Learning the Combinatorial Structure of Demonstrated Behaviors with Inverse Feedback Control

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Abstract. In many applications, such as virtual agents or humanoid robots, it is difficult to represent complex human behaviors and the full range of skills necessary to achieve them. Real life human behaviors are often the combination of several parts and never reproduced in the exact same way. In this work we introduce a new algorithm that is able to learn behaviors by assuming that the observed complex motions can be represented in a smaller dictionary of concurrent tasks. We present an optimization formalism and show how we can learn simultaneously the dictionary and the mixture coefficients that represent each demonstration. We present results on a idealized model where a set of potential functions represents human objectives or preferences for achieving a task.

1 Introduction

Robots are expected to have promising applications in fields such as domestic assistance, health care or education. However bringing robots to our everyday environment and improving their interaction capabilities requires that they are capable of understanding natural human behaviors.

Human activities are numerous and highly diverse, and feature large variability between individuals, situations, and times. Making robots or intelligent systems capable to recognize or even understand or reproduce such behaviors, thus requires a high level of adaptivity which makes learning algorithms promising candidates for this task.

It is however still a difficult problem to design or adapt learning algorithms so that they can deal well with essential properties of natural human behaviors. In fact natural human behaviors are complex and one won’t generally observe something as “fill a glass of water” but rather “grasp a glass, walk to the tap, open the tap while keeping the glass straight”. Being able to cope with the combinatorial structure of behaviors is thus necessary for their understanding.

In both examples each primitive behavior must be separated from the other behaviors composing the general activity and the relevant features must be identified as the glass being filled, not as the exact trajectory of the elbow or the position of the glass. These two difficulties are actually related to wider topics of research from which efficient algorithms and representations can benefit.
human behavior understanding by leveraging compositional structure of human activities and represent tasks or objectives that drive the activities.

First separating complex behaviors into simpler parts is very close to both the decomposition of complex motions into simpler motor primitives and dictionary learning techniques from machine learning.

Then, focusing on representations of behaviors in terms of the cost function they are optimizing rather than the specific way to solve it is closely related to inverse feedback control and inverse reinforcement learning approaches which can lead to better generalization properties, as for example when learning to imitate.

In this article we address aspects of the issues of representing, learning and reproducing human behaviors and their compositional structure. We introduce a dictionary learning approach for representing and reproducing the combinatorial structure of motor behaviors that are only observed through demonstrations of several concurrent motor behaviors. We focus on motor behavior representations that directly model the objective of the user underlying demonstrations. We illustrate the presented algorithm on a simple toy example.

2 Background and Related Work

2.1 Decomposition of Motor Skills: Motor Primitives

Motor primitives have been introduced as a form of re-usable motor skills that may be used as elementary building blocks for more complex motor control and skills. The concept of motor primitives that can be combined together has the appealing property to enable combinatorial growth of the skill repertoire. As detailed by Konczak [1], examples of motor primitives can be found both in biological and robotic systems, and can be either innate or acquired.

The notion of combination of motor primitives can take different forms. One could consider a behavior composed of a sequence of simple actions, like moving one’s hand to a glass, grasping it, bringing it back to one’s mouth, etc.

The structure of some behaviors however does not fit well in this sequential representation. Many behaviors or tasks are better described in terms of elementary movements executed simultaneously (e.g. on different parts of the body) or concurrently, like speaking while smiling and shaking someone’s hand. Concurrent combinations of behaviors is particularly studied in this article.

2.2 Using HMMs to Learn Motor Primitives

Hidden Markov models (HMM), often coupled with clustering techniques or mixture models, have been largely used to learn sequences of primitives. For example, Kulic and Nakamura have proposed in [2] a method that first performs an unsupervised segmentation of the motion signal into small successive blocks (the segmentation technique itself is based on HMMs), and then performs clustering over HMM representations of each segmented block. Each group of similar motions is interpreted as a motor primitive.