# Learning Coordinated Vehicle Maneuver Motion Primitives from Human Demonstration

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***Abstract*— High-fidelity computational human models provide a safe and cost-efficient method for the study of driver experience in vehicle maneuvers and for the validation of vehicle design. Compared to passive human model, an active human model that can reproduce the decision-making, as well as vehicle maneuver motion planning and control will be able to support more realistic simulation of human-vehicle interaction. In this paper, we propose a integrated human-vehicle interaction simulation framework that can learn the motion primitives of vehicle maneuver motions from human drivers, and use them to compose natural and contextual driving motions in simulation. Specifically, we recruit seven experienced drivers and record their vehicle maneuver motions on fixed-base driving simulation testbed. We further segmented the collected data and classified them based on their similarity in joint coordination. Using a combination of imitation learning methods, we extracted the regularity and variability of vehicle maneuver motions across subjects, and learned the dynamic motion primitives that can be used for motion reproduction in simulation. Our research efforts lead to a motion primitive library that can be used for planning natural and contextual driver motion, and will be integrated with the driving decision-making, motion control, and vehicle dynamics in the proposed framework for simulating human-vehicle interaction.**

## I. INTRODUCTION

The development of vehicle active safety and driver-assistance technologies has motivated the high-fidelity modeling of humans for driving tasks. Such human driver models provide automotive system designers with effective methods for investigating driver behavior as well as the dynamic physical interaction between driver and vehicle in a wide range of driving scenarios [1]. These insights contribute to the improved design and validation of active safety systems [1], [2], the usability and intelligence of driver-assistance systems [3], [4] as well as the vehicle ergonomics analysis [5], [6]. In addition, studying human-vehicle interactions in high-fidelity human models is usually preferred because the simulation tests performed using real human drivers are costly, time-consuming and strictly limited due to safety regulations.

To facilitate the study of human-vehicle interaction in simulation, it is necessary to build a computational human model that can simulate a driver's coordinated vehicle maneuver motions in response to the vehicle dynamics. For many driving tasks, a driver needs to coordinate the

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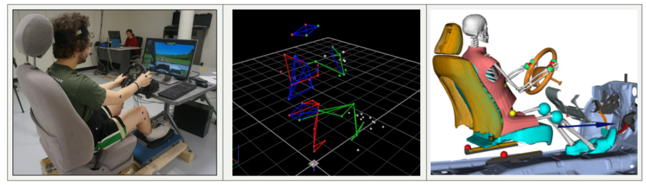

Fig. 1. Learning and reproducing natural vehicle maneuver motion.

motion for gas/braking pedaling with steering control, which results in complex motion response ranging from passively maintaining body posture to actively maneuvering the vehicle according to traffic and road condition. So far, there has been limited investigation on an integrated simulation framework which enables realistic rendering of both driver task reasoning as well as whole-body posture and manipulation motion. Existing research in the development of human driver models address either the task reasoning aspect, focusing on what maneuvers to perform based on desired vehicle motion, or physical interaction and considerations such as posture and manipulation [7]. In [7], an integrated cognitive-physical human model is proposed, based on the HUMOSIM Ergonomics Framework [6], for investigating driver behavior during in-vehicle tasks. Musculoskeletal models of human arms have also been integrated with steering control algorithms to render realistic steering manipulation [3], [4]. However, it is still unclear how to render realistic active whole-body coordinated motion in vehicle maneuvering tasks in response to the dynamics of the vehicle under maneuver.

In this paper, we propose a integrated motion planning and control framework for render whole-body coordination in physical interaction between human driver and the vehicle in typical driving scenarios. This framework incorporates an OpenSim human model [8] to simulate human body dynamics and uses the dynamic movement primitives learned from human drivers to compose coordinated vehicle maneuver motions. Imitation learning has been successfully implemented for transferring complex human motor skills to robotic systems for reaching [9] and object manipulation [10], [11]. In this study, we propose a systematic approach for autonomously identify the vehicle maneuver motion primitives, and integrate multiple imitation learning methods to extract and reproduce the motion regularity across experienced drivers (see Fig. 1).

The rest of the paper is organized as follows: Section II presents related work in the development of digital human models, autonomous motion segmentation and learning movement primitives from demonstrations. In Section III, we introduce our proposed framework for computational human driver model, and present our experiments for collecting vehicle maneuver motion data and methods for data analysis. Section IV describes the implementation of our framework on the simulated driver model. Results are presented in Section V.

## II. Background and Related Work

Digital human models have found increasing applications in various fields including computer animation [12], ergonomics research [6], biomedical studies [8], automotive safety research [1], [13] and many more. This is because they provide researchers will an effective means of analyzing and predicting human behavior in a variety of scenarios. Automotive researchers have employed digital human models for predicting human driver's maneuver behavior [1], [14], injury outcomes from crash scenarios [13], validation of driver-assistance systems [4], [3], analyzing driver comfort and vehicle ergonomics [6], [15]. However, limited work has been done on the development of a human driver model for full active rendering of whole-body coordinated motion in driving tasks.

Due to the complexity and sophistication of the multi-joint coordinated movement of humans, it is very challenging to plan and generate human-like motions in constrained contexts like driving. Therefore, we take the imitation learning approach, and compose natural vehicle maneuver motions based on the motion primitives learned from experienced human drivers. Learning from demonstration (LfD) has become a popular approach for the transfer of complex motor skills from human actors to non-human actors - robots, virtual models, etc. Various learning frameworks have been proposed in the literature. A review of existing techniques through a defined pipeline is presented in [16]. In order to transfer motor skills, the demonstrations need to be broken down into basic characteristic movement primitives (MP). These basic MP are then defined in a mathematical representation [17]. A summary of existing methods for learning and encoding MP are addressed in [17]. These methods include stochastic approaches such as hidden Markov Models (HMM) [18], Gaussian Mixture Models [19], [10]; as well as dynamical systems approaches [20].

Given the data collected from experienced drivers, efficient and accurate motion segmentation method is required to identify the driving motion primitives. Manual segmentation can be tedious and inaccurate when dealing with human motions that involve the coordination of many degrees of freedom [21]. For autonomous data segmentation, we use segmentation cues that can identify the transition points between the vehicle maneuvers that are significantly different in joint coordination. Previous research efforts have proposed many techniques that differ in application domain and computational resources. Lin *et al.* [21] describes online-based techniques as those where segment transition points are defined based on thresholding of some feature vector, without need for pretrained models. These techniques include Zero Velocity Crossing (ZVC) employed in [9], [22] to automatically segment arm movement data for generation of movement primitives, statistical methods such as Principal Component Analysis (PCA), Probabilistic PCA and Guassian Mixture Model (GMM) [23]. These techniques are computationally inexpensive and thus can be performed online. Other segmentation techniques including Dynamic Time Warping (DTW) [24], Viterbi Algorithm [25] and HMM [26] may yield more accurate results, but are typically computationally expensive and hence have to be performed offline [21].

## III. Methodology

This section describes our proposed framework for computational human driver model and our methods for learning and reproducing vehicle maneuver motions from human demonstration.

### A. A Framework for Computational Modeling of Human-vehicle Interaction

To investigate realistic whole-body coordination in physical interaction between human driver and vehicle, we propose a framework which integrates a full-body human driver model with a vehicle model in OpenSim [8], and provides a closed-loop control to render realistic passive and active driver motions. Shown in Fig. 2(a), the framework of the computational driver model consists of four major components. The **driving task reasoning layer** computes the desired pedal angles $\delta_p^d$ for longitudinal motion control and the steering wheel angle $\delta_{sw}^d$ for lateral motion control [27], while the **coordinated motion planning layer** computes the corresponding joint torques $\tau$ in the whole-body coordination. The **driver dynamics layer** uses OpenSim whole-body musculoskeletal model to simulate the human driver's forward kinematics and dynamics, and the resulted maneuver motions. It also estimates the muscle-level actuation, which can be used to analyze the comfort/potential injury resulted from the driver's reactive motion. The driver's commanded pedals $\delta_p$ and steering wheel $\delta_{sw}$ angles, resulting from the maneuver motions computed in the driver dynamics layer, are fed to the vehicle dynamics layer.

### B. Learning and reproducing vehicle maneuver motions

Shown in Fig. 2(b), we propose to learn the coordinated motion primitives for vehicle maneuver motions (e.g., wheel-steering, pedal pressing) from human drivers, and apply them to the motion planning of computational human model in the simulation of human-vehicle interactions. To be specific, we (1) collected vehicle maneuver motion data from experienced drivers in passive driving test bed, (2) clustered the segmented motion data, (3) extracted the regularity and variability of the same kind of vehicle maneuver motions using imitation learning algorithms, and (4) built a motion primitive library for reproducing contextual vehicle maneuver motions in simulation. In this section, we will describe our experiment for data collection and methods for data analysis, motion learning and reproduction.

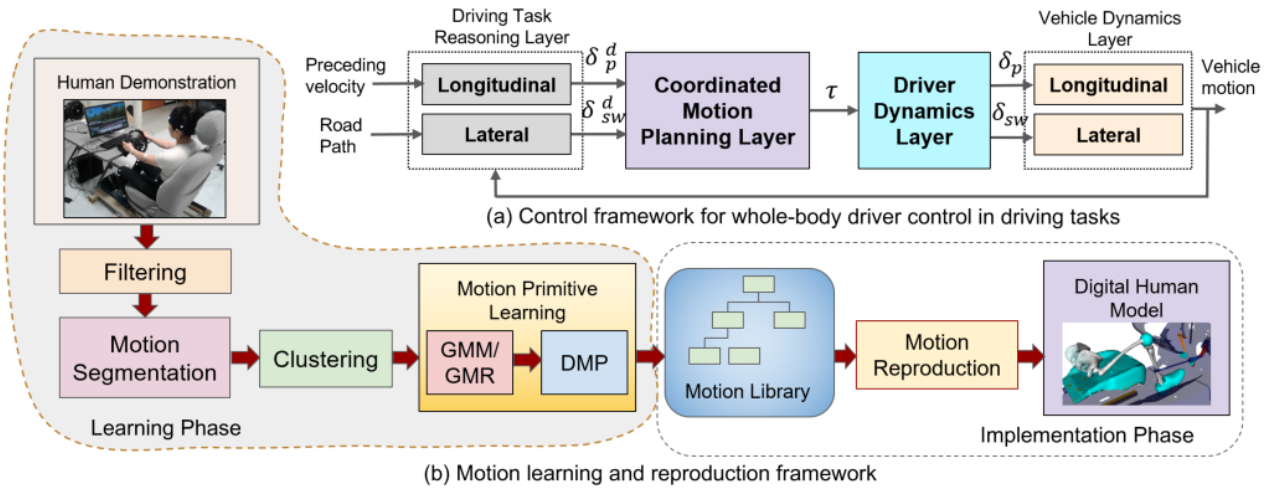


Fig. 2. Framework for understanding driver-vehicle interaction in driving tasks. (a) shows the control framework for rendering whole-body coordination in driving tasks. (b) shows the motion learning and reproduction framework.

Fig. 3. A subject is driving in fixed-base simulation testbed within motion capture laboratory. (Left): Experimental setup. (Right): Screen capture of the driving simulator game

## C. Experiments

Our experiment collected data of natural vehicle maneuver motions in daily driving tasks. We recruited 6 healthy subjects without vision, motor disability and with at least two years of licensed driving experience. During the experiment, the subject drove in a fixed-base driving simulation test bed (see Fig. 3). The operator console supports the control of a vehicle within a driving simulation environment (City Car Driving v1.5 Gaming Software) using Logitech G920 driving hardware, and displays the simulated driving context via a 21” monitor.

*a) Task description:* Our subjects were asked to drive in three different driving contexts: highway, city/town road, and country road. The subjects drove under each condition for six minutes. These contexts were selected to capture a wide range of driving behaviors under various road and traffic conditions. To avoid fatigue, subjects were allowed to take breaks between driving sessions.

*b) Intake Survey:* After giving informed consent, subjects were asked to complete a survey to collect demographic information (age, gender) and a description of their driving experience, style and video gaming experience.

*c) Practice session:* The subjects were required to pass a practice session before participating in the study. For each condition, the subject was allowed a maximum of 10 attempts to complete 3 successful practice runs. A practice run is considered successful if the subject drives for 2 minutes without getting into an accident or accumulating more than 30 driving errors including driving against traffic, lane changing without signaling, etc. (reported by the gaming software). Failure to pass the practice session would exclude the subject from participating in the rest of the study.

*d) Post-Session Surveys:* At the end of the study, subjects were asked to evaluate their experience in the driving study. The survey included the NASA-Task Load Index (NASA-TLX) on a five-point Likert scale to evaluate perceived workload as well as questions to evaluate the level of realistic rendering of driving provided by the simulator.

*e) Data Collection:* We attached passive reflective markers to the subject and record his/her whole-body motions using Vicon motion capture system at 100 Hz frequency. We simultaneously recorded the subject motions using video camera and driving context using screen capturing, to facilitate data segmentation and labeling, and to match driver’s motions to the driving context. Data for actual steering wheel and gas/break pedals motions were telemetered at a rate of 100Hz. A 2nd-order low-pass butterworth filter with a cutoff frequency of 5Hz was used for removing the high frequency noise from the data.

## D. Data Analysis

*1) Autonomous Data Segmentation:* In this paper, we focus on learning and producing the motion primitives that address the lower-extremity joint coordination during pedal pressing. To extract representative vehicle maneuver motions, we need to segment the long, continuous sequence of driving motion data into smaller components and cluster those with shared, distinct features. We use a feature vector thresholding method based on the characteristics of our movement data. In vehicle maneuvering tasks, drivers typically perform two basic foot movements: switching from one pedal to another, and pressing on a pedal. Our objective is to extract data segments when the foot is in the switching movement. To do this, we define a simplified feature vector as the position of the foot. Based on knowledge of the fixed positions of the pedals, threshold values are set to define the segment transition points in the data.

*2) Clustering Motion Segments using DMP:* The resulting sequence of motion segments are clustered in order to realize the characteristic motion primitives that address lower-extremity motion in driving. The characteristic features of each data segment are modeled by the Dynamic Movement Primitives (DMP) framework and encoded as the weighting coefficients of the Gaussian basis functions [20].

We use an unsupervised learning method—$K$-means clustering—to partition the respective weighting coefficients into $k$ clusters. To learn the motions for pedal operation tasks, we set $k$ = 3, to represent gas-to-brake foot motion, brake-to-gas foot motion and pedal pressing motion.

*3) Learning Movement Primitives for Motion Reproduction:* The next step is to extract the regularity and variability of respective vehicle maneuver motions using imitation learning algorithms and encode them as motion primitives.

*a) Learning motion regularity and variability:* we use GMM/GMR to learn an averaged behaviour (i.e. trajectories of the coordinated DOFs) from the clustered demonstrations of the same pedal operation task [10]. Note that GMM is used as a parametric model of the probability distribution of the clustered motion data [28]. This model is represented as a weighted sum of $M$ Gaussian component densities. The parameters of the mixture model, $\{w_i, \mu_i, \Sigma_i\}_{i=1}^{M}$ - mixture weights, mean vector and covariance matrix of the $i$-th Gaussian distribution respectively - are estimated iteratively using the expectation-maximization (EM) algorithm [29]. The choice of $M$ can be estimated based on the value which maximizes the Bayesian Information Criterion (BIC) [30]. This criterion computes a score that describes the optimal number of components required to accurately fit the data. On the other hand, a Gaussian mixture regression (GMR) [31] process is implemented on the mixture model to retrieve a generalized trajectory [10]. This averaged trajectory, $\hat{x} = \{\hat{x}_{t,i}, \hat{x}_{s,i}\}$, representing temporal values and the corresponding spatial values respectively are estimated through regression [10]. By combining GMM with GMR, we can extract the averaged motion for all the coordinated lower extremity joints, with the variability along the trajectory.

*b) Learning and reproducing averaged behaviors:* We further encode the averaged trajectories of the coordinated joint using DMP model [11]. The resulting generalized trajectory, $\hat{x}(t)$, is encoded by the DMP framework using a second-order differential equation which is interpreted as a linear spring-damper system perturbed by a non-linear forcing term [11], [20]. Specifically, the non-linear forcing term is a weighted Gaussian basis function with $w$ weights which is used to encode the generalized trajectory. The desired non-linear forcing function, $f_{des}(s)$, for a given behavior is computed by inserting the generalized trajectory, $\hat{x}(t)$, and its derivatives $v(t)$ and $\dot{v}$ into the differential equation. Then a linear regression problem is solved to define the weights $w_i$ that minimize the error criterion to drive the $f(s)$ to $f_{des}(s)$. The most common method used is the locally weighted regression (LWR). The weights, parameters of the DMP, are stored in the motion library. To reproduce a motion, a movement plan which includes a sequence of basic foot movements is defined to achieve the desired coordinated motion. These basic movements, which are already encoded as motion primitives in the motion library, can then be reused for different start and end positions for all the degrees of freedom [11].

## IV. Implementation

This section introduces our implementation of the computational driver model for high-fidelity simulation of human-vehicle interactions, and describes how to use the motion primitives learned from human drivers for planning contextual vehicle maneuver motions.

*1) Motion Planning and Control:* Our work in this paper implements the **Coordinated motion planning layer** in Fig. 2(a). This layer compiles a movement plan, sequence of motion primitives, which achieves the desired vehicle maneuver motion (pedal task) and defines the task specifications (start and goal positions for all the DOFs in the task space).

The OpenSim leg model includes 6 active DOFs actuated with ideal torque actuators and one passive joint on the foot (see Fig. 4). To guarantee the trajectory tracking performance, a task-space controller is used to command joint torques to the model joints.

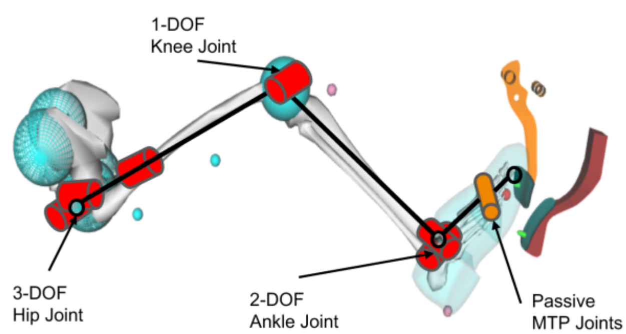


Fig. 4. Driver leg model with 6 active joints and one passive joint.

## V. Result

Here we present the results from motion learning and reproduction on pedal operation tasks. From the motion data collected from human drivers, we have learned the motion primitives for switching between gas and brake pedals.

### A. Data Segmentation

Fig. 5 plots the foot position in X-direction against time for a section of a driving demonstration. The motion data within each segment is interpolated to a fixed length of 200 elements in order to align the different demonstrations. Also, the amplitude of the data is normalized for ease of combination from different demonstrations.

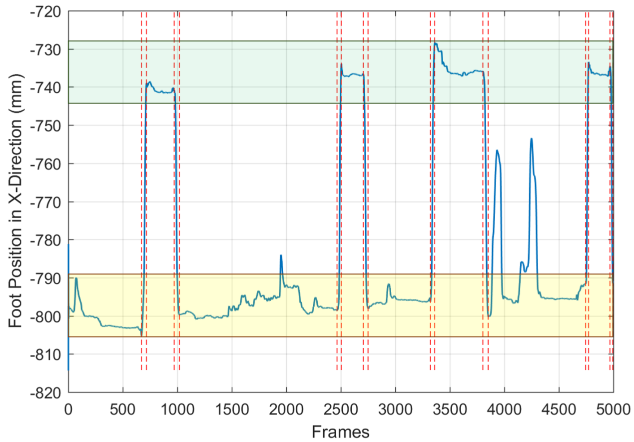


Fig. 5. Segmentation method using foot position along global X-direction. The segment transition points are defined by red dashed lines. The green and yellow blocks define the brake and gas regions respectively.

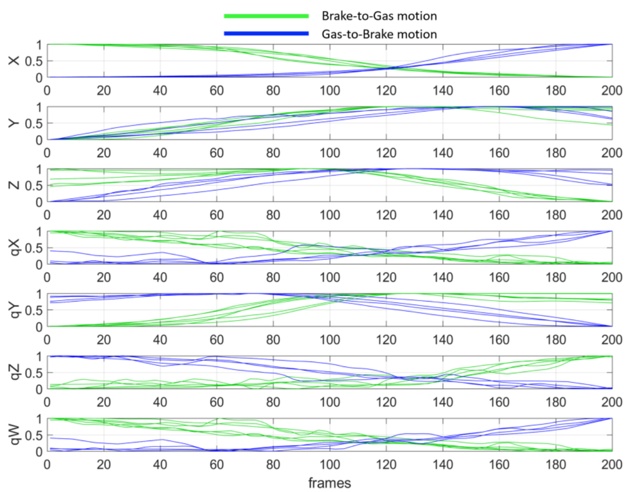


Fig. 6. Raw time-aligned trajectory data (position and orientation) from the motion segmentation section for both brake-to-gas and gas-to-brake motions

### B. Learning Motion Regularity and Variability

Fig. 6 shows the time-aligned $\{x,y,z\}$ position and $\{qx,qy,qz,qw\}$ quaternion orientation trajectories of the clustered pedal switching motions. The orientation trajectories segmented were not as smooth as the position trajectories due to the range of the motion. This is reflected in the shape of the mixture models generated using GMM (see Fig. 7). Fig. 8 shows the result of the regression process on the mixture model. The resulting trajectories are a generalized representation of the different trajectories obtained from multiple demonstrations.

### C. Learning and Reproducing Averaged Behavior

This generalized trajectories are then encoded using the DMP framework for ease of reproduction in new task specifications. Fig. 9 shows a plot of the generalized trajectory in 3-D space along with the DMP-reproduced trajectory for both the brake-to-gas and gas-to-brake motions. These trajectories

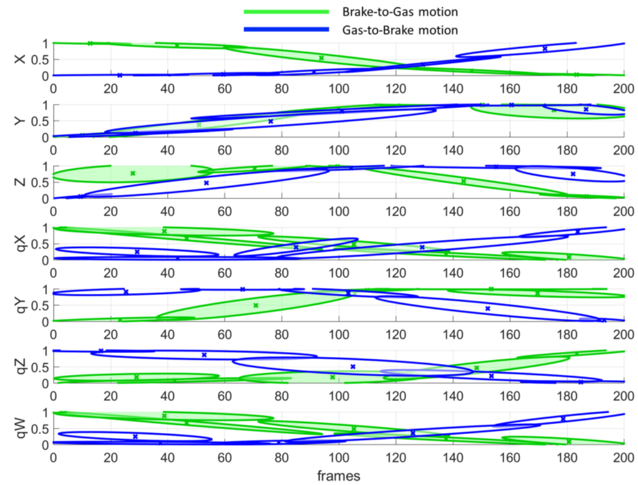


Fig. 7. Derivation of the mixture model describing the probability distribution of the segmented data trajectories.

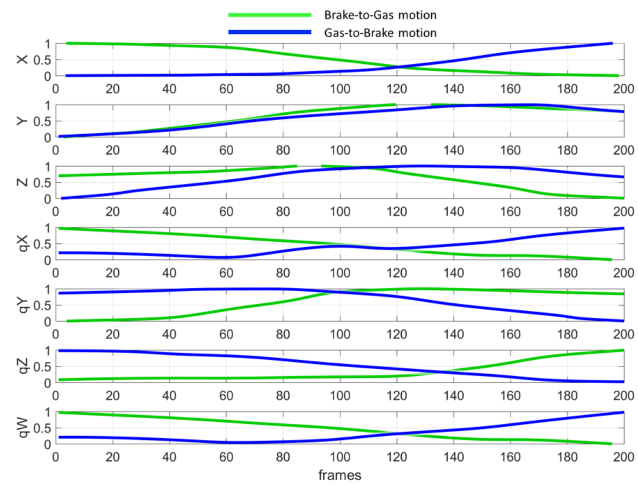


Fig. 8. Derivation of a generalized trajectory for pedaling task from multiple demonstrations using the GMR method.

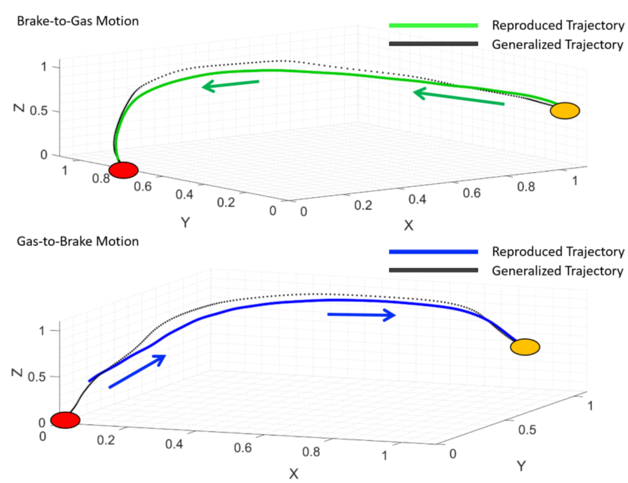


Fig. 9. Generalized and reproduced 3-D foot trajectories using DMP framework. (Top): brake-to-gas motion (Bottom): gas-to-brake motion. The gas and brake pedals are depicted as the red and orange balls respectively.

are reproduced from the DMP weights stored in the motion library.

For implementation on the digital driver model, a movement plan must be generated. To do so, a sequence of desired motions is defined based on the desired pedal angles from the Driver Task Reasoning Layer (see Fig. 2). For instance, if the foot is at the brake pedal position and the desired gas pedal angle is positive (meaning the gas pedal is to be engaged), the sequence of motions will be brake-to-gas motion then gas-press motion. To implement the brake-to-gas motion, the brake-to-gas motion primitive is selected from the library. Then the current pose of the foot is set as the start pose of the DMP and the end pose is set as the gas position. This defines a feasible human-like pedal switching trajectory to be implemented by the motion controller.

## VI. Conclusion

This paper proposed a framework that integrates active human model with vehicle dynamics model, to render high-fidelity simulation of human-vehicle interaction. In particular, we proposed a systematic approach to extract the regularity and variability of vehicle maneuver motion across subjects. We further use the dynamic motion primitives that represent the averaged behavior of experienced drivers for the motion planning in simulation. Using the proposed approach, we learned the motion coordination for pedal activation motion from the demonstrations and reproduced it on a digital driver model in the OpenSim platform. Our future work will construct a motion primitive library to support the motion planning module in the proposed framework for simulating human-vehicle interaction.

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