

Transition State Clustering for Interaction Segmentation and Learning

Fabian Hahne
Technische Universität Darmstadt
Darmstadt, Germany
fabian.hahne@stud.tu-darmstadt.de

Vignesh Prasad
Technische Universität Darmstadt
Darmstadt, Germany
vignesh.prasad@tu-darmstadt.de

Alap Kshirsagar
Technische Universität Darmstadt
Darmstadt, Germany
alap.kshirsagar92@gmail.com

Dorothea Koert
Technische Universität Darmstadt
Darmstadt, Germany
dorothea.koert@tu-darmstadt.de

Ruth Maria Stock-Homburg
Technische Universität Darmstadt
Darmstadt, Germany
rsh@bwl.tu-darmstadt.de

Jan Peters
Technische Universität Darmstadt
Darmstadt, Germany
German Research Center for AI
Darmstadt, Germany
Hessian Center for AI
Darmstadt, Germany
mail@jan-peters.net

Georgia Chalvatzaki
Technische Universität Darmstadt
Darmstadt, Germany
Hessian Center for AI
Darmstadt, Germany
georgia.chalvatzaki@tu-darmstadt.de

ABSTRACT

Hidden Markov Models with an underlying Mixture of Gaussian structure have proven effective in learning Human-Robot Interactions from demonstrations for various interactive tasks via Gaussian Mixture Regression. However, a mismatch occurs when segmenting the interaction using only the observed state of the human compared to the joint state of the human and the robot. To enhance this underlying segmentation and subsequently the predictive abilities of such Gaussian Mixture-based approaches, we take a hierarchical approach by learning an additional mixture distribution on the states at the transition boundary. This helps prevent misclassifications that usually occur in such states. We find that our framework improves the performance of the underlying Gaussian Mixture-based approach, which we evaluate on various interactive tasks such as handshaking and fistbumps.

CCS CONCEPTS

• **Theory of computation** → **Unsupervised learning and clustering**; • **Computing methodologies** → *Mixture modeling*; Learning from demonstrations.

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KEYWORDS

Hidden Markov Models, Learning from Demonstrations

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1 INTRODUCTION

Human-Human Interactions involve various non-verbal gestures, like handshakes, fostering societal trust and affiliation [9]. In the context of Human-Robot Interactions (HRI), non-verbal communication is crucial for robot acceptance, requiring robots to comprehend and execute social actions seamlessly without appearing uncanny to the human participants in the interaction [8]. Learning these interactions is challenging due to human diversity and subtle variations in actions. To address this problem of predicting accurate response behaviors in Human-Robot Interactions, Learning from Demonstrations (LfD) approaches have shown good performance by learning joint distributions over the observations of the human and the robot [7].

Since many interactive tasks can naturally be broken down into underlying segments or phases that are then sequenced to achieve suitable behavior, previous works have explored learning HRI from demonstrations using Gaussian Mixture Models (GMMs) or, additionally, Hidden Markov Models (HMMs) with an underlying Mixture of Gaussians structure [3, 4, 13, 14, 11, 10, 15]. However,

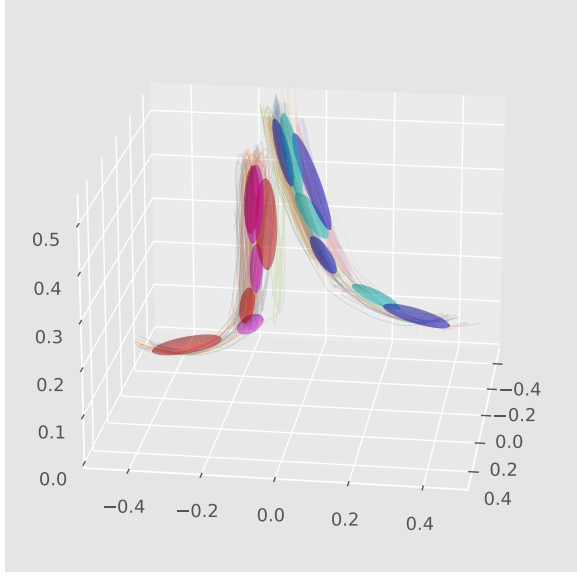


Figure 1: An example of the hidden states (Human - red, Robot - blue) learned by an HMM and the learned transition state clusters (Human - magenta, Robot - cyan) from demonstrations of handshaking.

Hidden Markov Models have limitations in representing transition states. In complex Human-Robot-Interaction settings, where dynamics are intricate and context-dependent, the simplistic representation of transitions may not capture the nuanced nature of human behaviors.

To enhance the segmentation abilities of GMM/HMM-based approaches, incorporating a separate mixture distribution over observations at the transition boundary between two underlying Gaussian states has demonstrated effectiveness in identifying key change points in a trajectory [6]. This leads to a hierarchical model with the first level learning from demonstrated trajectories and the second level focusing on “transition states” (Fig. 1). In this paper, we investigate how this hybrid model concept can enhance the performance of GMM/HMM approaches in learning Human-Robot Interaction (HRI). We demonstrate that the additional Transition State Clustering, implemented on top of an HMM model trained over the states of both the human and the robot, improves segmentation when using only human observations. Consequently, this enhancement leads to improved conditional predictions of robot actions based on human observations.

2 PRELIMINARIES

In this section, we provide a short overview of the fundamental concepts used in our approach, namely Hidden Markov Models (Sec. 2.1) and Transition State Clustering (Sec. 2.2).

2.1 Hidden Markov Models

Hidden Markov Models (HMMs) are probabilistic models derived from Discrete Markov Models and represent a sequence of observations via underlying hidden states. In HMMs, states are not directly observable but can only be inferred through another set

of stochastic processes that generate the sequence of observations. Generally, an HMM represents a sequence of observations $\mathbf{o}_{1:T}$ as a sequence of S hidden latent states with some emission probability. The HMM is characterized by its initial state distribution π_i over the states $i \in \{1 \dots S\}$ and the transition probability $\mathcal{T}_{i,j}$, describing the probability of transitioning from state i to state j . In our case, the emission probabilities for each state $i \in \{1 \dots S\}$ are characterized with a normal distribution $\mathcal{N}(\mathbf{o}_t; \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i)$ with mean $\boldsymbol{\mu}_i$ and covariance $\boldsymbol{\Sigma}_i$. This is, in essence, similar to learning a Gaussian Mixture Model over the observations followed by learning the transitions between the different components. Further information about Hidden Markov Models can be found in [12].

Once the underlying states are learned, HMMs predict the belief of the hidden states based on the observations via the learned forward variable $h_i(\mathbf{o}_t)$ that denotes the hidden state probability of the current observation based on the history

$$h_i(\mathbf{o}_t) = \frac{\alpha_i(\mathbf{o}_t)}{\sum_{k=1}^S \alpha_k(\mathbf{o}_t)} \quad (1)$$

where

$$\alpha_i(\mathbf{o}_t) = \mathcal{N}(\mathbf{o}_t; \boldsymbol{\mu}_i, \boldsymbol{\Sigma}_i) \sum_{k=1}^S \alpha_k(\mathbf{o}_{t-1}) \mathcal{T}_{k,i} \quad (2)$$

and $\alpha_i(\mathbf{o}_0) = \pi_i$. The forward variable describes the probability of observing the sequence $\mathbf{o}_{1:t}$ and ending up in state i at time step t .

The HMMs are trained using the Baum-Welch algorithm which is a special case of the Expectation-Maximization (EM) algorithm. The goal is to learn the model parameters $\boldsymbol{\mu}_i$ and $\boldsymbol{\Sigma}_i$ such that it maximizes the probability of observing a given sequence, $\mathbf{o}_{1:t}$. For more information on learning Hidden Markov Models in the context of robot learning, we refer to [2, 10]

To learn a joint distribution between both interacting partners, we concatenate Degrees of Freedom (DoFs) of both agents, resulting in the following decomposition of the learned distributions

$$\boldsymbol{\mu}_i = \begin{bmatrix} \boldsymbol{\mu}_i^1 \\ \boldsymbol{\mu}_i^2 \end{bmatrix} \quad (3)$$

and

$$\boldsymbol{\Sigma}_i = \begin{bmatrix} \boldsymbol{\Sigma}_i^{11} & \boldsymbol{\Sigma}_i^{12} \\ \boldsymbol{\Sigma}_i^{21} & \boldsymbol{\Sigma}_i^{22} \end{bmatrix} \quad (4)$$

for the mean and covariance. This decomposition can then be used to conditionally predict the robot’s actions $\mathbf{o}_{1:t}^2$ from the observed human motions $\mathbf{o}_{1:t}^1$ as

$$\mathbf{o}_{1:t}^2 = \sum_{i=1}^S \frac{\alpha_i(\mathbf{o}_{1:t}^1)}{\sum_{k=1}^S \alpha_k(\mathbf{o}_{1:t}^1)} (\boldsymbol{\mu}_i^1 + \boldsymbol{\Sigma}_i^{21} (\boldsymbol{\Sigma}_i^{12})^{-1} (\boldsymbol{\mu}_i^1 - \mathbf{o}_{1:t}^1)) \quad (5)$$

where $\alpha_k(\mathbf{o}_{1:t}^1)$ is the forward variable calculated using the marginal distribution for the human DoFs.

2.2 Transition State Clustering

Transition State Clustering (TSC) is an unsupervised segmentation algorithm proposed by Krishnan et. al. [6]. Given a set of demonstrations, the goal of Transition State Clustering is to fit mixture models to the demonstrations. To identify the transition states, initially a Gaussian Mixture Model (GMM) is fitted to the demonstrated trajectories and each observation \mathbf{o}_t is assigned to its most likely mixture component c_t . Subsequently, every state where $c_t \neq c_{t-1}$

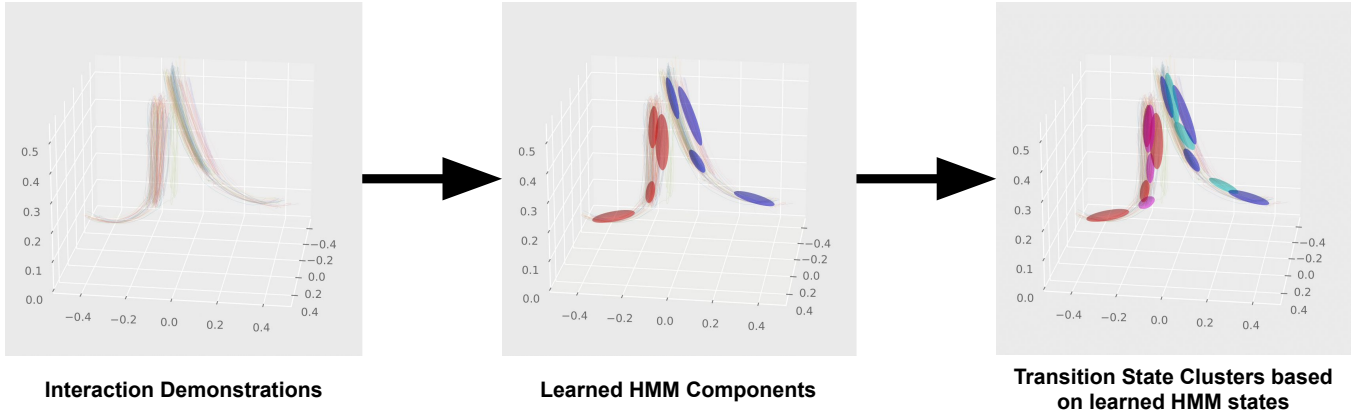


Figure 2: An overview of our proposed approach. Given demonstrations of an interaction (left), such as end-effector trajectories when performing a handshake, we first learn an HMM over the demonstrations (middle) to segment the interaction into underlying phases (red - human, blue - robot). Based on the learned HMM, we subsequently learn an additional distribution over the observations near the transition boundaries of the HMM hidden states, as shown in the image on the right (magenta - human, cyan - robot).

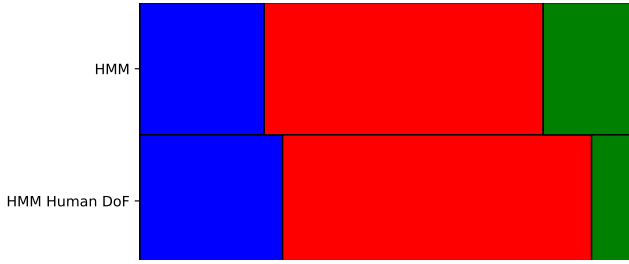


Figure 3: Example of the predicted segments when using the combined DoFs of the human and the robot (top row) and only the human DoFs (bottom row).

is marked as a transition state after which a second GMM is fitted over the transition state, thus grouping events that trigger the transitions between the first GMM. For a more in-depth understanding of Transition State Clustering, we refer the reader to [6].

3 INTERACTION SEGMENTATION AND LEARNING

In this section, we introduce our proposed approach, which uses Transition State Clustering (TSC) with Hidden Markov Models (HMMs) for learning Human-Robot Interaction. We perform trajectory segmentation with TSC by using an HMM as the underlying distribution and subsequently using the forward variable of the HMM to identify transition states. We then use the proposed HMM-TSC model for conditionally generating the robot’s actions based on the human’s observations instead of just using the model for segmentation as in [6].

Instead of only considering the state right before a transition as a transition state, we consider an arbitrary number of states around the transition as transition states (Fig. 2).

Moreover, we train the HMM with the combined observations of the human and the robot, however, during test time, we use only the human observations to calculate the HMM forward variable

and subsequently condition the HMM to predict the robot motions. By doing so, we find that a mismatch exists between the HMM forward variable calculated only with the human’s observations $h_i(o_t^1)$, and the HMM forward variable calculated with the observations of both the human and the robot $h_i(o_t^{1,2})$. We found that these observations where $h_i(o_t^1) \neq h_i(o_t^{1,2})$ usually occurred around transition boundaries between the hidden states (Fig. 3). Therefore, we learn a second HMM over the set of all observations o_t where $h_i(o_t^1) \neq h_i(o_t^{1,2})$ which give us the Transition state Clusters. The approach is outlined in algorithm 1. We then use the resulting TSC-HMM model for conditionally generating the trajectory of the robot given the observations of the human as shown in Eq. 5.

Algorithm 1 Transition State Clustering Adaption

Input:

1. training data $o_{1:T}$
2. number of states n
3. trained HMM λ

Output:

1. trained HMM λ_T
-

- 1: Identify transition states wherever $h_i(o_t^1) \neq h_i(o_t^{1,2})$ of λ
 - 2: Initialize a new HMM λ_T using transition states as training data
 - 3: Train λ_T according to the Baum-Welch EM algorithm
 - 4: **return** λ_T
-

4 EXPERIMENTS AND RESULTS

We use a dataset of social interactions [1] which consists of 3D Cartesian coordinates of two human partners interacting with one another captured using Rokoko motion capture suits at a frequency of 40Hz. From the dataset in [1], we use the handshake interactions and two types of fistbumps. The first, “rocket fistbump”, involves

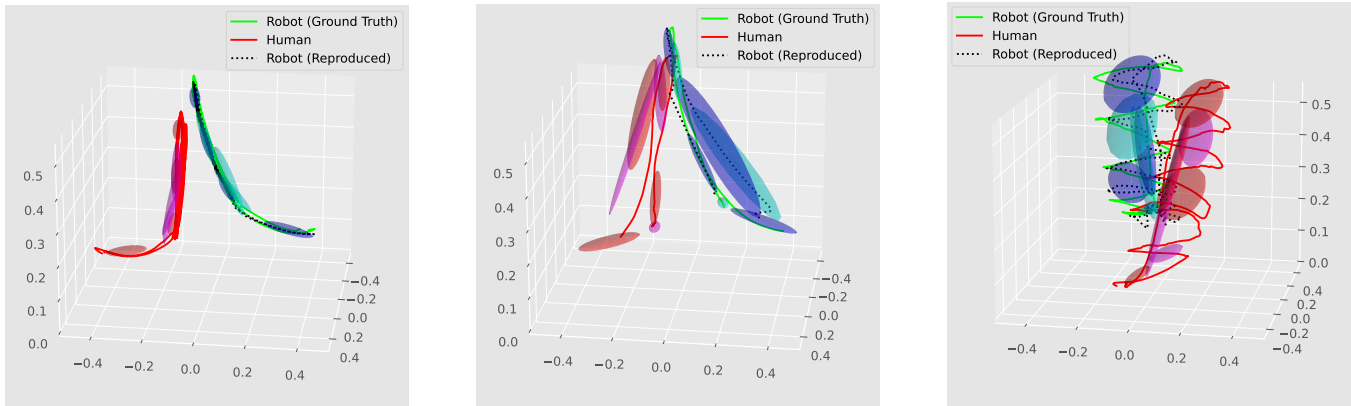


Figure 4: This figure shows example 3D plots of reconstructed trajectories for the different interactions considered in the work. Each plot consists of the input trajectory of the human, the ground truth trajectory for the robot and the reconstructed trajectory for the robot, along with the Gaussian states of the HMM and the transition state clusters.

partners bumping their fists at a waist level and raising them vertically to a suitable height and returning to a neutral pose. The second is called “parachute fistbump” where partners bump their fists at a shoulder height and then oscillate them horizontally while moving downwards. We use the hand trajectories of the first partner as the Human DoFs and the hand trajectories of the second partner as the robot DoFs. Along with the 3D positions, we use the position differences between the timesteps as well, which acts as a proxy for the velocity. The approach is implemented using the Python version of PbDlib developed by Pignat et al. [10]. The Baum-Welch algorithm for training the Hidden Markov Models runs for a maximum of 40 iterations. If the change in the log-likelihood does not exceed 10^{-4} , the algorithm is considered converged, and the Baum-Welch algorithm halts. The HMM and the TSC model are initialized by temporally dividing the corresponding input trajectories into 5 bins and calculating each bin’s mean and covariance. A regularization factor is added to the diagonal elements of the covariance matrices to prevent numeric instabilities. We used the same regularization factor of 10^{-2} for both the initial HMM and the TSC-HMM. For the dataset in [1], we used 4 states for the initial HMM and 3 states for the TSC-HMM. These parameters were determined using empirical testing. We sample a random batch of 15 training demonstrations as the input data for training the model. We run the training with 100 different random seeds and consequently, 100 different random batches of training samples thus providing a broad distribution of samples of each one of the interactions. To gauge the performance of the model, the Mean Squared Error between the predicted trajectory and the ground truth trajectory of the robot DoFs is used as a metric.

Table 1 shows the mean and the standard deviation across 100 runs of the experiment for the different interactions. It can be seen that our proposed approach with the Transition State Clusters on top of the HMM (TSC-HMM) outperforms the baseline HMM. Furthermore the proposed approach introduces a negligible amount of additional computational overhead.

Action	HMM[cm]	TSC-HMM[cm]
Handshake	9.4 ± 9.2	8.7 ± 8.9
Rocket Fistbump	5.2 ± 4.1	4.0 ± 4.0
Parachute Fistbump	3.8 ± 5.0	1.7 ± 2.5

Table 1: This table shows the Mean Squared Error and standard deviation for the different interactions and in centimeters resulting from 100 runs across all trajectories within the test dataset. In each run, the models are trained on a randomly selected batch of 15 demonstrations.

5 CONCLUSION AND FUTURE WORK

In this work, we present a framework for segmenting and learning Human-Robot Interactions (HRI) using Hidden Markov Models (HMMs) and Transition State Clustering (TSC). We find that the mismatch in the forward variable calculation between the training and testing scenarios helps identify the observations corresponding to the transition states. Learning a second HMM over these observations leads to an improvement in predicting the robot motions as compared to using a simple HMM, which we demonstrated through different interactive tasks such as handshakes and fistbumps. However, our approach currently depends on an ‘oracle’ for action recognition, lacking an automated mechanism for classifying the interaction to be performed. To enhance autonomy, integrating an action recognition method could automate interaction recognition. Additionally, our approach requires manual determination of Hidden Markov Model states, impacting flexibility. An automated solution, possibly using the G-Means algorithm proposed in [5], could improve flexibility, but direct application first requires some adaptation.

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