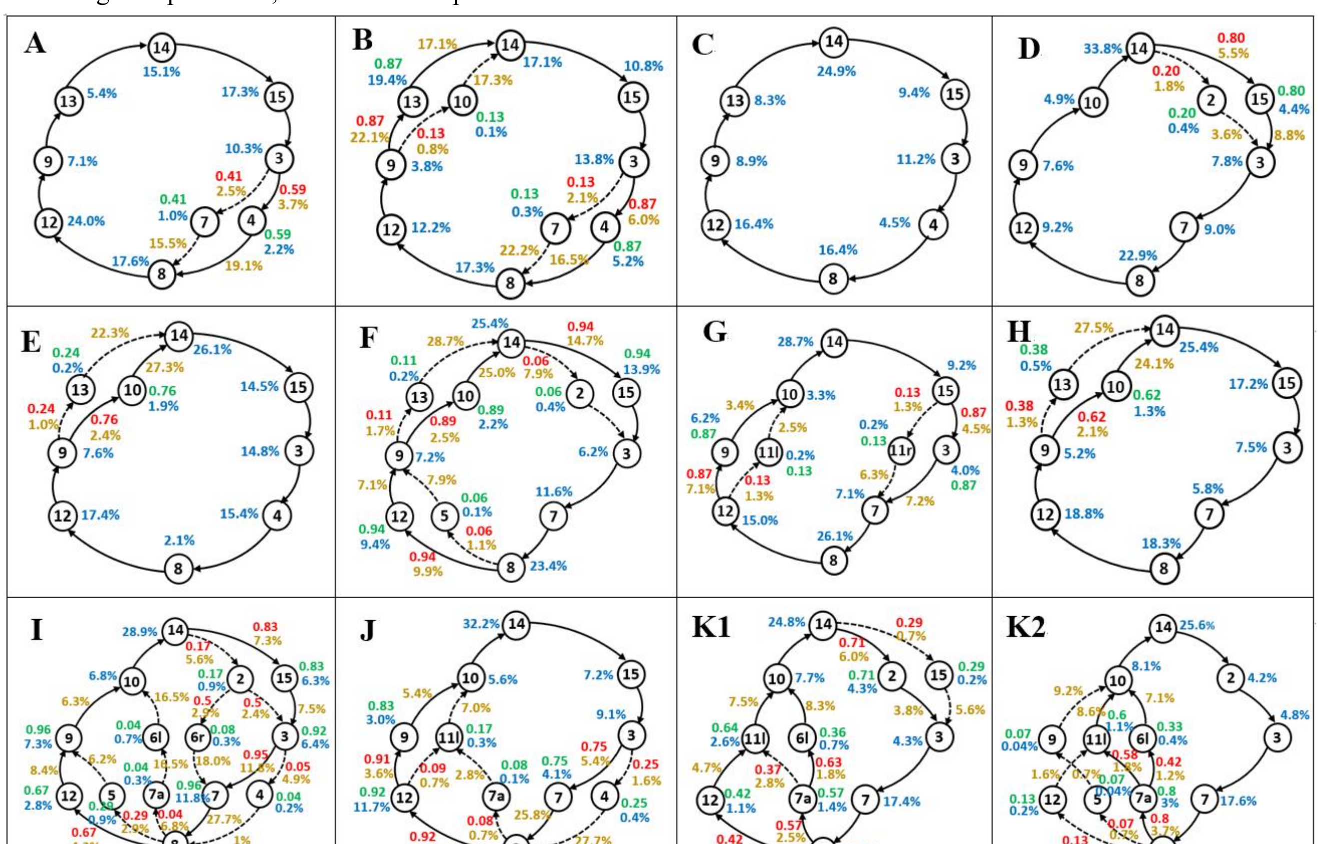

Figure 6. Individual gait pattern described as semi-Markov process

TABLE III. SUMMARY OF ABNORMAL EVALUATION INDEXES

Subject	AEI1	AEI2	AEI3	Total AEI
A	0	0.1245	0.196	0.3205
B	0.222	0.075	0.466	0.763
C	0	0	0.244	0.244
Y Avg	**0.074**	**0.066**	**0.302**	**0.442**
D	0.4	0.72	0.63	1.75
E	0	0.2295	0.396	0.6255
F	0.216	0.633	0.55	1.399
G	0.468	0.825	0.248	1.541
H	0	0.4845	0.268	0.7525
M Avg	**0.216**	**0.579**	**0.418**	**1.213**
I	0.94	1.0995	0.782	2.8215
J	0.182	0.675	0.284	1.141
E Avg	**0.562**	**0.888**	**0.534**	**1.984**
K1	1.388	2.571	0.906	4.865
K2	1.066	2.6805	0.978	4.7245
P Avg	**1.228**	**2.628**	**0.942**	**4.798**

The elderly group has significant individual differences. Subject J has a normal gait pattern similar to middle-aged group, while subject I has a more disordered gait. As shown in the SMP model, subject I still has a normal major state sequence, but gait pattern has more variations with larger chance to go through abnormal states. As a result, the AEI values of subject I are clearly larger than normal cases.

Patient K has participated in the gait experiment twice, and results are shown as K1 and K2. It can be found that gait pattern detected in two trials are quite close, which implies that with the developed method abnormal gait pattern can be successfully estimated within limited steps. The GMCs show quite different patterns compared to normal cases. High level abnormal states 7a, 11l or 6l, representing toe-to-heel walking of left leg, have large possibilities to occur in his hemiplegic gait. This gives significant large AEI2. Besides, he tended to have a much longer stance phase in the right leg, which can be found in percentages of state. This asymmetric motion results in quite different gait timing and a large AEI3.

C. Discussions

With SMP model, individual gait pattern can be successfully obtained and interpreted. By comparing the results of different groups, we can see that as age increases gait pattern is more variable, abnormal states have higher chance to occur, and the timing deviates more from normal case. And the patient's gait pattern has significant deviation from normal pattern. These analysis results are also in accordance with actual characteristics of gait in each group.

In order to verify the feasibility of the proposed gait model on both normal and abnormal cases, currently we selected 11 subjects with different health conditions. In the future, we plan to apply SMP model on more gait abnormal subjects, so that typical gait patterns of different patient groups can be summarized and differentiated for gait diagnosis. With more data AEIs can be further improved and thresholds can be set to assess different abnormality levels.

Gait analysis based on SMP describes the gait cycle into a fine segmented state diagram with duration of each state estimable. States with durations can be mapped to different joint functions during walking for control purpose. Besides, by comparing actual abnormal state transition with the corresponding desired case, we can further find the disordered foot events. This is useful for motion adjustment in abnormal gait assistance. In this case, gait analysis and control can form a feedback system during walking. According to abnormal state transition detected, PLLO can adjust joint motions correspondingly to avoid the abnormal foot events, so as to gradually reduce the gait abnormality. Therefore, the developed model also has good potential to be integrated into PLLO controller design for gait assistance.

V. CONCLUSION

In this study, a semi-Markov process based human gait modeling and analysis method was developed. Individual gait pattern was described by gait Markov chain and duration of each state, and the gait features were estimated online. Based on SMP model, a series of Abnormal Evaluation Indexes were proposed for abnormal gait diagnosis. Gait experiments were conducted on subjects with different health conditions. Results showed that individual gait pattern and its abnormality can be successfully modeled and evaluated. In the future, we will apply the proposed gait analysis method in both abnormal gait diagnosis and PLLO control.

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