# Incremental Learning of Primitive Skills from Demonstration of a Task

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## ABSTRACT

In this work, we propose methods for automatically generating primitive skills from the demonstration of a task. Additionally, we propose methods for improving existing primitive skills, and for automatically and incrementally adding new primitive skills. To validate our proposed methods, we present the experimental results of a human-like robot handling three gestures and a task of making coffee.

## Categories and Subject Descriptors

I.2.6 [**Artificial Intelligence**]: Learning—*Parameter learning, Knowledge acquisition*

## General Terms

Algorithms.

## Keywords

primitive skill, incremental learning, threshold model, hidden Markov model, KL-divergence

## 1. INTRODUCTION

An intelligent robot must be able to generate primitive skills to achieve a task, since any task can be usually accomplished by several actions. Here, primitive skills refer to actions that are useful in executing a task. To generate primitive skills, we propose methods for automatically generating a set of primitive trajectories from the full trajectories that are demonstrated by a human, and stochastically encoding these primitive skills using the set of primitive trajectories. Additionally, we propose methods for constructing classifiers and improving on or adding to primitive skills based on the classifiers. Our contributions are as follows. Primitive skills can be commonly generated for various tasks without prior knowledge or task constraints. New primitive skills can be also automatically and incrementally improved and augmented using our classifiers.

## 2. GENERATION OF PRIMITIVE SKILLS FROM DEMONSTRATION OF A TASK

To generate primitive skills, full trajectories required for achieving a task are segmented based on meaningful points. Here, a meaningful point indicates a segmentation point that has low variance. As an example, let us consider a robot that scoops coffee powder out of a cup when making coffee. The robot can approach the cup using various trajectories; however, the robot must always reach the mouth of the cup to scoop the coffee. This step is a segmentation point with low variance. Likewise, we can attempt to generate primitive trajectories by segmenting the full trajectories based on the segmentation points using their variances. To extract segmentation points, a variance trajectory should be extracted based on the full trajectories provided by a human via demonstration. The full trajectories in Figure 1-(a) have different lengths, times, and speeds, and are temporally aligned using the dynamic time warping (DTW) method. Here, the full trajectories are those paths for which the joint angles of a robot are recorded. To extract important features from the full trajectories in Figure 1-(b), these trajectories are transformed by the principal component analysis (PCA) method. The mean and covariance of the full trajectories in Figure 1-(c) are extracted by encoding a Gaussian mixture model (GMM). The GMM is temporally generalized by Gaussian mixture regression (GMR) method in order to generate the variance trajectory in Figure 1-(d) for segmenting the full trajectories. The segmentation points in Figure 1-(e) are extracted by local minima of second-order differentiation on the variance trajectory. The full trajectories in Figure 1-(b) are segmented based on the segmentation points. The segmented trajectories in Figure 1-(f) are referred to as the set of the primitive trajectories. The primitive skills in Figure 1-(g) are encoded as HMMs using the primitive trajectories, respectively.

## 3. INCREMENTAL LEARNING FROM DEMONSTRATION OF A TASK

There should be a mechanism for improving primitive skills, or automatically and incrementally adding to them, since it is difficult to guarantee the performance of the primitive skills or to generate all primitive skills at once. To resolve this issue, classifiers are constructed using the primitive skills and a threshold model that is a HMM. The threshold model is an ergodic HMM generated using states of the existing primitive skills [**?**]. As new trajectories are added, they are segmented as the set of the primitive trajectories according to the steps indicated in Figure 1. In Figure 1-(h), the primitive trajectories are classified using the classifiers, and they are used for generating new primitive skills or improving the existing primitive skills in the Incremental Learner phase. In Figure 1-(i), the primitive trajectories that are classified as the threshold model are encoded as new primitive skills. On the other hand, the primitive trajectories that are classified as existing primitive skills are used to improve these existing skills. Existing primitive skills

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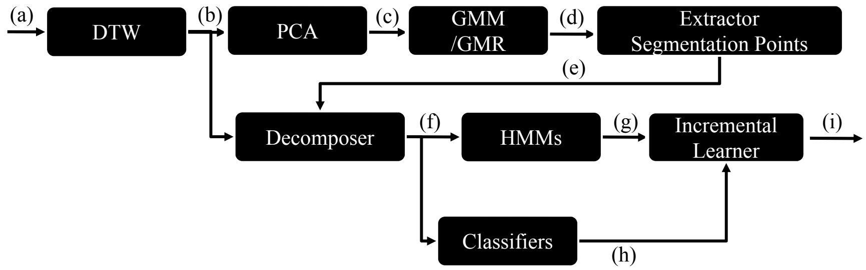


**Figure 1: Graphical flow for generating and improving primitive skills: (a) full trajectories provided by a human; (b) full trajectories temporally aligned by DTW; (c) full trajectories where the dimension is reduced by PCA; (d) variance trajectory generated by GMM/GMR; (e) segmentation points extracted based on variance trajectory; (f) set of primitive trajectories that are generated by segmenting full trajectories based on the segmentation points; (g) primitive skills that are encoded as HMMs using the set of primitive trajectories; (h) models that are classified by classifiers; and (i) existing primitive skills that are improved, or new primitive skills.**

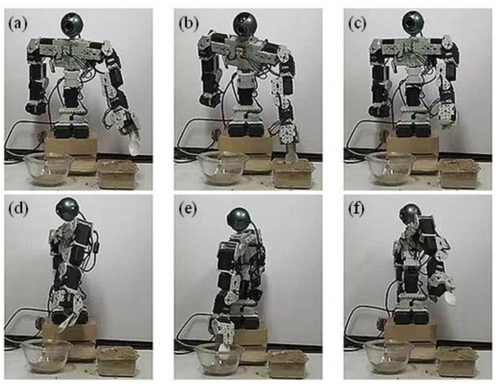


**Figure 2: Results of incrementally generating primitive skills for making coffee: (a) approaching; (b) scooping; (c) delivering; (d) pouring; (e) stirring; and (f) returning.**

can be improved by merging and adding the states of two HMMs based on Kullback-Leibler (KL) divergence [**?**].

## 4. EXPERIMENTAL RESULTS

To validate our proposed methods, three gestures 'A', 'B', and 'C' were tested experimentally using a human-like robot as shown in Figure 2. Additionally, the task of making coffee was performed to validate our method for improving primitive skills. The robot had 12 degrees of freedom (DOFs), of which the arms had 10 DOFs and the torso had 2 DOFs. Each joint was recorded at a rate of 10 Hz for all tasks involving kinesthetic teaching. We first generated full trajectories for primitive skills of three gestures, using demonstrations. The full trajectories of the three gestures were segmented and encoded as three primitive skills that consisted of three states using the processing steps in Figure 1-(a)–(g), respectively. Additionally, a full trajectory for making coffee was segmented and encoded as six new primitive skills by incrementally learning the primitive skills as in Figure 1-(a)–(i). The new primitive skills consisted of approaching, scooping, delivering, pouring, stirring, and returning, respectively, as shown in Figure 2. Here, new primitive skills for making coffee were encoded as HMMs that had three or four states. The success rate of the classifiers was measured by the accuracy of matching HMMs using the forward algorithm. The success rate of reproduction was measured by the frequency of goal accomplishment, using sampling and interpolation of HMMs. All tasks were recognized and reproduced with a success rate greater than 90%. Additionally, the robot was able to complete slightly different tasks using the same primitive skills. The robot could gesture 'P' by combining some primitive skills of the gesture 'B', and it could make coffee with a different strength and degree of mixing by repeatedly combining some primitive skills of making coffee. Also, the primitive skill that was improved by our methods was reproduced with a success rate of greater than 90% when the primitive skill was improved using two primitive trajectories for approaching coffee, with success rates 48% and 95%. The primitive skill that was improved by KL divergence could be reproduced by selecting a reasonable path from a few options. The primitive skill that was improved using the batch of two primitive trajectories led to the robot approaching the coffee with success rate of 38%. By using our methods, primitive skills can be easily reused for executing slightly different tasks. Primitive skills can be improved efficiently and quickly, since they are improved based on KL divergence. Additionally, primitive skills are incrementally and automatically added to using our classifiers.

## 5. CONCLUSION

We have proposed methods for generating primitive skills. To this end, the full trajectories that were demonstrated by robot PbD were segmented based on variance trajectories. The set of primitive trajectories were encoded as HMMs. The HMMs are the primitive skills used to achieve the given task. To improve the primitive skills automatically and incrementally, the classifiers were constructed using existing primitive skills and a threshold model. New and existing primitive skills were improved or added to based on our classifiers.

## 6. ACKNOWLEDGMENTS

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