Walking Pattern Prediction with Partial Observation for Partial Walking Assistance by using an Exoskeleton System

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***Abstract*—Movement prediction is a key ingredient in exoskeleton robot control for walking assistance. In this paper, we propose a movement prediction method with following two desirable fundamental properties: 1) fast online calibration for a novel user, and 2) applicability to partially observable situations. Using this method, for example, 1) we can use previously collected other subjects' walking data to quickly adapt to a novel user's movements in exoskeleton robot control, or 2) we can generate the exoskeleton robot movement for assisting right leg behavior by only observing the movement of the left leg. To validate our proposed method, we conducted experiments in walking movement prediction using a one-leg three DOFs exoskeleton robot with nine healthy subjects. The experimental results suggest that our method is able to predict a new user's walking pattern and to cope with the partial observations.**

I. INTRODUCTION

One of the central points of research in exoskeletons is walking assistance [1]. Walking movement assistance is needed and fundamental for most application scenarios, where exoskeletons are used either for power augmentation of healthy persons or in the rehabilitation of persons with movement limitations [2]–[4]. Prediction and synchronization of the robot with the wearer, is the critical point in all exoskeleton systems, as they are supposed to actively support motions and are neither supposed to impede the user, nor force him unwillingly into a movement.

Since walking patterns are periodic, oscillator-based approaches for motion generation have received special attention. Such approaches use an oscillator model to generate coordinated periodic trajectories with user intentions as references to the robot controller. Zhang et al. proposed a synchronization-based control scheme using a neural oscillator model for a motion assistance device [5]. Ronsse et al. developed the protocols of oscillator-based motion assistance for robot-assisted therapy [6] and evaluated its effectiveness using a gait rehabilitation robot suspended by frames over a treadmill [7]. However, these previous methods do not explicitly consider the variations of user motions. For constructing a controller suitable for walking assistance, adaptability to different walking patterns needs to be provided.

In this study, we consider separating the pattern adaptation problem into spatial and temporal factors, i.e., style parameter and phase variable. By separating the problem, we can extract the phase information from wide variety of walking patterns with different styles. Therefore, we can deal with the variations of user motions for the oscillator-based method which requires phase information of the walking movements. We adopt our previously proposed method [8] for separating style and phase from observed walking behaviors. We presented that the style-phase separation method can be useful for the exoskeleton robot control by applying the method to assisting movements of a solo subject [9], [10]. In this paper, we particularly demonstrate that 1) the proposed style-phase separation approach can be used to adapt for multi-user movements through the fast online calibration mechanism, and 2) can be used to predict user's movements even when the movements are partially observable.

To validate our proposed method, we conducted experiments in walking movement prediction using a one-leg three DOFs exoskeleton robot with nine healthy subjects. The first experiment is conducted to investigate the prediction performance for novel subjects under full observations. The second one is to validate its capability for managing partial observations with known subjects data. The experimental results suggest that our method is able to predict a new user's walking pattern and to cope with the partial observations.

The rest of the paper is organized as follows. We first present the walking pattern prediction method with partial observations in Section II and continue to give an overview over our experimental setup in Section III. There we will also explain the process of gathering and pre-processing the training data. In Section IV, we show our experimental results. Although the application to the real patients is out of scope of this paper, we discuss how to approach it with this method in Section V.

II. METHOD

In the following sections, we describe the walking pattern prediction method with 1) fast online calibration and with 2) applicability to partially observable situations for

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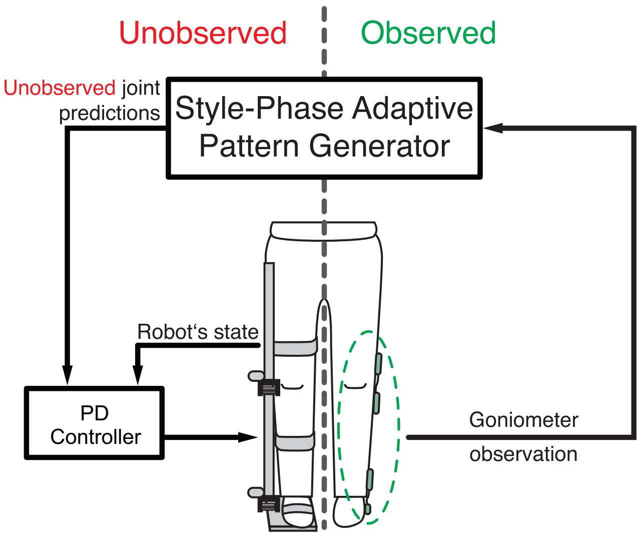


Fig. 1: A schematic overview of the desired control scheme of an exoskeleton with partial observation. Signals describing joint angles are sent to the pattern generator from the sensors attached to the left leg. The generator recognizes the movement style and phase and sends predicted reference joint angles to the exoskeleton controller. This controller receives joint-angle positions of the exoskeleton and thus can actuate the motors to execute the recognized movement for the right leg to assist.

partial walking assistance using an exoskeleton system. The schematic diagram of our scheme is illustrated in Fig. 1. The user wears an exoskeleton system on the right leg, and attaches the goniometers to measure the joint angles of the left leg. The objective of the method is to predict the patterns of the exoskeleton system for assisting the right leg behaviors by only observing the values of goniomenters on the left leg. Beforehand the walking pattern prediction, the method assumes that full observation of both legs is available.

A. Generative Model

Here we describe a pattern generative model suitable to predict walking patterns of a novel user based on the style-phase adaptation. Concretely, we prepare the training data from *multiple* users and learn the adaptive pattern generator model with the style parameter and phase variable [8]. The style parameter can be defined so that it captures the spatio variations among the multiple users.

Assuming additive Gaussian noise in the phase transition and the observation, the generative model can be defined with the following normal distributions:

$$p(\mathbf{x}_{t+1}|\mathbf{x}_t) = \mathcal{N}(\mu_x(\mathbf{x}_t), \mathbf{Q}), \tag{1}$$
$$p(\mathbf{y}_t|\mathbf{x}_t; \mathbf{w}) = \mathcal{N}(\mu_y(\mathbf{x}_t; \mathbf{w}), \mathbf{R}) \tag{2}$$

where $\mu_y(\mathbf{x}_t; \mathbf{w})$ is a map to a joint configuration from the style parameter $\mathbf{w}$ and state $\mathbf{x} = [\phi, \omega]$ and ϕ and ω are the phase and its velocity. $\mu_x(\mathbf{x}) = \mathbf{A}\mathbf{x}$ predicts the phase and velocity of the next time-step with the state transition matrix

$$\mathbf{A} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}. \tag{3}$$

$\mathbf{Q}$ and $\mathbf{R}$ are covariance matrices and model the additive Gaussian noise in the state transition and the observation. The style parameter represents the spatial description of a movement by expressing linear combination weights of the observation bases $\bar{\mathbf{Y}}^j \in \mathbb{R}^{C \times D}$ where C specifies the sample-length of our trained curves, D the number of joints and j the index of the observation bases with J independent axes. These bases are formed through executing an SVD on all S training data captured from multiple users and aligned by the phase variable, and used to learn $\mu_y(\mathbf{x}_t; \mathbf{w})$ with Gaussian Process Regression. See the details in [8].

B. Online Style and Phase Estimation

Given the generative model, the use of an on-line EM algorithm allows to derive the following estimation scheme of style and phase variables:

$$\mathbf{x}_t \leftarrow U(\mathbf{x}_{t-1}, \mathbf{w}_t, \mathbf{y}_t), \tag{4}$$
$$\mathbf{w}_t \leftarrow V(\mathbf{w}_{t-1}, \mathbf{x}_t, \mathbf{y}_t; \lambda) \tag{5}$$

where λ $(0 \leq \lambda \leq 1)$ is a forgetting factor. This procedure is called style-phase adaptation. In each timestep $U(\cdot)$ and $V(\cdot)$ are used to update the phase and style variables fitted to more recent data. For details about these update rules described in [8]. After executing these steps, the generative model of equations (1) and (2) can be used to compute a prediction. By applying $\mu_x(\mathbf{x})$ several times recursively, it is possible to predict the phase farther into the future based on the current estimate of style and phase variables. Therefore, this algorithm with the generative model can be used as a fast online calibration mechanism for a novel user.

C. Partial Observations

To manage the partial observations in the style-phase adaptation procedure, we first slice out the observation $\mathbf{y}_{\text{ob},t} \in \mathbb{R}^{D_{\text{ob}}}$ from the current joint angle configuration $\mathbf{y}_t \in \mathbb{R}^D$ with $D_{\text{ob}} \leq D$ and D being the total number of joints of our system. With defining the counterpart containing the unobserved joint values $\mathbf{y}_{\text{un},t} \in \mathbb{R}^{D_{\text{un}}}$ with $D_{un} = D - D_{ob}$, the generative model can be re-written:

$$p\left(\left[\begin{array}{c} \mathbf{y}_{\text{ob}} \\ \mathbf{y}_{\text{un}} \end{array}\right]_t \middle| \mathbf{x}_t; \mathbf{w}\right) = \mathcal{N}\left(\left[\begin{array}{c} \mu_{\text{ob},y}(\mathbf{x}_t; \mathbf{w}) \\ \mu_{\text{un},y}(\mathbf{x}_t; \mathbf{w}) \end{array}\right], \mathbf{R}_{\text{split}}\right) \tag{6}$$

where the covariance matrix is described by

$$\mathbf{R}_{\text{split}} = \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{R}_{22} + \sigma_p \mathbf{I}_{D_{\text{un}}} \end{bmatrix} \tag{7}$$

and $\mathbf{R}_{ij}$ are given by dividing the original covariance matrix $\mathbf{R}$ into parts:

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_{11} & \mathbf{R}_{12} \\ \mathbf{R}_{21} & \mathbf{R}_{22} \end{bmatrix} \tag{8}$$

and $\mathbf{R}_{11}$ is a $\mathbb{R}^{D_{\text{ob}} \times D_{\text{ob}}}$, $\mathbf{R}_{12} = \mathbf{R}_{21}^T$ a $\mathbb{R}^{D_{\text{ob}} \times D_{\text{un}}}$ and $\mathbf{R}_{22}$ a $\mathbb{R}^{D_{\text{un}} \times D_{\text{un}}}$ matrix.

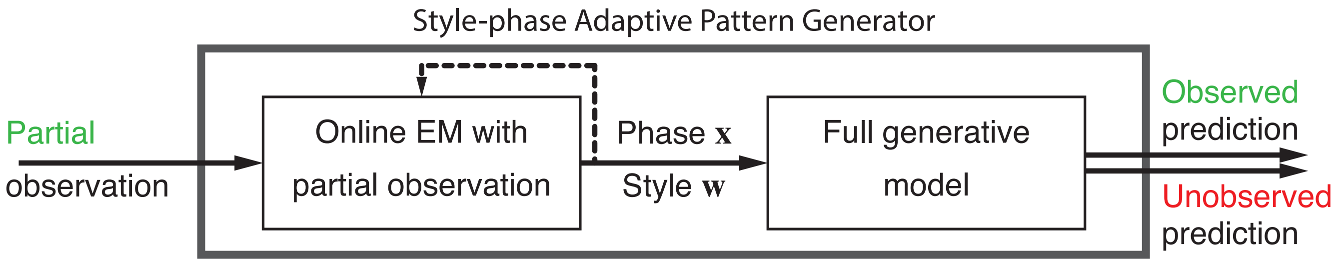


Fig. 2: A simple overview on how the style-phase adaption under partial observation works. Assuming our real setup, we have two observed joints: the left knee and ankle. Each timestep new joint values are read out and the current phase $\mathbf{x}_t$ and style parameter $\mathbf{w}$ can be estimated. These values can be fed back into our generative model shown in Eq. (2), which results in obtaining new configurations of all joints. Through predicting the phase $\mathbf{x}_{t+1}$ of the next time-step, we can compute the prediction of a joint-configuration one timestep ahead.

By setting $\sigma_p \to \infty$, we can formally cancel the contribution of the unobserved joints for the style and phase variables estimation. In practice the unobserved dimensions are simply disregarded and removed from the matrices for estimating $\mathbf{x}_t$ and $\mathbf{w}$. After the E- and M-steps have been executed, a new complete prediction $\mathbf{y}_{t+1}$ of all joint angles can be achieved by using the original generative model spanning all D joint dimensions. This approach is illustrated along with our application setting in Fig. 2.

III. EXPERIMENTAL SETUP

A. *One Leg Three DOFs Exoskeleton Robot System*

Our exoskeleton robot system used in the experiments is shown in Fig. 3. The robot has three DOFs: one passive joint on the hip, and two active joints with DC motors and encoders on the knee and ankle. It is a simplified version of the system used in [10]. The robot is controlled by a PC with Xenomai real-time operating system.

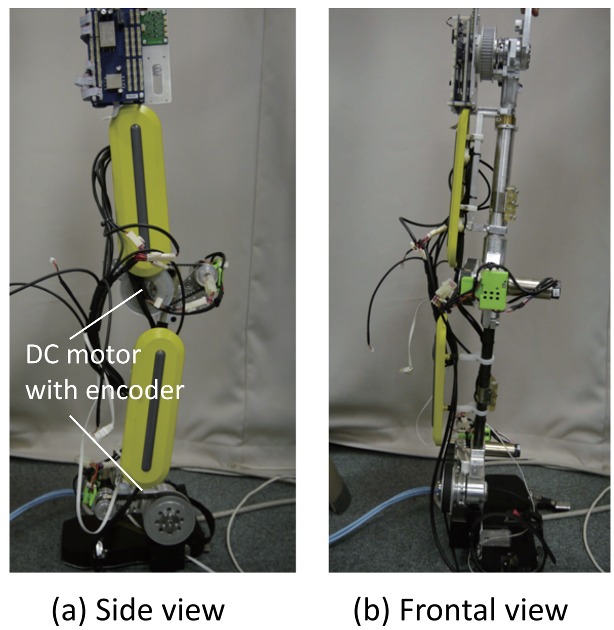


Fig. 3: One-leg three DOFs exoskeleton robot system.

B. *Experimental Settings*

We asked nine healthy subjects in total, two females, seven males, with various body heights, to wear our one-leg exoskeleton on the right leg and each a goniometer on the left knee and ankle joints. Detailed information about the subjects can be found in Table I. As the exoskeleton is only able to actuate the knee and ankle joints, the subjects were forced to bear the whole weight of the robot, so it was attached to a harness to relieve the subjects to some extent.

Each subject had two tasks to perform:

- walking on a level treadmill
- walking on a treadmill with a slope of 6%

as seen as in the example snapshot-sequence of Fig. 4. These two tasks were chosen for specific reasons. While focusing on walking movements, we wanted to see how the algorithm reacts to subtle changes in movement patterns due to the environmental change and if it's still able to discern these two movements from each other.

Subject	Gender	Body height
1	m	1.75m
2	m	1.74m
3	m	1.79m
4	f	1.77m
5	m	1.72m
6	m	1.59m
7	f	1.68m
8	m	1.78m
9	m	1.67m

TABLE I: Test subjects, their gender and body height.

As the exoskeleton is only able to actuate the knee and ankle joints, the subjects were forced to bear the whole weight of the robot, so it was attached to a harness to relieve the subjects to some extent.

Each data-collection trial took 100 seconds at 50 Hz sampling rate. Data contains both exoskeleton's encoder values of the right leg and goniometers' values of the left

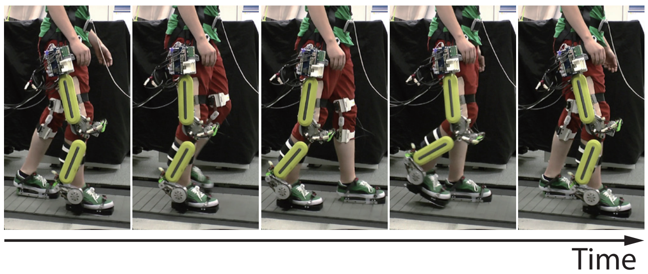


Fig. 4: A snapshot-sequence of a subject walking on the treadmill with the one-leg exoskeleton attached to the right leg while having the goniometers attached to the left leg (in the image concealed by the leg). With this setup we have a total of 4 joints: the left knee and ankle, which are observed by goniometers and the right left and ankle, which are the controlled exoskeleton-joints.

leg. Prior to the data collection, we asked each subject to find out a walking pace that was comfortable for him/her, then adjusted a metronome to that pace to follow that rhythm during the data collection trial. All recorded sequences start with the subject standing until the treadmill started running, even though the static postures are not focused for the algorithm.

In the beginning of the experiment two data-collection trials were done without support enabled. Subsequently we cut out three movement-phases out of each of these training sequences and re-sampled and aligned them for training. This results in having a training set of 6 curves of walking patterns for each subject: 3 curves for walking normally and 3 curves for walking up-slope. After training in these curves, we asked the the subjects to do each movement again for 100 seconds each to run the predictions on. In these sessions we enabled the motors of the exoskeleton on low power, to make the subjects feel the assistance, but not have it influence the movement.

Following the gathering of these sequences, we used the prediction algorithm to execute predictions for the second set of observations by using all training data of the 8 other subjects. In this case each subject has a set of 48 training curves from the other subjects and none of his own ones. We applied the prediction method on the same observation data to improve comparability of prediction accuracy between using the user's own and cross-subject training data. Purely on-line computation has been used and no knowledge of the future was taken into account. Several parameters were set as follows; Only the choice of J was kept dynamic and part of the training process. J was chosen by determining the number of dimensions needed to represent at least 80% of the sum of the eigenvalues determined by the SVD. In tests this value has been proven to be a good choice. For the sake of reproducibility, the other determined tuning parameters of the EM-algorithm are as follows. $\lambda = 0.99$, $\mathbf{Q}_{1,1} = 0.05$, $\mathbf{Q}_{2,2} = 0.0001$ and $\mathbf{R} = 5 * \mathbf{I}_D$, with D being the number of joints in our system.

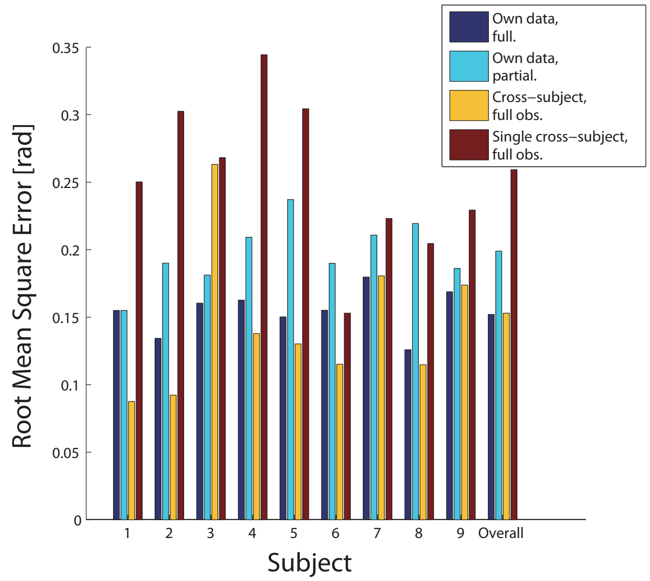


Fig. 5: A comparison-plot of the RMSE results of the approaches with subject-own training data in combination with full and partial observation to two cases of cross-subject training with full observation. In total this figure shows that it is indeed possible to express a person's gait with the generative model constructed from others' data.

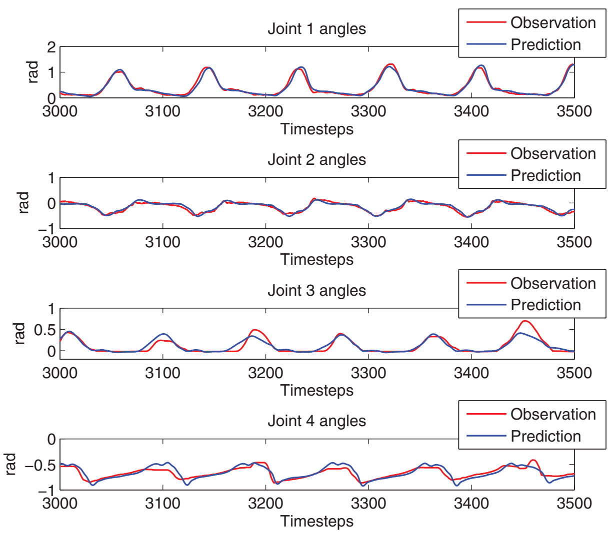
IV. EXPERIMENTAL RESULTS

We conducted the experiments with two scenarios: full observation with cross-subject training data as shown in IV-A, and partial observation with subject-own training data in IV-B. All the experiments were approved by ATR Ethics Committee.

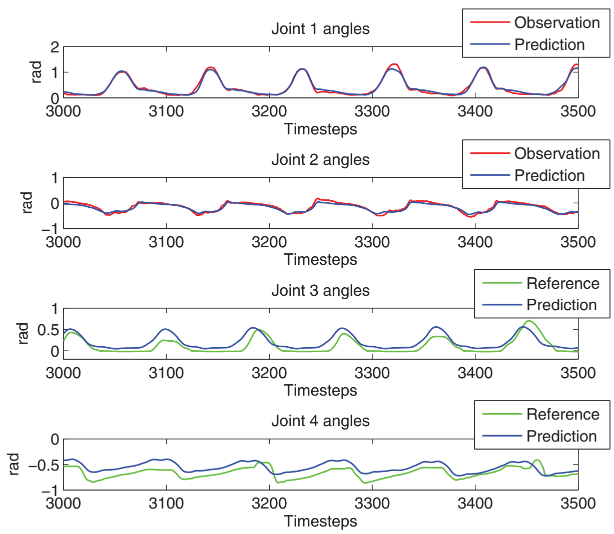
A. Full Observation with Cross-subject Training Data

We first examined the prediction performance of the algorithm with full observation in cross-subject setting: By using the generative model learned with the data of eight subjects, prediction errors on the data of the ninth subject is computed. It is then repeated for all the combinations. For learning the generative model, in total 24 curves of flat surface walking and another 24 curves of up-slope walking were used. In most cases, our automatic decision strategy of dimension in the style parameter with reconstruction error chose the style-parameter to be 8-dimensional, only for one subject (subject 3) 9 dimensions were chosen.

All predictions are made for one time-step, meaning we predict those values of 20 ms in the future which was suggested in a simulation study [9]. An example of prediction result is plotted in Fig. 6a. Fig. 5 shows the overall prediction results. We compared the prediction performance of our method (Cross-subject full) with that of using only one randomly chosen other curves (Single cross-subject full). The figure shows that using training data from only one subject to predict a new subject's walking movement is unsuitable, whereas our method, i.e., using training data set obtained from other subjects, is in average as good



(a) Results of a prediction of the same sequence as shown in Fig. 6b but under cross-subject training data. In this case all joints are observed.



(b) Results of a prediction sequence with subject-own training data under partial observation. Joints 1 and 2 are the observed goniometers, joints 3 and 4 the unobserved exoskeleton-joints.

Fig. 6: Above there are one plot for each prediction scenario. Fig. 6a shows the same for the case of full observation but with cross-subject training data and Fig. 6b shows prediction performance with subject-own training data but partial observation. The joints 1 and 2 are the left knee and ankle joints that are observed with goniometers, while joints 3 and 4 are respectively the unobserved knee and ankle exoskeleton-joints. Both observation sequences are the same and the plot has been zoomed into the same time-frame to allow better comparison of the results. With 50 Hz sampling rate the displayed interval equals 10 s. The blue curves are the predicted values, whereas red indicates the observed values and green the unobserved exoskeleton position-values at that time.

as subject-own training (Own data full). In most cases prediction with cross-subject training yielded even better results than with training data originating from the subject him-or herself may be due to overfitting: Own data full uses a model learned from only six own curves. On the other hand, Cross-subject full uses a model learned from 54 curves of all the subjects. Therefore, the model used in the latter case can be more general and robust for the inter-subject variations. All the results in numbers can also be found in Table II and can be confirmed that gaits of unknown subjects can be predicted within reasonable errors by our method.

B. Partial Observation with Subject-own Training Data

It is intuitive to expect good results when using training data of the subject itself since no changes in gait are to be assumed and neither are changes in body-height between the training and test data. This resulted in our automatic decision strategy of dimension in the style parameter to set a style parameter dimension J of 1 in most cases, for four subjects it was 2.

However, the question remains whether it can identify phase and style of walking movements by exclusively regarding the joints of one single leg or not. In our experiments, overall we were able to successfully estimate the phase and style variables in a stable manner. An example is plotted in Fig. 6b. One can see that the trajectory pattern is correctly identified and replicated. The prediction error on the unobserved joints is a bit higher than that of the observed joints. However it is easily seen that the phase can be correctly identified with only two of four joints in the case of walking.

Subject	Flat walking	Upslope walking	Total
1	0.080	0.095	0.088
2	0.095	0.090	0.092
3	0.256	0.270	0.263
4	0.163	0.107	0.138
5	0.104	0.152	0.130
6	0.106	0.124	0.115
7	0.178	0.183	0.181
8	0.109	0.120	0.115
9	0.175	0.173	0.174
Overall	0.150	0.156	0.153

TABLE II: RMSE results of the predictions under full observation and cross-subject training data across all joints. All values are in radian.

The results are also summarized in Fig. 5. Results by joint can be found in Table III. Overall we achieved an RMSE of about 0.2 rad (Own data partial), which is equivalent to roughly 11°. The biggest contributor to this

Subject	Joint 1	Joint 2	Joint 3	Joint 4
1	0.102	0.082	0.155	0.234
2	0.179	0.119	0.149	0.276
3	0.111	0.115	0.201	0.207
4	0.226	0.113	0.197	0.269
5	0.209	0.196	0.255	0.279
6	0.155	0.118	0.166	0.281
7	0.134	0.109	0.297	0.244
8	0.117	0.079	0.268	0.317
9	0.176	0.136	0.206	0.216
Overall	0.162	0.123	0.222	0.260

TABLE III: RMSE results of the experiment listed by joint. Joint 1 and 2 are observed and are thus taken into account for determining the current phase and style. As the algorithm tries to minimize of the prediction errors, it can be expected that error between the predictions and the observation is smaller for joints 1 and 2 than for joints 3 and 4. All values are in radian.

error are slight offsets on the unobserved joints, such as the one of joint 4 in Fig. 6b, even though the trajectories follow the right patterns. In the case with full observation we were achieved an RMSE of 0.15 rad, about 9°. The slight decrease of accuracy stems from small offsets and distortions, like the one in the joint 4 predictions seen in Fig. 6b. This effect can be explained as follows: It might be possible to represent a movement by the generative model. As the EM algorithm does not have any information about the last two joints, it has some freedom of choice to get the best match for the observed joints. This in turn can cause distortions for the unobserved joints while still generating the right pattern itself.

As summary, our method can manage partial observations, however, the prediction performance might be degraded when some essential part of observation is missing as a matter of course.

V. Discussion

We presented a movement prediction method equipped with following two desirable properties: 1) fast online calibration for a novel user, and 2) applicability to partially observable situations. To validate our proposed method, we conducted experiments in walking movement prediction using a one-leg three DOFs exoskeleton robot with nine healthy subjects. The first experiment was conducted to investigate the prediction performance for novel subjects under full observations. The second one was to validate its capability for managing partial observations with known subjects data. The experimental results suggested that our method can adapt to a novel user and partial observation.

The proposed method is eventually aiming for exoskeleton-based walking assistance for patients with partially paralyzed limbs. One open question is how to prepare training data with full observation to learn the full generative model since the data requires both legs' movements. A simple approach is just collect training data from healthy subjects. A more promising approach would be to collect the data from therapists who can "perform" walking patterns similar to the patients by considering their conditions. We will further proceed this direction and report the experimental results in near future. Furthermore, it is important to consider the stability maintenance issue of the user when the proposed method is used for the patients. This is another direction of our future work.

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