Received January 12, 2018, accepted February 4, 2018, date of publication February 15, 2018, date of current version March 13, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2806563

Data-Driven Human-Robot Coordination Based Walking State Monitoring With Cane-Type Robot

QINGYANG YAN[1], JIAN HUANG[1], (Senior Member, IEEE), CAIHUA XIONG[2], (Member, IEEE), ZHAN YANG[3], (Member, IEEE), AND ZHAOHUI YANG[4]

[1]Key Laboratory of Ministry of Education for Image Processing and Intelligent Control, School of Automation, Huazhong University of Science and Technology, Wuhan 430074, China
[2]State Key Laboratory of Digital Manufacturing Equipment and Technology, School of Mechanical Science Engineering, Huazhong University of Science and Technology, Wuhan 430074, China
[3]Jiangsu Key Laboratory of Advanced Robotics, Collaborative Innovation Center of Suzhou Nano Science and Technology, Soochow University, Suzhou 215021, China
[4]Department of Rehabilitation, Union Hospital, Tongji Medical College, Huazhong University of Science and Technology, Wuhan 430022, China

Corresponding authors: Jian Huang (huang_jan@mail.hust.edu.cn), Caihua Xiong (chxiong@hust.edu.cn), and Zhaohui Yang (annyhao430@163.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 61473130 and Grant 51335004, in part by the Applied Basic Research Program of Wuhan under Grant 2016010101010014, and in part by the Key Technology Innovation Project of Hubei Province under Grant 2016AAA039.

ABSTRACT The walking state monitoring is indispensable during the robot-aided walking of people with lower limb dysfunctions. In this paper, the existence of human–robot coordination state is first statistically verified in the process of using a walking-aid cane-type robot during walking. Based on this coordination, a new walking state monitoring method is proposed by using the principal component analysis (PCA). The abnormal or emergency walking state is promptly detected if the new sample data are found to deviate from an off-line PCA model, which is generated from plentiful normal walking data of different subjects. Furthermore, a state diagnosis algorithm based on the contribution plot is also developed for the walking state recognition and diagnosis. In this way, typical abnormal states like the leg restrictions can be distinguished from the emergency states including falls and the stumbling. Moreover, the human–robot coordination analysis can be performed using less sensors built-in the robot without needing the posture information of full human body. The effectiveness of the proposed method is proven by experiments. Better recognition rate and real-time performance of the method are also verified by comparing with conventional center of pressure based monitoring method.

INDEX TERMS Walking-aid robot, state monitoring, human-robot coordination, fall detection.

I. INTRODUCTION

Due to the growth of the aging population and the relative lack of professional nursing, there exist great demands for mobile care tools for the elderly and the disabled suffering from lower limb disorders or visual defects. For people with lower limbs dysfunction such as paraplegic patients and fracture patients, the sedentary injuries and inappropriate rehabilitation ways will lead to a faster decline of their body function if they do not accept correct walking exercise. And the muscle of their lower limbs will also atrophy faster, which will bring serious damages to their health [1]. Thus, appropriate walking exercise is indispensable in improving the life quality for our targeted users.

To help the individuals with limited mobility in the daily life, various walking-aid devices have been developed to provide assistance in locomotion. Common devices such as canes, walkers and manual wheelchairs can provide strength support for limbs. Although lightweight and simple, these devices are unpowered to provide effective assistance. For example, a user has to move the device (such as a walker) forward after each step, disrupting normal walking pace and increasing the energy consumption for these already frail users [2]. Another kind of powered wheelchairs have also been developed [3], which makes it easy for users to reach the destination and minimizes the additional consumption of the user's energy but may also leads to a faster decline of user's body function in its sedentary motion mode. Similar devices eg. Mobile Inverted Pendulum [4], [5] as a human-aided transporter has also been widely used as the travel tools.

Considering the deficiencies of existing mobility tools, intelligent walking-aid robots are extensively studied in this decade [6]–[13]. A walking-aid robot can assist a user's mobility and enable them to be physically active through assisted walking. Furthermore, some walking-aid robots can also recognize user's walking states (both normal walking and falls) online and react immediately to an emergency. The correct and real-time walking state monitoring is vital for the robots to provide a safe and effective assistance.

Current methods of the walking state detection have been studied a lot on the walking-aid robots. Lee *et al.* [14] and Huang *et al.* [15] propose vision based methods to estimate the user's walking states while operating the walking-aid robot. Di *et al.* [16] propose the Zero Moment Point (ZMP) method to measure the position of the user's gravity to estimate the user's stability in using the walking-aid robot. And Yan *et al.* [17] propose the human robot coordination stability (HRCS) to measure the walking states of both human and the walking robot. Di *et al.* [18] propose the Center of the Pressure (COP)-based method to estimate the posture during the operation of the walking-aid robot. In [19], the user's state is estimated by a couple of laser ranger finders that predict the possibility of falling down. Huang *et al.* [20], Yi *et al.* [21], Pierleoni *et al.* [22], Pivato *et al.* [23], Qiu *et al.* [24], and Ma *et al.* [25] propose posture estimation methods using wearable sensors to measure the movements of the whole body.

It should be pointed out that there are some drawbacks in the current methods of walking state monitoring while operating the walking-aid robot. First, a lot of existing methods are lack of sound theoretical foundations and implemented based on detecting whether a signal reaches some predefined thresholds. Secondly, most of the monitoring methods can only distinguish the normal walking and emergency states (falls). Meanwhile, the robot is also needed to have the ability to recognize some abnormal walking states (e.g. the antalgic gait, the hemiplegic gait, etc.) so that it can better assist the specific users accordingly. These abnormal gaits are a kind of intermittent states between normal and emergency walking states, and are not well addressed so far. Thirdly, some model-based walking state monitoring methods need to acquire the whole body's posture information by utilizing a large amount of wearable sensors thus unfavorable for system integration and inconvenient for users.

The arm-leg coordination circumstance has been found during normal human walking [26]–[30], which is also called limb synergy [31]. And abnormal gaits and falls break the arm-leg coordination. It is natural to hypothesize that there still exist certain coordinations during the normal walking with the walking-aid robot, and these coordinations can be used as an important features to judge whether the walking state is normal or not. If this hypothesis is tenable, a human-robot coordination based walking state monitoring method is supposed to be obtained. Several possible advantages of this method are listed as: 1) Since this coordination is prevalent in the robot-aided human walking, the proposed coordination based monitoring method has a profound theoretical basis; 2) Although both abnormal and emergency walking states can break the coordination, some statistical features might be dug out to recognize their difference; 3) Without knowing all the limbs posture information of the whole body, the coordination can be easily detected with few sensors on the robot.

The data-driven statistical process monitoring methods are very popular nowadays for the purpose of process monitoring and fault diagnosis ([32]–[35]), such as the diagnosis of three-phase electrical machines [36], the fault detection and diagnosis in chemical processes [37]. Among current data-driven statistical process monitoring methods, the principal component analysis (PCA) method stands out in handling large numbers of highly correlated variables in the process for its convenience and effectiveness, which is also widely applied in the analysis of the inter-joint coordination and limb synergies [38]–[40]. Thus, the PCA method is supposed to be adopted to detect and confirm the correlated relationships of the variables during the human-robot coordination. In traditional PCA based process monitoring and fault diagnosis method, the normal data is collected as the standard sample, and the test statistics are calculated corresponding to the sample. If online detected data does not belong to the mode of standard sample, an alarm is activated. In [41], based on square prediction errors (SPE), a probability mixture based PCA model is proposed and a fault detection logic is used. The use of multimode PCA and dynamic PCA for multimodal process monitoring is proposed in [42] and [43], respectively. Other efforts on PCA-based multimodal process monitoring can be found in [44] and [45].

A. CONTRIBUTION OF OUR PAPER

This paper proposes a new walking state monitoring method based on the human-robot coordination. The PCA is used to detect the abnormal walking movements and capture the user's emergency states while using the cane-type robot. The main contributions of this study mainly include three aspects: 1) the human-robot coordination state during the robot-aided walking is statistically verified based on a lot of experimental data; 2) a new walking monitoring method is obtained which uses a small number of sensors built-in the robot and is able to distinguish the normal, abnormal and emergency walking states; and 3) plentiful experiments are conducted to prove the effectiveness and better performance of the proposed method.

B. ORGANIZATION OF THIS PAPER

The remainder of this paper is organized as follows. Section II describes all preliminaries related to the proposed methodology. Section III illustrates details about the proposed method that includes a PCA based walking states monitoring algorithm and a state diagnosis algorithm. In Section IV, various experiments of normal walking, fall states and leg restriction states of different users are conducted and experiment results are compared with each other. Finally, the conclusions are given in Section V.

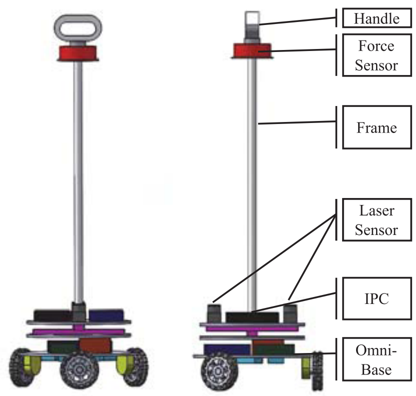


FIGURE 1. The intelligent cane-type walking-aid robot system.

II. BACKGROUND

In this section, the cane-type walking-aid robot will be introduced. The brief description of principle component analysis (PCA) based fault diagnosis, different modes during walking monitoring and the walking states are also explained.

A. THE CANE-TYPE WALKING-AID ROBOT

The proto-graph of the cane-type walking-aid robot system is shown in the Fig. 1. This robot consists of an omni-directional platform, an industrial personal computer (IPC), a six-axis force sensor under the handle and two laser sensors. The force sensor is used for detecting the interaction force from the user to estimate the user's motion intention. The forward laser sensor is used to detect the information of obstacles in the environment. The backward laser sensor is used to detect the motion velocities of the user's legs.

The intention based admittance control (IBAC) algorithm is assumed in this study, which was proposed in our former work [12]. The relationship between the input force and desired robot velocity in the intentional direction can be described by the following transfer function:

$$G(s) = \frac{V(s)}{F(s)} = \frac{1}{Ms + B}, \tag{1}$$

where F is the interaction force between the human and the robot, V is the velocity of the robot. M and B are the mass and damping parameters respectively. Thus, while the robot moves at the desired velocity under the user's intention detected from the input force, the robot can help support the user during the walking.

B. PCA BASED FAULT DIAGNOSIS

The PCA was first introduced in [46]. It is widely used in process monitoring and fault diagnosis. The following elements are required in describing a PCA model based fault diagnosis [47].

In order to find the fault information in the data, the the hypothesis test of statistics can be established to judge whether the process data deviate from the principal component model.

Before monitoring the states online, the normal data should be collected and pre-processed. Assume that the sample data of normal states is $X \in R^{n\times m}$ with n samples and m variables. After standardization and normalization, the standard data $\bar{X}$ is obtained. The statistic index T^2 is used to evaluate the change of the principal component sub space $\hat{X}$, and SPE is used to evaluate the change of the residual sub space E [48]. If the fault state happens, some variables of the process will lead to the change of the principal component sub space $\hat{X}$, or some variables of the process will lead to the change of the residual sub space E. By monitoring both SPE and T^2, the monitoring of the process is realized in the PCA based process monitoring methods ([49]–[51]). The monitoring statistics T^2 and SPE for the sample $\bar{X}(i)$ are then calculated by Eq. (6) and (7) (see [48]):

$$T^2(i) = \bar{X}(i)^T P\lambda^{-1}P^T\bar{X}(i) \tag{2}$$

$$SPE(i) = \bar{X}(i)(I - P_k P_k^T)\bar{X}(i) \tag{3}$$

T_α^2 is used to denote the control limit of T^2 under the state that the confidence of F distribution is α.

$$T_\alpha^2 = \frac{k(m^2-1)}{m(m-k)}F_{k,m-k,\alpha}\ , \tag{4}$$

where $F_{k,m-1,\alpha}$ is the critical value of the F distribution corresponding to the α test level, k degrees of freedom and the $m-k$ condition [48]. m is the number of the variables of the sample, and k is the number of the main PCs.

SPE_α is used to denote the control limit of SPE under the condition that the confidence is α:

$$SPE_\alpha = \theta_1[1 + \frac{h_0 C_\alpha\sqrt{2\theta_2}}{\theta_1} + \frac{\theta_2 h_0(h_0-1)}{{\theta_1}^2}]^{1/h_0}, \tag{5}$$

where $\theta_1 = \sum_{i=k+1}^{m}\lambda_i$, $\theta_2 = \sum_{i=k+1}^{m}{\lambda_i}^2$, $\theta_3 = \sum_{i=k+1}^{m}{\lambda_i}^3$, $h_0 = \frac{1-2\theta_2\theta_3}{3{\theta_2}^2}$. C_α is the threshold of the standard normal distribution with the confidence is α.

For a new sampling point, if the value of the statistic index T^2 and the statistic index SPE are less than the control limits, it indicates that the new data point falls in the same statistical distribution as the normal process data. If not, the new data point falls beyond the same statistical distribution with the normal data, then there may be an abnormal situation in the process. The detection strategy can be summarized by the following simple "IF-THEN" rule:

IF :

$$T^2 > T_\alpha^2 \tag{6}$$

or

$$SPE > SPE_\alpha \tag{7}$$

THEN: The fault state is detected.

C. WALKING STATES

Note that there exists different walking states in using the walking-aid robot due to the different degrees of the upper and lower limbs coordination and human-robot coordination,

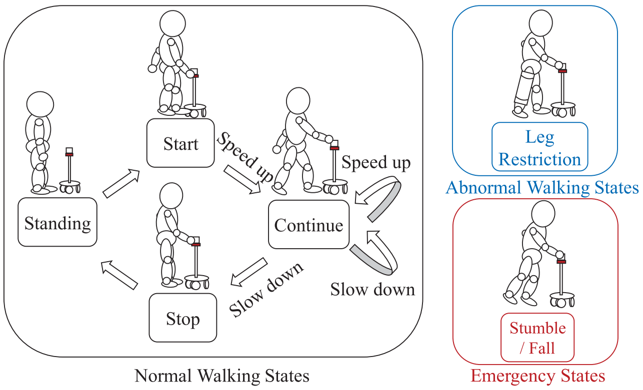


FIGURE 2. Walking states.

as shown in Fig. 2. It's significant to monitor the different walking states and recognize them quickly in using the walking-aid robot so as to provide the safe and comfortable operation experience. In this article, we mainly categorize the walking states into the three kinds: normal walking state, emergency state, abnormal state, as below:

1) NORMAL WALKING STATE

During the normal walking, there is a good coordination between upper limbs, lower limbs and the robot. When a healthy adult is walking normally with nothing assisted, the arms move out-of-phase with each other at a frequency that is synchronized with stride frequency [28]. According to [52], though assembling the sliding handles as the assistance during walking, the arms and legs were similarly coordinated with and without the use of sliding handles, thus, the sliding handles don't affect the degree of arm−leg coordination. Besides, Hassan *et al.* [53] show the good coordination pattern of using a cane during the walking. In using the cane-type walking-aid robot, function purposes of the cane and the sliding handles as well as the ways to use them are similar, we can assume that there is also a good coordination between the arm, leg and the cane-type walking-aid robot during the normal walking with the robot. The normal walking states in using the walking-aid robot could be described in Fig. 2.

2) EMERGENCY STATE

Falls and stumbles are defined as the emergency states during the walking in Fig. 2. If the falling or stumbling happens during the walking, the subject will be dangerous. To avoid injuries of the subjects, it is necessary to conduct researches on the emergency state detection during the walking states monitoring when using the cane-type walking-aid robot.

3) ABNORMAL STATE

Although there are numerous abnormal walking states, a large amount of the abnormal gaits include the feature of leg restriction, e.g. the antalgic gait and the gait during the knee-ankle-foot orthosis for cripple and paraplegic patients' recovery training [54]. Thus, compared with the normal walking state, we define the leg restriction states as the abnormal states in this study (see Fig. 2).

(a) (b) (c)

FIGURE 3. Leg restriction. (a) Right leg restriction. (b) Left leg restriction. (c) Both legs restriction.

The lower limb holders as shown in Fig. 3 are used to restrict the motion of subjects' legs and decrease subjects' mobility for simulating the abnormal states. Though this leg restriction always exists during the rehabilitation process or in daily walking of the subjects suffering from leg fracture or paralysis, they are far less dangerous than the emergency states [55]. Thus, it is important to distinguish the emergency states from the leg restriction states.

III. PROPOSED METHODOLOGY

The human-robot coordination based walking state monitoring method is outlined in Fig. 4. The proposed method has two main steps: off-line design of the PCA model and online monitoring with the state diagnosis using the model. Prior to off-line design of the PCA model, it is necessary to conduct the preliminary experiments for analyzing the human-robot coordination movements of different users while using the walking-aid robot. Details about these steps are presented as follows.

A. PRELIMINARY MOVEMENTS ANALYSIS OF USING WALKING-AID ROBOT

In order to investigate the human-robot coordination of different users' walking in using the cane-type walking-aid robot, five healthy subjects are invited to conduct experiments for normal walking data collection with the cane-type walking-aid robot.

1) SUBJECTS

Five healthy subjects are a female and 4 males. All the subjects are right handed, they all used the cane-type walking-aid robot in the right hand. The information of the five healthy subjects is shown in Tab. 1. Since at least 60% of falling behaviors occur in the forward direction [56], subjects were informed of the experiment goal and requested to perform the walking trials in forward direction with the cane robot.

2) DATA COLLECTION

The collected data of movements of the human-robot coordination system is denoted as $X \in R^{n\times m}$ with n measurement states and m state variables as shown in Fig. 5. The user's interaction force matrix is denoted as F_H, which consists of

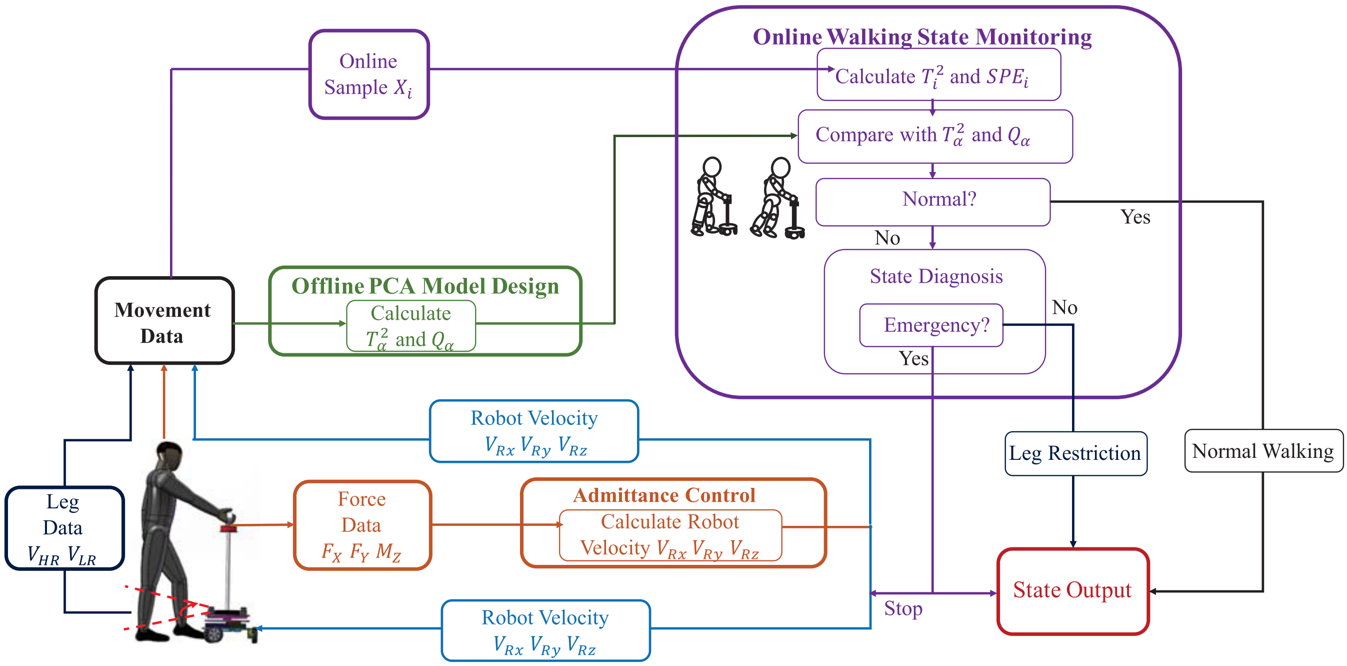


FIGURE 4. Human-robot coordination based walking state monitoring with cane-type robot. (Firstly, the force data F_X, F_Y and M_Z are used to calculate the desired velocity of the robot V_{Rx},V_{Ry} and V_{Rz} based on the IBAC algorithm respectively. Then, the movement data of normal walking including the velocities of the legs V_{HR},V_{HL}, the force data F_X, F_Y, M_Z and the velocities of the robot V_{Rx},V_{Ry}, V_{Rz} are used to calculate the control limits T_α^2 and SPE_α in the off-line design of the PCA model. Finally, the online movement sample X_i is used to calculate the statistic indexes T_i^2 and SPE_i. If $T_i^2 < T_\alpha^2$ and $SPE_i < SPE_\alpha$, the walking state is normal walking and the desired velocity of the robot V_{Rx},V_{Ry} and V_{Rz} will be sent to the omni-base. If $T_i^2 > T_\alpha^2$ or $SPE_i > SPE_\alpha$, the abnormal or emergency state is detected. If the state is diagnosed as the abnormal walking state, i.e. the walking state is the leg restriction state, the desired velocity of the robot V_{Rx},V_{Ry} and V_{Rz} will also be sent to the omni-base. If the state is diagnosed as the emergency state in the state diagnosis algorithm, then the robot will stop).

TABLE 1. The information of subjects.

Subject	Sex	Age (years)	Height (m)	Weight (Kg)	Mean Stride Length (cm)
1	M	28	1.69	59.0	51
2	F	22	1.57	41.2	32
3	M	24	1.80	65	57
4	M	23	1.68	56	48
5	M	22	1.70	74	53

the force F_X in the X-axis direction and the force F_Y in the Y-axis direction, as well as the torque M_Z around the Z-axis, thus we have:

$$F_H = [F_X \quad F_Y \quad M_Z] \tag{8}$$

The velocity of the right leg and left leg is V_{HR} and V_{HL} respectively:

$$V_{HR} = [V_{HRX}\ V_{HRY}] \tag{9}$$

$$V_{HL} = [V_{HLX}\ V_{HLY}] \tag{10}$$

V_{HRX} is the component velocity of V_{HR} in X direction. V_{HRY} is the component velocity of V_{HR} in Y direction. V_{HLX} is the component velocity of V_{HL} in X direction. V_{HLY} is the component velocity of V_{HL} in Y direction. The velocity of the walking-aid robot is denoted as:

$$V_R = [V_{Rx}\ V_{Ry}\ V_{Rz}] \tag{11}$$

V_{Rx} is the velocity of the robot in the X-axis direction, V_{Ry} is the velocity of the robot in the Y-axis direction, and V_{Rz} is the velocity of the robot around the Z-axis.

Then the movements could be described as:

$$X = [F_X\ F_Y\ M_Z\ V_{HRX}\ V_{HRY}\ V_{HLX}\ V_{HLY}\ V_{Rx}\ V_{Ry}\ V_{Rz}] \tag{12}$$

3) HUMAN-ROBOT COORDINATION

The contribution proportion of the principal components (PCs) of the five subjects' movements is shown in Fig. 7.

The accumulated contribution proportion of the first eight variables is more than 95%. It indicates that the first eight PCs could be the main PCs. Hence, it is effective to use the first eight PCs to analyze the movements by PCA.

4) SIMILARITY ANALYSIS OF SUBJECTS

In the preliminary experiments we also analyzed the similarities between the different movements of the healthy subjects's normal walking as shown in Tab. 2. The similarities of the different healthy subjects' movements are measured by the angles $\theta_{ij}(i = 1, 2, 3, 4, 5, j = 1, 2, 3, 4, 5, i \neq j)$ between the first PCs among the subjects' movements data:

$$\theta_{ij} = arccos(\frac{PC(1)_i \cdot PC(1)_j}{||PC(1)_i|| \times ||PC(1)_j||}) \tag{13}$$

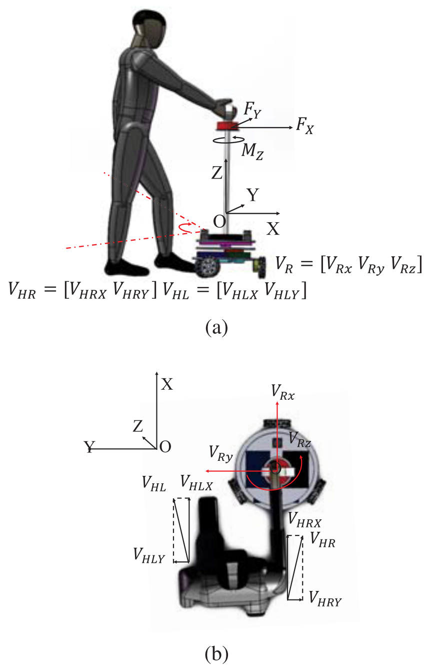


FIGURE 5. The movements data collected. (a) Side view. (b) Top view.

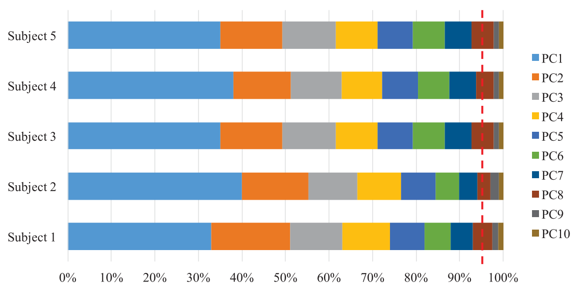


FIGURE 6. The contribution proportion of the PCs.

Although it was not consistent with what can be seen in Tab. 2 among all the subjects' movements data, these low values of the angles between PCs indicate that the different users operate the cane-type walking-aid robot in a similar way, which means there indeed exists the common coordination of the limbs and the robot thus the similar walking pattern of different users can be categorized as the same state so that different user's walking states could be analyzed by the PCA method.

B. OFF-LINE DESIGN OF PCA MODEL

In the off-line design of the PCA model, the control limits T_α^2 and SPE_α are obtained as the thresholds of the normal walking under the human-robot coordination. Among different walking states, we select the normal walking state as the standard state to design the standard walking model. **Algorithm 1** outlines the complete procedure for off-line standard model design based on PCA. In the algorithm, the sample data is denoted as X_{normal} and the test data is denoted as X_{test}.

TABLE 2. The similarities of the different subjects' normal walking.

Similarity (Subject \ Subject)	1	2	3	4	5
1		19.15	10.02	17.90	26.13
2	19.15		11.28	16.77	15.51
3	10.02	11.28		14.46	16.97
4	17.90	16.77	14.46		29.22
5	26.13	15.51	16.97	29.22	

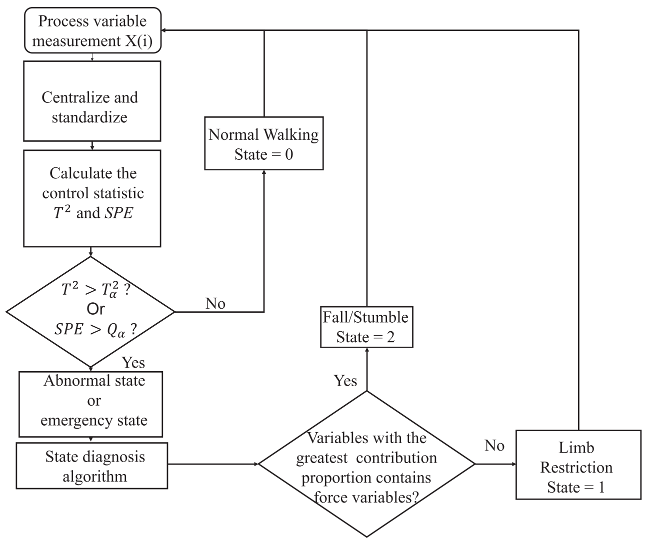


FIGURE 7. Online monitoring and states diagnosis.

X_{normal} and X_{test} are the experiment data of all the subjects during the normal walking in forward direction. $X_{mnormal}$ and X_{mtest} are the processed data of centralizing and standardizing the samples X_{normal} and X_{test}. The covariance matrix σ of $X_{mnormal}$ could be obtained:

$$\sigma = \frac{1}{n-1} X_{mnormal}^T X_{mnormal} \tag{14}$$

The eigenvectors $\delta = [\delta_1, \delta_2, \delta_3, \ldots, \delta_m]$ sorted in descending order with respect to the eigenvalues $\lambda = [\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_m]$ of σ could be used to obtain the number of the main PCs. According to the accumulated contribution proportion $\sum_{i=1}^{k} \beta_i$, if the first k PCs reaches 95 %, then the effective number of the main PCs is k.

Then the model X_{model} of the normal walking could be obtained by $PC_i = X_{mnormal}(i)\delta_i$, and we have

$$X_{model} = PC_1\delta_1^T + PC_2\delta_2^T + PC_3\delta_3^T \ldots.. + PC_k\delta_k^T \tag{15}$$

Substituting X_{mtest} into X_{model}, if X_{model} can ensure that the model error $E = X_{mtest} - X_{model}$ is the least, then the X_{model} is the standard model. Finally the control limits T_α^2 and SPE_α of T^2 and SPE can be calculated by Eq. (4) and (5).

C. ONLINE WALKING STATE MONITORING AND DIAGNOSIS

The standard model of normal walking in the off-line design is used to carry out the online walking state monitoring as

Algorithm 1 Off-Line Design of The PCA Model

In: X_{normal}, X_{test}
Out: T_{α}^2, α

1: Centralize and standardize $X_{normal} \in R^{n\times m}, X_{test}$.
2: $X_{mnormal}$ and X_{mtest} are obtained.
3: Calculate covariance matrix σ of $X_{mnormal}$.
4: Calculate the eigenvectors $\delta = [\delta_1, \delta_2, \delta_3, \ldots, \delta_m]$ sorted in descending order with respect to the eigenvalues $\lambda = [\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_m]$ of σ.
5: Calculate the accumulated contribution proportion $\sum_{i=1}^{k} \beta_i$ of PCs, $k \in [1, m]$.
6: **if** $\sum_{i=1}^{k} \beta_i \geq 95\%$ **then**
7: The first k PCs are the main PCs needed.
8: **else**
9: k = k + 1.
10: **end if**
11: Obtain the model X_{model} by Eq. (15).
12: Substituting X_{mtest} into X_{model}.
13: **if** Model error $E = X_{mtest} - X_{model}$ is the least **then**
14: X_{model} is the standard PCA model.
15: **else**
16: Input another set of normal walking data as X_{normal}. **Goto** Step 1.
17: **end if**
18: Calculate the control limits T_{α}^2 and SPE_{α} of the monitoring statistics T^2 and SPE by Eq. (4) and (5).
19: **Return** T_{α}^2 and SPE_{α}

shown in Fig. 7. Comparing the control statistics $T^2(i)$ and $SPE(i)$ of the online measurement $X(i)$ with the control limits T_{α}^2 and SPE_{α}, if none of the statistic indexes is bigger than the corresponding control limit, the walking state is thought to be normal walking, denoted as $State = 0$. If the state is leg restriction state, the walking state is denoted as $State = 1$. And if the emergency state is detected, the walking state is denoted as $State = 2$. The leg restriction state and the emergency state are distinguished by the proposed state diagnosis algorithm in the following.

1) ONLINE MONITORING

The procedures of online walking state monitoring are introduced in the **Algorithm 2**. The variable measurement X_i at the time $t = i$ is collected online. After centralization and standardization of $X(i)$, $X_m(i)$ is obtained. Then, the statistical indexes $T^2(i)$ and $SPE(i)$ of $X_m(i)$ are obtained by Eq. (2) and (3). Compare the $T^2(i)$ and $SPE(i)$ with T_{α}^2 and SPE_{α}, if $T^2(i) < T_{\alpha}^2$ and $SPE(i) < SPE_{\alpha}$, $X(i)$ is under the human-robot coordination state, thus, it is a normal walking state. If (6) and (7) are satisfied, the abnormal or emergency state is then detected. The potential root causes of this abnormal state could be identified by the proposed state diagnosis algorithm based on the contribution plot of variables to determine whether the state is the leg restriction state or the emergency state.

Algorithm 2 Online Walking State Monitoring

In: $X(i)$, T_{α}^2, SPE_{α}
Out: $State$

1: Collect $X(i)$ at $t = i$.
2: Centralize and standardize $X(i)$
$X_m(i)$ is obtained
3: Calculate the monitoring statistics $T^2(i)$ and $SPE(i)$ by Eq. (2) and (3).
4: Compare $T^2(i)$ and $SPE(i)$ with the limits T_{α}^2 and SPE_{α}
5: **if** $T^2(i) < T_{\alpha}^2$ and $SPE(i) < SPE_{\alpha}$ **then**
6: The state of X(i) is normal walking.
$State = 0$
7: **else**
8: The state is the abnormal state or emergency state.
$State = 1$ or $State = 2$
9: **Call** the **State Diagnosis Algorithm 3**
10: **if** The state is the abnormal state "Leg Restricition" **then**
11: $State = 1$
Alarm won't be generated
12: **else**
13: The state is the emergency state "Fall/Stumble"
$State = 2$
Alarm is generated
14: **end if**
15: **end if**
16: **Return** $State$
17: Update
$X(i-1) \leftarrow X(i)$
18: **Goto** Step 1

2) STATE DIAGNOSIS

The monitoring of the T^2 and SPE just can detect the abnormal states, but it cannot distinguish the abnormal state from the emergency state. Wannier *et al.* [52] point out that the arm movements will be improved to keep the balance during the fall. Besides, the arm movement range under the fall state is much larger than the one under the leg restriction state. Thus, the potential root causes of the stumbling or falling states will be accompanied by the sudden upper limbs movements. Hence, the movement of upper limbs could be used to distinguish the abnormal state from the emergency state. The contribution plot method [57] can reflect influences of the change of each variables on the stability of the statistic model and is widely applied in the fault diagnosis. Accordingly, if one of the variables with greatest proportion in the contribution plot is a force variable (reflecting the upper limb movements) in the abnormal states, then the emergency state is detected. Otherwise, the abnormal state is detected as the leg restriction state as shown in **Algorithm 3**.

The proportion of variables for T^2 in the contribution plot is denoted as $\eta(j)$, and the proportion of variables for SPE in the contribution plot is denoted as $\xi(j)$ with $j = 1, 2 \ldots k$.

FIGURE 8. Experiment of normal walking.

For the variable x_j, the $\eta(j)$and $\xi(j)$ can be obtained (see [58]):

$$\eta(j) = x_j^T P^T \Lambda^{-1} P x_j \tag{16}$$

$$\xi(j) = (I - P(j)P(j)^T)^2 \tag{17}$$

Algorithm 3 State Diagnosis Algorithm

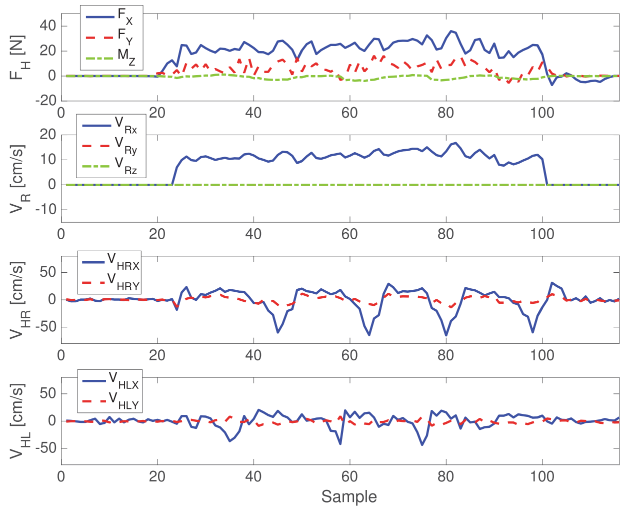
In: $X_m(i)$
Out: *State*

1: Calculate the proportion $\eta(j)$ and $\xi(j)$ $(j = 1, 2, \ldots k)$ of each variables of $X_m(i)$ by Eq. (16) and (17).
2: **if** $\eta(j) = max(\eta_1, \eta_2 \ldots, \eta_k)$ or $\xi(j) = max(\xi_1, \xi_2 \ldots, \xi_k)$ **then**
3:     **if** The variable with greatest proportion in contribution plot $X(i)_j$is not a force variable, $j \notin [1, 3]$ **then**
4:         There is no sudden movement of upper limbs
        The state is an abnormal state
        $State = 1$
5:     **else**
6:         The variable with greatest proportion in contribution plot $X(i)_j$ is a force variable, $j \in [1, 3]$.
        The sudden movement of upper limbs is detected.
        The state is an emergency state "Fall/Stumble".
        $State = 2$.
        Alarm is generated.
7:     **end if**
8: **end if**
9: **Return** *State*

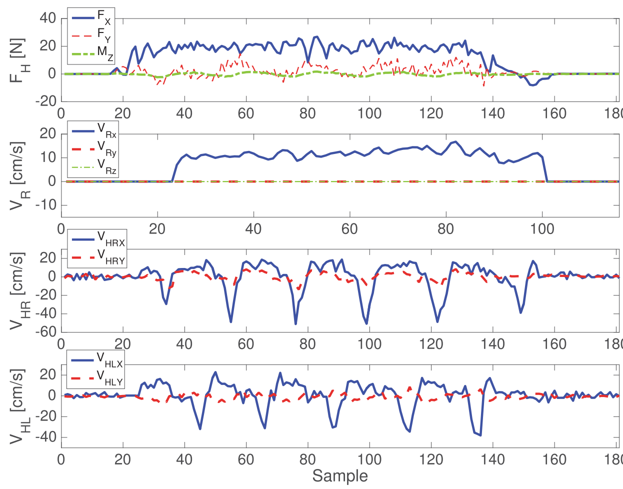
IV. EXPERIMENT

Since it's significant to monitor the different walking states and recognize them quickly in using the walking-aid robots so as to provide the safe and comfortable operation experience, experiments have been conducted to evaluate the proposed method in recognizing the different walking states. Besides, there exists great possibility of falling forward, the walking experiments were conducted in the forward direction, including speeding up and slowing down. The experiments were conducted in a space of $5 \times 8\ m^2$. The information of the 5 subjects are also given in Tab. 1.

Firstly, the online normal walking experiments are conducted to evaluate the effectiveness of the proposed method under the normal walking state. Secondly, the leg restriction experiments are conducted to evaluate the performance of the proposed method for detecting the abnormal states. In order to simulate the leg fracture and paralysis, the lower limb holders (see Fig. 3) are used to restrict the motion of subjects' legs. Additionally, while walking with the robot, the binding belt is tied on one leg of the healthy subject which may be pulled randomly as a constraint to cause the stumbling or falling behavior so as to check the effectiveness



(a)



(b)

FIGURE 9. Motion data of normal walking. (a) Subject 1. (b) Subject 2.

TABLE 3. The motion data of 5 subjects during normal walking.

Number	Variable	Max out of 5 Subjects	Mean out of 5 Subjects
1	F_X	38.71 [N]	23.20 [N]
2	F_Y	11.62 [N]	4.35[N]
3	M_Z	4.43 [N]	1.7274[N]
4	V_{HRX}	65. 12[cm/s]	28.34[cm/s]
5	V_{HRY}	13.27 [cm/s]	2.80[cm/s]
6	V_{HLX}	64.35 [cm/s]	27.46 [cm/s]
7	V_{HLY}	14.13[cm/s]	2.453[cm/s]
8	V_{Rx}	36.32[cm/s]	22.49 [cm/s]
9	V_{Ry}	0.00[cm/s]	0.00[cm/s]
10	V_{Rz}	0.00[cm/s]	0.00 [cm/s]

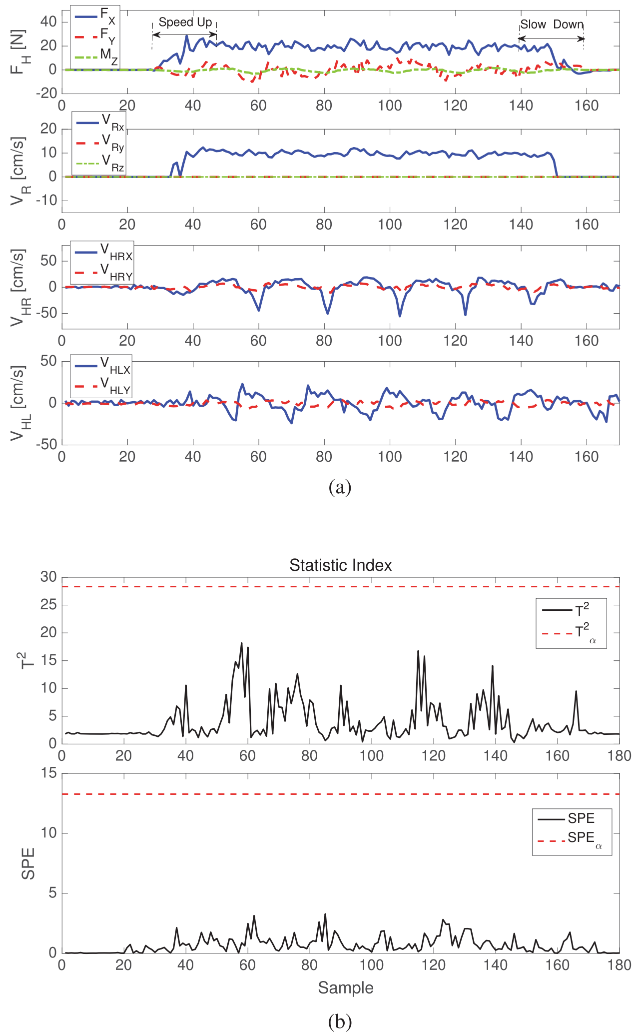


FIGURE 10. Online monitoring of normal walking. (a) Motion data of subject 4. (b) Online monitoring.

TABLE 4. Detection rate.

	Left Leg Restriction	Right Leg Restriction	Both Legs Restriction
Success	10	9	10
Fault	0	1	0
Miss	0	0	0

of the proposed method for distinguishing the emergency states and the abnormal states.

A. NORMAL WALKING

In this normal walking experiments, all the 5 subjects are informed to walking forward normally at a comfortable speed as shown in Fig. 8. The data collected from subject 1 and subject 2 in the experiment of normal walking is shown in Fig. 9. The analysis of the motion data collected from all the 5 subjects is shown in Tab. 3, and all the data was used for off-line design of the PCA model. The confidence probability α in Eq. (8) and (9) is 99%, then the control limits $T_\alpha^2 = 26.84$, $SPE_\alpha = 15.46$ are calculated.

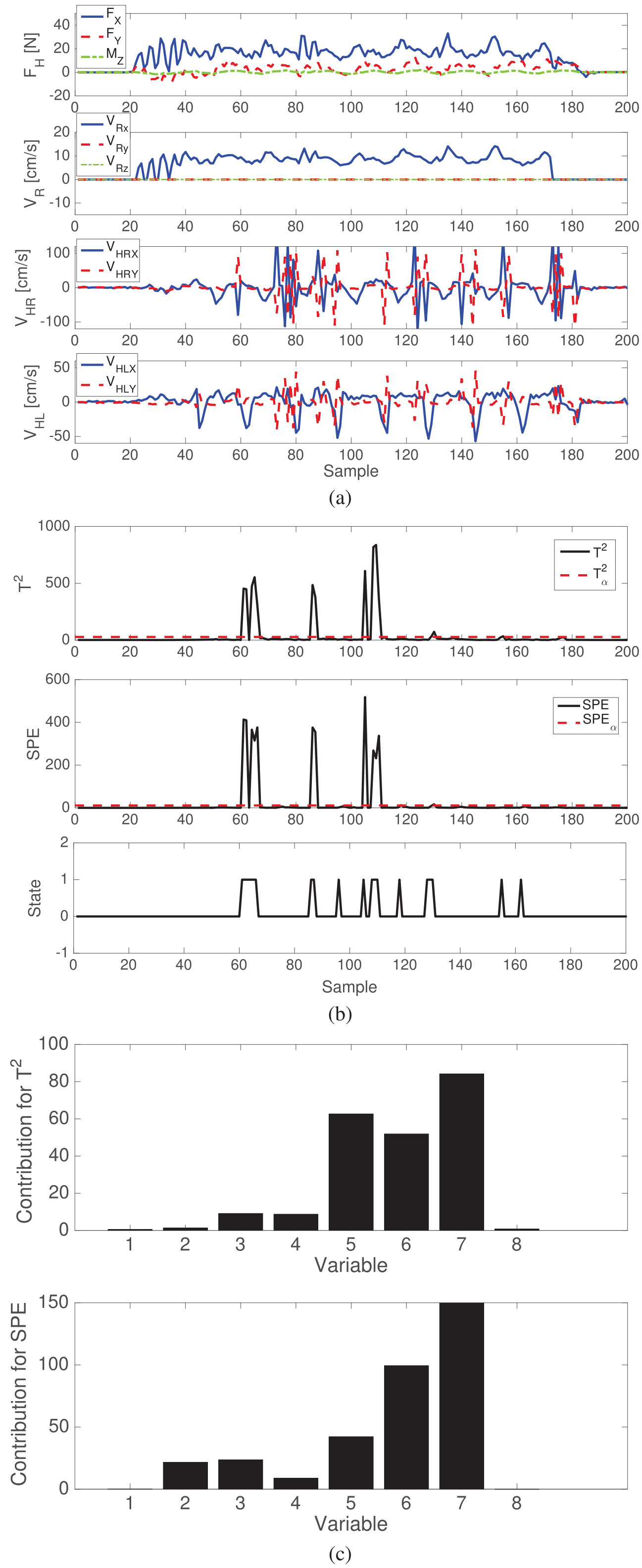


FIGURE 11. Online monitoring of walking with leg restriction. (a) Motion data of subject 4. (b) Online monitoring. (c) Contribution plot of *Sample* = 63.

In the online walking state monitoring experiment of subject 4, the online motion data, static index T^2 and SPE are shown in Fig. 10. In the monitoring experiment, T^2 and SPE

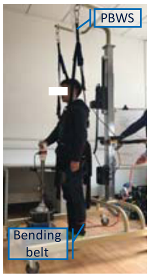


FIGURE 12. Experiment of stumble and fall.

TABLE 5. Emergency state detection rate.

	Times
Stumble/Fall Setting	15
Emergency State Detected	16
Fault	1
Miss	0

TABLE 6. Performance comparison.

	Proposed Method	COP-FD [16]
Success	15	9
Fault	1	2
Miss	0	1
Average Detection Time	55∼110[ms]	200∼350[ms]

are under the limits no matter how the subject speeds up and slows down, then the walking state is kept at $State = 0$, which indicates that the subject keeps normal walking state in the experiment.

B. LEG RESTRICTION

In daily life, there exists huge desires of rehabilitation and walking assistance for people with leg fracture or paralysis. In consideration of the users' safety, it is necessary to monitor the walking state and distinguish the abnormal states caused by the leg restriction from the emergency state caused by the fall or stumble when using the walking-aid robot.

In the experiments, the subjects are informed to walk forward with the leg holder fixed on his/her legs to simulate the fracture/paralysis condition as shown in Fig. 3. Due to the motion limitations, the subjects' walking movements are different from normal walking. The motion data of subject 4 in Fig. 12(a) reflects that there exists much more fluctuations in the velocities of the legs compared with the normal walking shown in Fig. 10.

In the online walking monitoring under the leg restriction condition, the walking state is analyzed based on the PCA method. The statistic indexes T^2 and SPE exceed the control limits in Fig. 11(b), which means that the abnormal states are detected. After diagnosis by the state diagnosis algorithm, the walking state changes between $State = 0$ and $State = 1$ in Fig. 11(c). For example, at $Sample = 63$, the statistic indexes T^2 and SPE exceed the control limits, and the contribution plot in Fig. 11(d) indicates that the abnormal state at $Sample = 63$ is affected by the 7-th variable, which

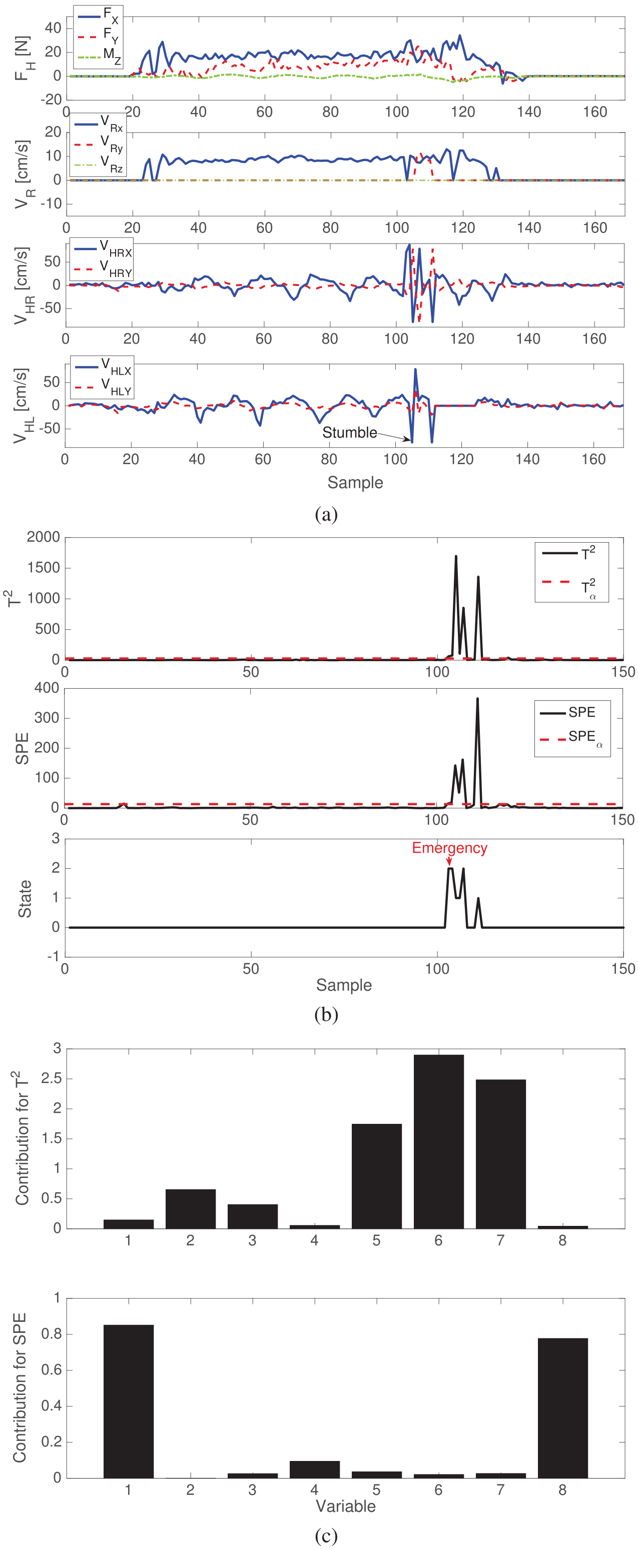


FIGURE 13. The motion data of walking with stumble and fall. (a) Motion data of subject 4. (b) Online monitoring. (c) Contribution plot of $Sample = 104$.

is the component velocity V_{LHY} of the left leg in Y-axis direction.

Besides, all the 5 subjects are invited to walk twice with wearing the limb holders on the left leg, right leg and both legs

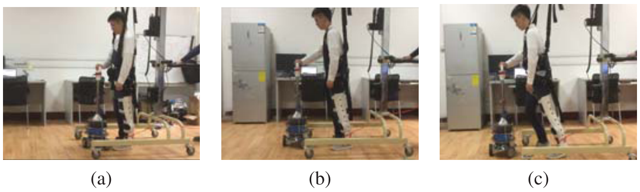


FIGURE 14. Leg restriction and stumble. (a) Start. (b) Leg restriction state. (c) Stumble.

respectively. The experiment results of left leg restriction, right leg restriction and both legs restriction are shown in Tab. 4. Among the 10 experiments of 5 subjects, there is only one failure detection of the right leg restriction. Thus, the abnormal state of swing phases affected by the leg restriction can be effectively detected in the monitoring by the proposed method.

C. FALL/STUMBLE

In the fall experiment, the binding belt is tied on the subject's left leg which may be dragged by a device at a random time without any indication to simulate natural stumble or fall, and the partial body weight support (PBWS) device as shown in Fig. 12 is used for the subject protection.

The motion data of the experiment is shown in Fig. 13(a). In Fig. 13(b), the fall happens at $Sample = 103$. According to the online walking state monitoring and state diagnosis algorithms, T^2 and SPE exceed the control limits T^2_α and SPE_α at $Sample = 104$ in Fig. 13(c). The contribution plot of the abnormal state at $Sample = 104$ shows that the abnormal state is affected by the 6-th and 1-st variables, which are the component velocity V_{HLX} of left leg in X-axis direction and the force F_X. Thus, the movements of upper limbs and the movements of the left leg are main reasons causing this walking state. Consequently, the walking state is detected and categorized as the emergency state at $Sample = 104$. Since the sampling time of the intelligent cane-type robot is 55 ms, then the emergency state detection time is 55 ms.

Furthermore, the experiments on the leg restriction state and the emergency state distinction are conducted. As shown in Fig. 14, the subject with leg motion limitations is stumbled by the tied belt at random time points. Three stumbling states happened at $Sample = 131$, $Sample = 171$ and $Sample = 223$ in Fig. 15(a), and the emergency state are detected at $Sample = 132$, $Sample = 173$ and $Sample = 224$ in Fig.15(b). Thus, all the three stumbling states are successfully detected, and the emergency state detection time is within 55∼110 ms.

Fifteen stumbling records of the 5 subjects in the experiments are shown in Tab. 5. All the emergency states are detected, and only one leg restriction state is mistakenly diagnosed as the emergency state.

Compared with the COP-based motion monitoring detection method whose average detection time is 200 ∼350 ms [18] as shown in Tab. 6, the method proposed in this paper is more effective and faster to detect the emergency state.

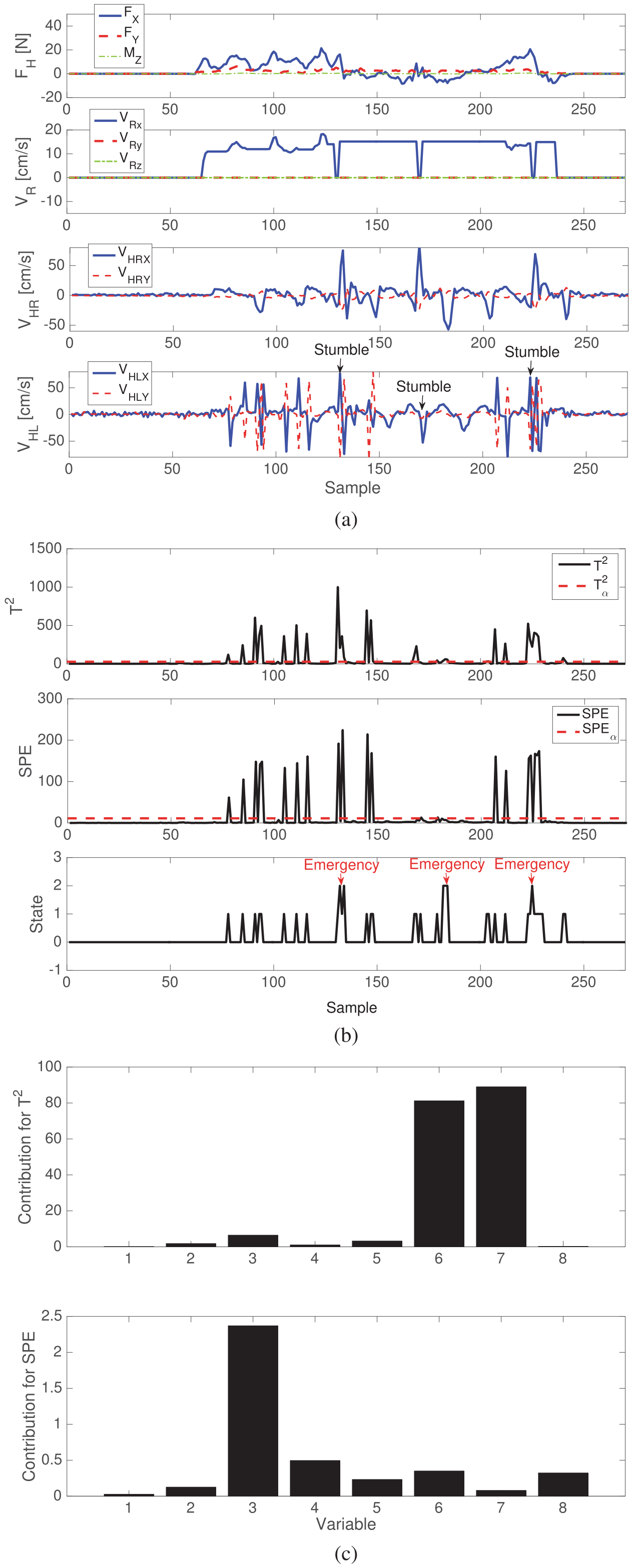


FIGURE 15. The motion data of walking with leg restriction and stumble. (a) Motion data of subject 5. (b) Online monitoring. (c) Contribution plot of *Sample* = 171.

V. CONCLUSION

By analyzing normal walking data of different people using a cane-type robot, the hypothesis that there exist human-robot coordination states is verified. A new walking state monitoring method is obtained by applying the PCA, which is a conventional data-driven statistical approach. With a small number of built-in sensors, the proposed monitoring method can promptly detect the loss of human-robot coordination, which means an abnormal or emergency state has occurred. Furthermore, typical abnormal walking states (leg restrictions) and the emergency states (falls and the stumbling) can be successfully distinguished. The experimental results show that the proposed method has better recognition rate and faster emergency detection ability than the COP-based method.

In the future, more efforts will be put into the abnormal walking cases monitoring (e.g. the circumduction gait and the scissoring gait), and effective prevention measures research to avoid injuries of the users based on the walking state monitoring.

REFERENCES

[1] N. Owen *et al.*, "Too much sitting: The population health science of sedentary behavior," *Exercise Sport Sci. Rev.*, vol. 38, no. 3, pp. 105–113, 2010.

[2] X. Shen and M. Goldfarb, "On the enhanced passivity of pneumatically actuated impedance-type haptic interfaces," *IEEE Trans. Robot.*, vol. 22, no. 3, pp. 470–480, Jun. 2006.

[3] B. E. Dicianno, D. M. Spaeth, R. A. Cooper, S. G. Fitzgerald, M. L. Boninger, and K. W. Brown, "Force control strategies while driving electric powered wheelchairs with isometric and movement-sensing joysticks," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 15, no. 1, pp. 144–150, Mar. 2007.

[4] J. Huang, F. Ding, T. Fukuda, and T. Matsuno, "Modeling and velocity control for a novel narrow vehicle based on mobile wheeled inverted pendulum," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 5, pp. 1607–1617, Sep. 2013.

[5] R. M. Brisilla and V. Sankaranarayanan, "Nonlinear control of mobile inverted pendulum," *Robot. Auto. Syst.*, vol. 70, no. 5, pp. 145–155, 2015.

[6] Y. Hirata, A. Hara, and K. Kosuge, "Passive-type intelligent walking support system 'RT Walker,'" in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, vol. 4. Oct. 2004, pp. 3871–3876.

[7] T. Hayashi, H. Kawamoto, and Y. Sankai, "Control method of robot suit HAL working as operator's muscle using biological and dynamical information," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Aug. 2005, pp. 3455–3460.

[8] K. Kong and D. Jeon, "Design and control of an exoskeleton for the elderly and patients," *IEEE/ASME Trans. Mechatronics*, vol. 11, no. 4, pp. 428–432, Aug. 2006.

[9] H. Kawamoto, T. Hayashi, T. Sakurai, K. Eguchi, and Y. Sankai, "Development of single leg version of HAL for hemiplegia," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Minneapolis, MN, USA, Sep. 2009, pp. 5038–5043.

[10] T. Ohnuma, G. Lee, and N. Y. Chong, "Particle filter based feedback control of JAIST Active Robotic Walker," in *Proc. RO-MAN*, Atlanta, GA, USA, 2011, pp. 264–269.

[11] C.-Y. Lee, I.-K. Jeong, I.-H. Lee, K.-H. Seo, and J.-J. Lee, "Development of rehabilitation robot systems for walking-aid," in *Proc. IEEE Int. Conf. Robot. Autom.*, vol. 3. May 2004, pp. 2468–2473.

[12] K. Wakita, J. Huang, P. Di, K. Sekiyama, and T. Fukuda, "Human-walking-intention-based motion control of an omnidirectional-type cane robot," *IEEE/ASME Trans. Mechatronics*, vol. 18, no. 1, pp. 285–296, Feb. 2013.

[13] R. Han, C. Tao, J. Huang, Y. Wang, H. Yan, and L. Ma, "Design and control of an intelligent walking-aid robot," in *Proc. Int. Conf. Modeling, Identificat. Control*, Melbourne, VIC, Australia, 2014, pp. 53–58.

[14] C. P. Lee, A. W. C. Tan, and S. C. Tan, "Gait probability image: An information-theoretic model of gait representation," *J. Vis. Commun. Image Represent.*, vol. 25, no. 6, pp. 1489–1492, 2014.

[15] J. Huang, P. Di, K. Wakita, T. Fukuda, and K. Sekiyama, "Study of fall detection using intelligent cane based on sensor fusion," in *Proc. IEEE Int. Symp. Micro-Nano Mechatronics Human Sci.*, Nov. 2008, pp. 495–500.

[16] P. Di, J. Huang, S. Nakagawa, K. Sekiyama, and T. Fukuda, "Fall detection and prevention in the elderly based on the ZMP stability control," in *Proc. IEEE Workshop Adv. Robot. Social Impacts*, Tokyo, Japan, Nov. 2013, pp. 82–87.

[17] Q. Yan, J. Huang, and Z. Luo, "Human-robot coordination stability for fall detection and prevention using cane robot," in *Proc. Int. Symp. Micro-NanoMechatronics Human Sci. (MHS)*, 2016, pp. 1–7.

[18] P. Di *et al.*, "Fall detection and prevention control using walking-aid cane robot," *IEEE/ASME Trans. Mechatronics*, vol. 21, no. 2, pp. 625–637, Apr. 2016.

[19] Y. Hirata, A. Muraki, and K. Kosuge, "Motion control of intelligent passive-type walker for fall-prevention function based on estimation of user state," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2006, pp. 3498–3503.

[20] J. Huang, W. Xu, S. Mohammed, and Z. Shu, "Posture estimation and human support using wearable sensors and walking-aid robot," *Robot. Auto. Syst.*, vol. 73, pp. 24–43, Nov. 2015.

[21] W.-J. Yi, O. Sarkar, S. Mathavan, and J. Saniie, "Wearable sensor data fusion for remote health assessment and fall detection," in *Proc. IEEE Int. Conf. Electro/Inf. Technol.*, Milwaukee, WI, USA, Jun. 2014, pp. 303–307.

[22] P. Pierleoni, A. Belli, L. Palma, M. Pellegrini, L. Pernini, and S. Valenti, "A high reliability wearable device for elderly fall detection," *IEEE Sensors J.*, vol. 15, no. 8, pp. 4544–4553, Aug. 2015.

[23] P. Pivato, S. Dalpez, D. Macii, and D. Petri, "A wearable wireless sensor node for body fall detection," in *Proc. IEEE Int. Workshop Meas. Netw. (MN)*, Anacapri, Italy, Oct. 2011, pp. 116–121.

[24] S. Qiu, Z. Wang, H. Zhao, and H. Hu, "Using distributed wearable sensors to measure and evaluate human lower limb motions," *IEEE Trans. Instrum. Meas.*, vol. 65, no. 4, pp. 939–950, Apr. 2016.

[25] Y. Ma, R. Fallahzadeh, and H. Ghasemzadeh, "Glaucoma-specific gait pattern assessment using body-worn sensors," *IEEE Sensors J.*, vol. 16, no. 16, pp. 6406–6415, Aug. 2016.

[26] D. Webb, R. H. Tuttle, and M. Baksh, "Pendular activity of human upper limbs during slow and normal walking," *Amer. J. Phys. Anthropol.*, vol. 93, no. 4, pp. 477–489, 1994.

[27] J. Massion, "Movement, posture and equilibrium: Interaction and coordination," *Prog. Neurobiol.*, vol. 38, no. 1, pp. 35–36, 1992.

[28] R. C. Wagenaar and R. E. van Emmerik, "Resonant frequencies of arms and legs identify different walking patterns," *J. Biomech.*, vol. 33, no. 7, pp. 853–861, 2000.

[29] J. L. Stephenson, A. Lamontagne, and S. J. D. Serres, "The coordination of upper and lower limb movements during gait in healthy and stroke individuals," *Gait Posture*, vol. 29, no. 1, pp. 11–16, 2009.

[30] H. Dejnabadi, B. M. Jolles, and K. Aminian, "A new approach for quantitative analysis of inter-joint coordination during gait," *IEEE Trans. Biomed. Eng.*, vol. 55, no. 2, pp. 755–764, Feb. 2008.

[31] T. R. Kaminski, "The coupling between upper and lower extremity synergies during whole body reaching," *Gait Posture*, vol. 26, no. 2, pp. 256–262, 2007.

[32] S. Yin, S. X. Ding, X. Xie, and H. Luo, "A review on basic data-driven approaches for industrial process monitoring," *IEEE Trans. Ind. Electron.*, vol. 61, no. 11, pp. 6418–6428, Nov. 2014.

[33] C. Sankavaram, A. Kodali, K. R. Pattipati, and S. Singh, "Incremental classifiers for data-driven fault diagnosis applied to automotive systems," *IEEE Access*, vol. 3, pp. 407–419, 2015.

[34] J. Dong, M. Wang, X. Zhang, L. Ma, and K. Peng, "Joint data-driven fault diagnosis integrating causality graph with statistical process monitoring for complex industrial processes," *IEEE Access*, vol. 5, pp. 25217–25225, 2017.

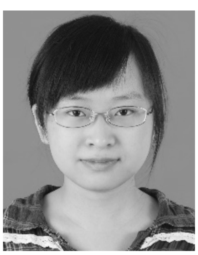
[35] Y. Wang, Q. Jiang, and J. Fu, "Data-driven optimized distributed dynamic PCA for efficient monitoring of large-scale dynamic processes," *IEEE Access*, vol. 5, pp. 18325–18333, 2017.

[36] V. Choqueuse, M. E. H. Benbouzid, Y. Amirat, and S. Turri, "Diagnosis of three-phase electrical machines using multidimensional demodulation techniques," *IEEE Trans. Ind. Electron.*, vol. 59, no. 4, pp. 2014–2023, Apr. 2012.

[37] E. Russell, L. Chiang, and R. Braatz, *Data-Driven Methods for Fault Detection and Diagnosis in Chemical Processes*. London, U.K.: Springer-Verlag, 2000.

[38] N. St-Onge and A. Feldman, "Interjoint coordination in lower limbs during different movements in humans," *Experim. Brain Res.*, vol. 148, no. 2, pp. 139–149, 2003.

[39] H. Vallery and M. Buss, "Complementary limb motion estimation based on interjoint coordination using principal components analysis," in *Proc. IEEE Int. Conf. Control Appl.*, Oct. 2006, pp. 933–938.
[40] H. Vallery, E. H. F. V. Asseldonk, M. Buss, and H. V. D. Kooij, "Reference trajectory generation for rehabilitation robots: Complementary limb motion estimation," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, no. 1, pp. 23–30, Feb. 2009.
[41] F. Zhang, "A mixture probabilistic PCA model for multivariate processes monitoring," in *Proc. Amer. Control Conf.*, Boston, MA, USA, 2004, pp. 3111–3115.
[42] J. Yu and S. J. Qin, "Multimode process monitoring with Bayesian inference-based finite Gaussian mixture models," *AIChE J.*, vol. 54, no. 7, pp. 1811–1829, 2008.
[43] X. Xu, L. Xie, and S. Wang, "Multimode process monitoring with PCA mixture model," *Comput. Elect. Eng.*, vol. 40, no. 7, pp. 2101–2112, Oct. 2014.
[44] J. Yu, "Local and global principal component analysis for process monitoring," *Process Control*, vol. 22, no. 7, pp. 1358–1373, 2012.
[45] B. Song, H. Shi, Y. Ma, and J. Wang, "Multisubspace principal component analysis with local outlier factor for multimode process monitoring," *Ind. Eng. Chem. Res.*, vol. 53, no. 42, pp. 16453–16464, 2014.
[46] S. Wold, K. Esbensen, and P. Geladi, "Principal component analysis," *Chemometrics Intell. Lab. Syst.*, vol. 2, nos. 1–3, pp. 37–52, 1987.
[47] S. Qin, "Data-driven fault detection and diagnosis for complex industrial processes," in *Proc. IFAC Symp.*, 2009, pp. 1115–1125.
[48] S. Yin, X. D. Steven, A. Naik, P. Deng, and A. Haghani, "On PCA-based fault diagnosis techniques," in *Proc. Conf. Control Fault-Tolerant Syst. (SysTol)*, Oct. 2010, pp. 179–184.
[49] W. F. Godoy, I. N. da Silva, A. Goedtel, R. H. C. Palácios, G. H. Bazan, and D. Morííñigo-Sotelo, "An application of artificial neural networks and PCA for stator fault diagnosis in inverter-fed induction motors," in *Proc. Int. Conf. Elect. Mach. (ICEM)*, 2016, pp. 2165–2171.
[50] T. Wang, H. Xu, J. Han, E. Elbouchikhi, and M. E. H. Benbouzid, "Cascaded H-bridge multilevel inverter system fault diagnosis using a PCA and multiclass relevance vector machine approach," *IEEE Trans. Power Electron.*, vol. 30, no. 12, pp. 7006–7018, Dec. 2015.
[51] J. F. Martins, V. F. Pires, C. Lima, and A. J. Pires, "Fault detection and diagnosis of grid-connected power inverters using PCA and current mean value," in *Proc. 38th Annu. Conf.*, 2012, pp. 5185–5190.
[52] T. Wannier, C. Bastiaanse, G. Colombo, and V. Dietz, "Arm to leg coordination in humans during walking, creeping and swimming activities," *Experim. Brain Res.*, vol. 141, no. 3, pp. 375–379, 2001.
[53] M. Hassan, H. Kadone, K. Suzuki, and Y. Sankai, "Exoskeleton robot control based on cane and body joint synergies," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Oct. 2012, pp. 1609–1614.
[54] K. North, E. N. Kubiak, R. W. Hitchcock, and T. J. Petelenz, "Load monitoring system for partial weight bearing therapy for rehabilitation of lower extremity fractures," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Osaka, Japan, Jul. 2013, pp. 152–155.
[55] A. Schillings, T. Mulder, and J. Duysens, "Stumbling over obstacles in older adults compared to young adults," *J. Neurophysiol.*, vol. 94, no. 2, pp. 1158–1168, 2005.
[56] A. J. Blake *et al.*, "Falls by elderly people at home: Prevalence and associated factors," *Age Ageing*, vol. 17, no. 6, pp. 365–372, 1988.
[57] P. Van den Kerkhof, J. Vanlaer, G. Gins, and J. F. M. VanImpe, "Contribution plots for statistical process control: Analysis of the smearing-out effect," in *Proc. Eur. Control Conf. (ECC)*, 2013, pp. 428–433.
[58] P. Miller, R. E. Swanson, and C. E. Heckler, "Contribution plots: A missing link in multivariate quality control," *Appl. Math. Comp. Sci.*, vol. 8, no. 4, pp. 775–792, 1998.



QINGYANG YAN received the bachelor's degree in measurement techniques and instrumentation from the Huazhong University of Science and Technology in 2015, where she is currently pursuing the Ph.D. degree with the School of Automation. Her main research interest is motion control of walking aid robot.

JIAN HUANG (M'07–SM'17) received the bachelor's, M.Eng., and Ph.D. degrees from the Huazhong University of Science and Technology (HUST), Wuhan, China, in 1997, 2000, and 2005, respectively. From 2006 to 2008, he was a Post-Doctoral Researcher with the Department of Micro-Nano System Engineering and the Department of Mechano-Informatics and Systems, Nagoya University, Japan. He is currently a Full Professor with the School of Automation, HUST. His main research interests include rehabilitation robot, robotic assembly, networked control systems, and bioinformatics.

CAIHUA XIONG (M'12) received the Ph.D. degree in mechanical engineering from the Huazhong University of Science and Technology (HUST), Wuhan, China, in 1998. From 1999 to 2003, he was a Post-Doctoral Fellow with the City University of Hong Kong, Hong Kong, and The Chinese University of Hong Kong, Hong Kong, and also a Research Scientist with the Worcester Polytechnic Institute, Worcester, MA, USA. Since 2008, he has been a Chang Jiang Professor with HUST, where he is currently the Director of the Institute of Rehabilitation and Medical Robotics. His current research interests include the field of biomechatronic prosthesis, rehabilitation robotics, and robot motion planning and control.

ZHAN YANG (S'07–M'13) received the B.S. degree from the Department of Automation, Harbin University of Science and Technology, Harbin, China, and the M.S. and Dr. Eng. degrees from the Department of Micro-Nano Systems Engineering, Nagoya University, Nagoya, Japan, in 2004, 2010, and 2013, respectively. He is currently a Lecturer with the Robotics and Microsystem Center, Soochow University, Suzhou, China, and also with the Collaborative Innovation Center of Suzhou Nano Science and Technology, Soochow University, Taipei, Taiwan. His research interests include nanomanipulation, nanosensor, and nanorobotics.

ZHAOHUI YANG received the bachelor's and master's degrees from Tongji Medical University, Wuhan, China, in 1991 and 1997, respectively, and the Ph.D. degree from the Tongji Medical College, HUST, in 2004. She is currently an Associate Chief Physician with the Department of Rehabilitation, Union Hospital, Tongji Medical College. Her main research interests include osteoarticular disease rehabilitation, rehabilitation robots, and nerve injury rehabilitation.