Human Learning and Coordination in Lower-limb Physical Interactions

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***Abstract*— This paper explores the gait learning and coordination through physical human-human interaction. The interaction and coordination are modeled as a two-step process: 1) encoding the human gait as a periodic process and 2) adjustment of the periodic gait cycle based on the external forces due to physical interactions. Three-legged walking experiments are conducted with two human dyads. Magnitude and direction of the interaction force, as well as the knee joint angles and ground reaction forces of the tied legs are collected. The knee joint trajectory of the two participants is modeled using dynamic movement primitives (DMP) coupled with force feedback though iterative learning. Gait coordination is modeled as a learning process based on kinematics from the last gait cycle and real-time interaction force feedback. The proposed method is compared with a popular baseline DMP model, which performs batch regression based on data from the previous gait cycle. The proposed model performed better in modeling one pair in the cooperative experiment compared to the baseline algorithm. The results and approaches for improving the algorithm are further discussed.**

I. Introduction

Humans use physical interaction to learn about the environment and to successfully complete tasks that require sophisticated coordination [?]. Principles that guide human-human sensorimotor interactions have led to the development of robots that physically interact with humans in a natural and efficient manner [?], [?]. Recently, there has been a growing interests of such robots in physical human-robot interaction (pHRI) for medical applications, including lower-extremity exoskeletons which have been developed for effective human augmentation, and rehabilitation [?]. To provide efficient and natural assistance, the robot needs to understand and adapt to the human sensori-motor learning [?].

In recent years, control strategies based on advanced sensing and adaptive controllers have been utilized to model human learning for rehabilitation that modifies the level of robotic support by changing torque required by the user in lower limb [?]. Furthermore, such systems often need to have an accurate real-time assessment of human motor functions for modeling and learning. It has been suggested that differential game theory can be used as a framework to describe the learning between a robot and the human user [?]. However, both adaptive controller and differential game theory framework require an accurate dynamic model of each user, which is challenging to acquire in practise [?].

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As an alternative to such model-based approaches, dynamical movement primitives (DMPs) have been applied in modeling human motor control, particularly for rhythmic movements such as locomotion [?]. DMPs encode a trajectory as a second-order differential equation with an added nonlinear forcing term. The forcing term in a DMP allows for online learning and adaptation of trajectories to external forces and perturbations [?], [?]. The forcing term can be further used for adapting parts of a trajectory as new sensor data becomes available, using incremental regression [?]. Furthermore, the structure of the DMPs enables incorporation of the sensorimotor feedback. Gams et. al. proposed cooperative DMPs (Co-DMPs) for bimanual tasks where a coupling term based on the interaction force measurements was learned online using iterative learning control (ILC) [?]. Huang et. al. further implemented Co-DMPs with reinforcement learning to reduce interaction force between a powered knee exoskeleton and its user [?].

Our goal of this paper is to develop a robust model for human walking which incorporates human learning. The proposed algorithm can be used for robot-aided rehabilitation. We model human gait as a DMP with adaptive learning based on interaction force. The force based learning is modeled within individual gait cycles and between successive gait cycles using incremental regression and iterative learning, respectively. We propose a three-legged walking experiment, in which two participants are asked to walk side-by-side as one of their legs is tied to each other. This experiment would provide valuable data on how two humans use the lower-limb interaction force to achieve a synchronized walking pattern. To the best of authors' knowledge, such a study has not been performed before. We have developed a custom sensing framework to measure interaction forces and knee joint angles of the participants. The Co-DMPs with learning framework is employed to model the participants' knee angles in which modulation of the DMPs take place through a coupled force term. Iterative learning is chosen as the learning procedure of the coupling term because it shares similarities with the human natural learning process through trial and error, and it is widely used in physical training [?]. The main contributions of this work are as follows:

- A custom sensing framework is developed to collect the interaction forces and knee kinematics during the three-legged walking experiments
- A Co-DMP with learning framework is developed and compared with the standard baseline DMP framework to model human-human lower-limb interaction

The rest of the paper is organized as follows: Section II

TABLE I: Anthropometric information of the participants

Pair	ID	Gender	Age	Height (cm)	Weight (kg)	Dominant leg	Tied leg
1	11	Female	27	158	55	R	R
1	12	Female	25	165	58	R	L
2	21	Female	28	159	56	R	R
2	22	Female	27	158	58	R	L

discusses the experimental setup of the three-legged walking experiments. Section III elaborates on the proposed formulation of Co-DMP with iterative learning. The results and discussions are presented in section IV. Section V concludes the paper and presents some future work.

II. Hardware and Experiment Design

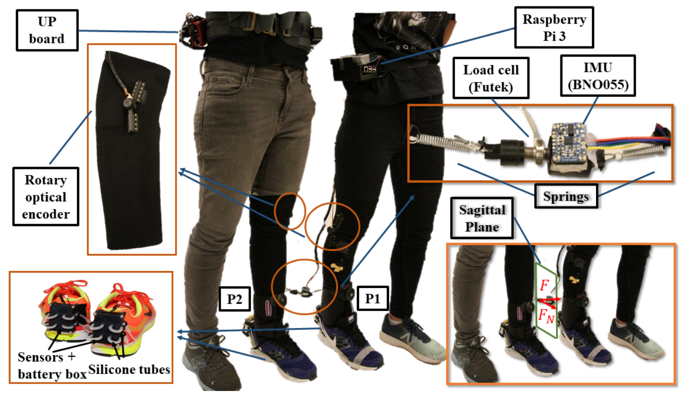
A. Experimental Setup

A custom fabric brace was designed to collect force and kinematic data during the three-legged walking with two participants, as shown in Fig. 1(a). Two ankle braces were used as the basis for connecting the legs of the two participants. The two ankle braces were attached with retractable cable mechanisms to adjust the distance between the attached legs. A load cell (Futek LCM200, Irvine, CA) was attached to the cable mechanism to measure the tensile interaction forces between the two participants. An absolute orientation IMU sensor (Adafruite BNO055, New York, NY) was implemented at the top of the load cell to determine the direction of the interaction force. The participants were required to wear a fabric knee brace with an embedded rotary encoder (US Digital S4T, 400CPR, Los Alamitos, CA) to measure their knee angles when walking. The encoder acted as the hinge of two rigid bars on the brace, and was made sure to be aligned with the knee joint. Smart shoes were used to capture the ground reaction forces at heel, the first and fourth metatarsophalangeal joints, and toe [?]. A single-board computer (Raspberry Pi 3, Rpi, Caldecote, Cambs, UK) was used to collect and synchronize data from all the sensors. An Intel UP-board (Santa Clara, CA) was added to transmit some of the sensor data to the Rpi. Fig. 1(b) shows the data collection schematic, including the data transmission protocol for each sensor and board.

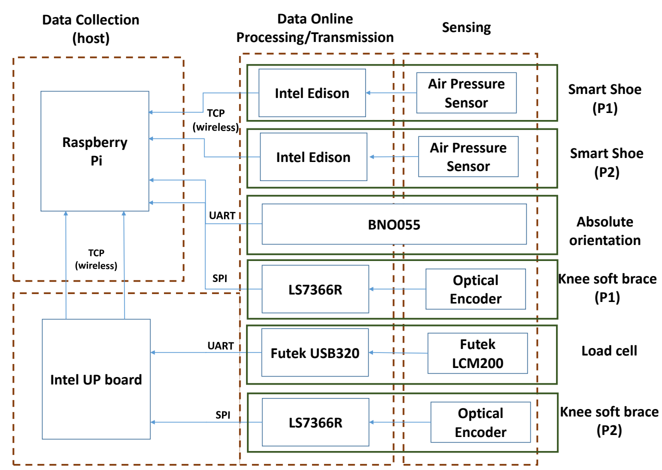
To study gait collaboration, two participants were asked to walk in a straight path for $10m$ with the left leg of one participant (P2) attached to the right leg of the other participant (P1), using the aforementioned system setup (shown in Fig. 1(a)). Anthropometric information of the participants is given in Table I. The participants were not allowed to verbally cue each other during the experiment. They were asked to only rely on the interaction forces to reach gait synchronization, and avoid any visual feedback by only looking straight ahead. This would help eliminate the undesired forms of communication and signalling. The walking experiment was repeated for two pairs of participants, with three trials for each pair.

B. Data Post-Processing

The data collected from the sensors were processed offline. The force data from the load cell was filtered using a second-order Butterworth low-pass filter with a cut-off frequency of



(a) Hardware components for the human experiments. The sagittal plane between the two participant is also shown, where F_N is the projected component of the total interaction force (F) measured by the load cell.



(b) Data collection diagram for the human experiments

Fig. 1: Experimental setup for collecting the knee joint angles, interaction forces and its orientation, and the ground reaction forces while performing the three-legged walking. P1 and P2 refer to the two participants.

10 Hz. The smart shoes were used to detect heel strikes for segmentation. The IMU sensor was oriented such that the yaw axis was aligned with the sagittal plane in which the knee flexion/extension occured. The interaction forces in the sagittal plane were obtained by:

$$F_N = F \cdot sin(\alpha - \alpha_0), \tag{1}$$

where F refers to the total interaction forces in the three-dimensional space, α is the measured yaw angle (the angle between F and F_N in Fig. 1(a)), and α_0 is the initial yaw angle where the tied legs are parallel to each other with no interaction forces in the sagittal plane. F_N is the projection of F into the sagittal plane which is considered the effective interaction force for participants to adjust their gaits.

The resultant knee extension/flexion angles and the interaction forces for one pair of participants in three trials are shown in Fig. 2. We observe 1) a significant difference between the total force (F) and the effective force (F_N), 2) an instantaneous change in the force affecting the gait cycle, 3) a significant reduction of force for the successive gait

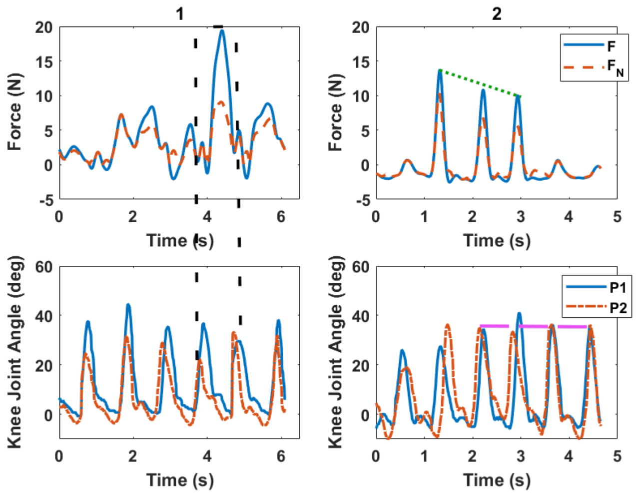


Fig. 2: The collected knee joint angles and interaction forces for three trials for pair 2. The order of performing the experiments is from 1 to 2. F is the total interaction forces, F_N is the projected interaction forces in the sagittal plane. P1 and P2 refers to each participant. Instantaneous change in gait pattern is observed (marked by black lines). Reduction in forces for successive gait cycle is observed (marked by green dashed line). Synchronized knee angle pattern is observed (marked by pink dashed line).

cycle which indicates learning, and 4) a highly synchronized knee angle pattern between the participants in trial 3. The pattern further justifies the use of DMP with incremental regression for adaptation to instantaneous force change and iterative learning to model the learning between gait cycles in the three legged walking. The processed data is fed into the proposed algorithm, Co-DMP with learning framework, which is further explained in the Section III.

III. METHODOLOGY

In this section, details of the proposed framework are presented, with a brief review of the periodic DMP. We also highlight the learning elements of the DMP. At the end, the overall algorithm to model the two participants' knee angles using Co-DMP and iterative learning is presented.

A. Dynamic Movement Primitive

Dynamic movement primitive (DMP) is an adaptive representation for modeling autonomous nonlinear goal-directed behaviour [?], [?], [?]. The general idea is to encode a recorded trajectory as a dynamical system, which can be used to generate different variations of the original movement. A DMP uses limit-cycle oscillators to model periodic trajectories. A DMP is described as

$$\tau\dot{z} = \alpha(\beta(g-y)-z)+f(x) \tag{2}$$

$$\tau\dot{y} = z \tag{3}$$

where τ is a time scaling factor, and α and β are positive constants. For our experiments we selected $\alpha = 8$ and $\beta = 2$ as used in [?]. The state variable y is the joint angle, g is the anchor point for the oscillatory trajectory, which can be changed to accommodate any baseline oscillation. For modeling a rhythmic motion, g is the average value of the trajectory. The last term, $f(x)$, is the nonlinear forcing function defined as

$$f(x) = \frac{\sum_{i=1}^{m}\psi_i(x)w_i}{\sum_{i=1}^{m}\psi_i(x)}\cdot r \tag{4}$$

where $\psi(x)$ is the exponential basis function and w is the corresponding weight vector. The basis functions only depend on the phase variable x, the state of a canonical system. The m exponential basis functions $\psi_i(x)$ is defined as

$$\psi_i(x) = \exp(h_i(cos(\phi-c_i)-1)) \tag{5}$$

where h_i is variance that determines the width, and c_i is the constant that determines center of the basis functions. We set center c_i of the Gaussian basis function to be spaced evenly throughout 0 to 2π run time. The variance h_i is set equal to the number of basis functions $m = 25$ for modeling human knee angles as used in [?]. A higher number of basis functions results in over-fitting and longer computation time. The phase variable ϕ is a simple choice of a canonical system for learning a limit cycle and represented as

$$\tau\dot{\phi}_i(x) = 1 \tag{6}$$

B. Incremental Regression

Given a set of $f(x)$, the equation can be manipulated to get a set of w_i in one shot. This formulation is called batch regression, which is also the baseline for our evaluation. Although the linear part of (2) defines the convergence to the goal, the weights of the kernel functions in (4) actually define the correct shape of the trajectory. The shape of the trajectory can be learned online by applying incremental weighted regression. The target trajectory is generated by rearranging equation (2) and inserting the demonstrated trajectory, y_{demo}.

$$f_{goal} = \tau^2\ddot{y}_{demo} - \alpha(\beta(g-y_{demo})-\tau\dot{y}_{demo}) \tag{7}$$

The f_{goal} is the target $f(x)$ for a demonstrated trajectory. For a f_{goal}, the w_i can be updated incrementally for each basis function $i \in \{1,\cdots,N\}$ at each time step j to better model highly dynamic motion cycles using

$$w_{i,j+1} = w_{i,j} + \Psi_i P_{i,j+1} r e_j \tag{8}$$

$$P_{i,j+1} = \frac{1}{\lambda}\left(P_{i,j} - \frac{P_{i,j}^2 r^2}{\frac{\lambda}{\Psi_i} + P_{i,j} r^2}\right) \tag{9}$$

$$e_j = f_{\mathrm{goal},j} - w_{i,j} r \tag{10}$$

where P_i is the inverse covariance of w_i, which we initialize with $w_{i,0} = 0$ and $P_{i,0} = 1$ for all basis functions. r and λ are the amplitude gain and forgetting factor, respectively. If $\lambda < 1$, the incremental regression provides more weight to the recent data.

C. Cooperative DMPs

DMPs can be modulated online to take into account the dynamic events occurring in the environment such as obstacle avoidance and external force [?], [?]. In three-legged walking, the two participants approach a motion synchronization after a few gait cycles. This can be achieved through the interaction force (F_i) between the participants. The desired interaction force between the participants is minimum, thus the force feedback term is a function of a measured force between two participants, given as $C_{2,1} = -C_{1,2}$. This term is introduced in the DMP formulation from equation 2-3 into the Co-DMP as

$$\tau \dot{z_1} = \alpha_z(\beta_z(g_1 - y_1) - z_1) + f_1(x) + c_2 \dot{C}_{1,2}, \tag{11}$$

$$\tau \dot{y_1} = z_1 + c_1 C_{1,2}, \tag{12}$$

$$\tau \dot{z_2} = \alpha_z(\beta_z(g_2 - y_2) - z_2) + f_2(x) + c_2 \dot{C}_{2,1}, \tag{13}$$

$$\tau \dot{y_2} = z_2 + c_1 C_{2,1} \tag{14}$$

where c_1 and c_2 are positive coefficients for the velocity and the acceleration term of individual DMPs.

D. Iterative Learning

To ensure the system converges, the measured force must be reduced after each cycle. As humans learn based on previous experiences, we propose an iterative learning algorithm to adjust the term $C_{1,2}$ and $C_{2,1}$ in Co-DMP. After the first gait cycle, the interaction forces between the participants are collected which are then fed in a feedforward manner. F_k is a set of force recorded in each gait cycle from time step $j \in \{1, \cdots, 2\pi\}$. For the coupled term C_k at the k_{th} trial, $C_{1,2} = -C_{2,1}$, is inspired by the idea of ILC

$$C_k = c\, e_k + F_{c,k}, \tag{15}$$

$$F_{c,k} = Q(F_{c,k-1} + L e_{k-1}), \tag{16}$$

$$e_k = -F_k \tag{17}$$

where c is the force gain, e_k is the coupling force error. Q and L are positive scalars which define the Q-filter and learning function, respectively [**?**].

E. Co-DMP with Learning Framework

Based on the demonstrated first gait cycle, the DMPs of each participant are modeled. The interaction forces are fed into the iterative learning algorithm. Based on the previous gait cycles and coupling term, both DMPs are updated to track the observed knee angles. At each gait cycle, the iterative learning algorithm will provide the learned coupled term based on the interaction forces, while the $f(x)$ term will provide the internal gait learning for the DMP in the system as described in Fig. 3.

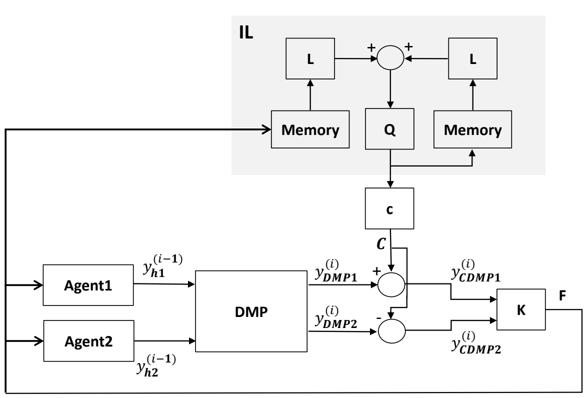


Fig. 3: The proposed Co-DMP for modeling knee trajectories in three-legged walking. y_h refers to the knee angle measurement. y_{DMP} refers to the encoded trajectory by the DMP without considering the environmental interaction, C is the coupled term learned through iterative learning based on interaction forces, and y_{CDMP} refers to the output of the coupled DMP.

Algorithm 1: Co-DMP with learning framework for three-legged walking

for *Both Participants* **do**
  Obtain the motion trajectory for both participants
  if *first gait cycle* **then**
    Update w_i based on batch regression, Eq. (4)
  else
    Get coupling term for DMP using Eq. (15-17)
  end
  Calculate f_{goal} based on Eq. (7)
  for *all* $i \in [1, m]$ **do**
    Update w_i based on Eq. (8-10)
  end
  Calculate reshaped Coupled DMPs from Eq. (11-14)
  Compare DMP trajectory and observed trajectory
end

IV. Testing and Evaluation

The force feedforward term could improve the accuracy of DMP since the memory-based feed-forward controller helps learn from previous iterations [**?**]. We hypothesize that humans learn and adjust to the other's gait pattern based on the interaction force from the previous gait cycle.

We performed parameter search and empirically found that setting Q, L and c values to 0.9, 0.1 and 0.1, respectively, would give us the smallest modeling error. The root mean square error (RMSE) between the measured data and model output is provided in Table II. The proposed approach is compared with the baseline batch regression-based DMP as described in Eq. (4).

The modelling error for the first five gait cycles for each trial was calculated. For the first and the second trial for both pairs, we observed that Co-DMP modeled a better trajectory for one of the two participants, as the results show a reduction in modelling error for P2 of pair 2 with a lower RMSE of 0.980° and 1.680° as seen in Table II. Similarly, for pair 1, the error of P1 with an RMSE of 1.163° and 1.894° is significantly lower compared to the baseline. However, there is a larger error for pair 1 in trial 3 compared to the baseline algorithm. As seen in Fig. 4, this is due to an abrupt and large force at the third time-step. The Co-DMP models the gait cycle considering the abrupt force, however the measured gait cycle is not affected by it. We are also able to observe a consistent gait pattern by the third trial for both pairs. Larger modeling error is also observed for Co-DMP in trial 3 with pair 2, and this is due to the

TABLE II: The comparison of RMSE using the proposed approach and DMP with batch regression

Pair	Trial	RMSE P1 (°)		RMSE P2 (°)	
		Co-DMP	Baseline	Co-DMP	Baseline
1	1	1.163	2.167	3.829	2.355
1	2	1.894	3.095	3.261	2.128
1	3	2.823	1.834	5.232	2.944
2	1	2.329	1.012	0.980	1.709
2	2	3.806	3.519	1.680	3.077
2	3	1.973	2.073	2.364	1.975

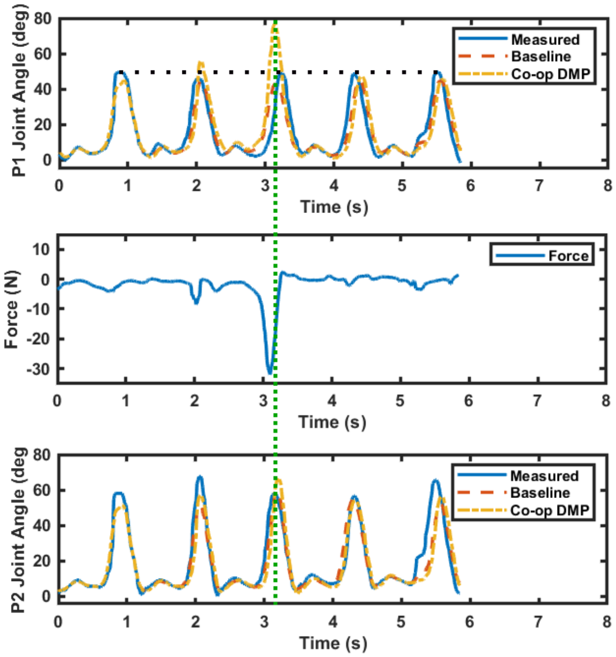


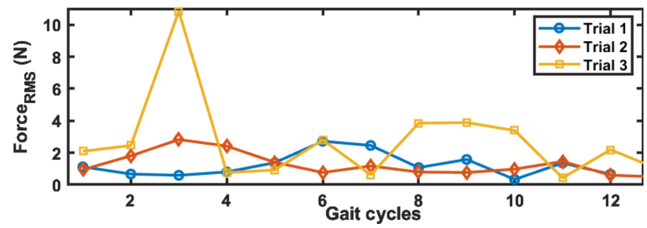
Fig. 4: The force, knee joint angles of pair 1 for the Co-DMP and baseline algorithms in trial 3, where Co-DMP models high error due to high instantaneous force (marked by green vertical dashed line). Consistent gait pattern observed for P1 (marked by black horizontal dashed line).

reduced forces which are used in the Co-DMP model but does not seem to alter the gait cycle as observed in Fig. 6(b). Figure 5 compares the average interaction forces at each gait cycle for all the trials. It can be clearly observed that the interaction forces are generally higher at the first trial for both pairs, and they reduce in the next trials (except trial 3 where participants tripped momentarily and recovered). This shows the learning by participants between trials where they adapt to each other's gait pattern. However, this learning process is not very obvious or consistent across gait cycles in a trial.

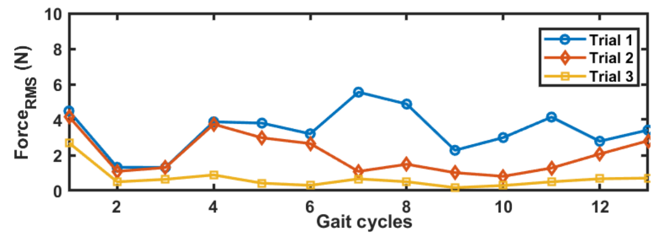
The Co-DMP models one participant better than the other. For pair 2, the change in phase causes both algorithms to perform poorly as seen in Fig. 6(a) where a change in the frequency of the oscillator was not identified by either model for P1. We observe that P2 has a consistent frequency from one gait cycle to another as seen in pair 2 for trials 2 and 3 in Fig. 6(b).

V. Discussion and Limitation

As shown in Figure 5, the gait adaptation based on interaction forces is not instantaneous, rather it takes time and depends on the individual motor skills. Humans might



(a) Pair 1



(b) Pair 2

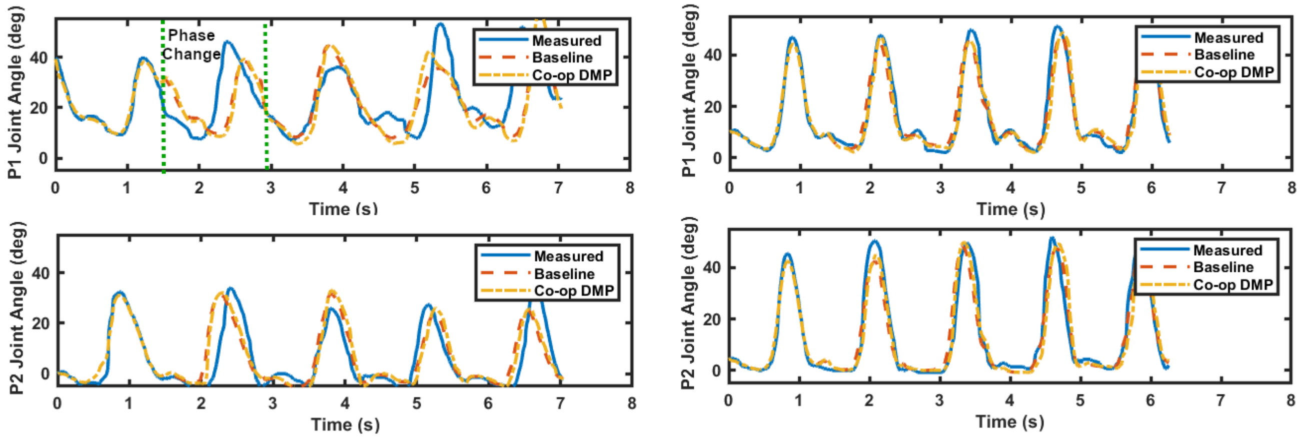
Fig. 5: The RMS of interaction forces (sagittal plane) during each gait cycle for pair 1 (a) and pair 2 (b) during the three consecutive trials

be using the interaction forces for lower-limb movement co-ordination but the mechanism on how they interpret that force remains unclear. It was shown that humans used interaction forces for lower-body movement synchronization [?], [?]. However, there has been no observed correlation between the magnitude of the force and the learning process in those studies. In our work, the synchronization of the knee movement is directly coupled to the interaction forces through the springs and we claim that the magnitude of the force is directly correlated to gait synchronization. Therefore we proposed the Co-DMP with iterative learning to model the knee joint trajectory. The results showed improvement over the baseline approach only in some cases which could be due to the following reasons:

- Limitation of iterative learning: as discussed above, the gait adaptation happens over trials rather than across gait cycles, but the iterative learning taking place at each time step. Although iterative learning has been shown to be an effective mechanism for humans to learn and improve motor skills, it remains unknown how the learning actually takes place.
- Force measurement noise/inaccuracy: noise and error are highly likely in our measurement especially in the effective interaction force (force in sagittal plane). The IMU sensor might provide inaccurate measurement under the impacts and oscillation during walking.
- Learning mechanism: in our proposed framework the gait adaptation happens through the coupled term which is based on interaction forces. However, visual and auditory feedback also play an important role in human learning, which is not considered in this paper.

VI. Conclusion and Future Work

In this paper, a three-legged walking experiment was conducted to infer human-human lower-limb physical interaction. A Co-DMP with learning algorithm was implemented



(a) (b)

Fig. 6: Knee joint angles of pair 2 for the Co-DMP and baseline algorithms, (a) for trial 2 where change is phase is observed, and (b) for trial 3 where both baseline and Co-DMP show a similar trajectory.

to model the knee angle in the three-legged walking scenario. The proposed algorithm was evaluated in six trials for two pairs of participants, three trials each. The algorithm was compared with baseline DMP. The developed framework was able to provide lower RMSE of the knee angle for one of the two participants in some trials.

A phase and time based framework can be explored as future work for the system. Future work will also include implementation of the proposed Co-DMP model in a exoskeleton. Co-DMP can be further be explored by including different cooperative learning methods such as reinforcement learning or differential game theory. More trials will be conducted with other participant pairs for identifying different learning strategies.

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