A Metric for the Evaluation of Imitation

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Introduction

Stick out your tongue at a toddler and she will likely imitate by sticking out her tongue. Imitation is a very common and natural form of learning ubiquitous in humans. Dolphins and some species of apes also show imitative abilities, but only humans are attributed with 'true' imitation that enables the acquisition of entirely novel skills (Miklosi 1999). Imitation learning has become a very attractive topic for robotics researchers with the recent advent of humanoid robots and other highly articulated systems (Schaal 1999). Various research groups are working on the problem of endowing robots with the ability to learn and acquire new skills by imitation through demonstration (Atkeson & Schaal 1997; Billard & Matarić 2001; Ijspeert, Nakanishi, & Schaal 2001; Jenkins, Matarić, & Weber 2000; Matarić 2001; Nicolescu & Matarić 2001; Schaal 1997; 1999).

One of the primary issues in imitation is finding corresponding actions. When a dolphin nods its head to imitate the nod of its human instructor, it has somehow figured out what action is the one that best corresponds to the demonstration. Similarly, when a child claps her hands to imitate an adult, she has successfully deduced the action that closely corresponds to what the adult did. In both of these cases, the imitators were able to sieve through their motor programs and select a suitable action sequence. This suggests the presence of an intrinsic measure of similarity between actions, which leads us to the *correspondence problem*. The correspondence problem asks the question: "how similar is an action sequence to the demonstration?". This problem lies at the very core of imitation.

Despite the significance of this problem in imitation, there is almost no work to date in robotics that explicitly addresses it. The bulk of imitation research in robotics has focused on recognition of actions and learning and execution of motor programs. The correspondence problem has largely been implicitly "solved" by making use of very specific heuristic criteria appropriate for the considered task.

We are specifically interested in addressing the correspondence problem in imitation. Our aim is to develop a comprehensive *correspondence metric* that can provide a scalar measure of dissimilarity/distance between any pair of action sequences executed by agents with similar or different embodiments. By developing such a metric, we intend to provide a standardized means to quantitatively evaluate imitation. The metric can also be employed for action selection by an imitating agent. In addition, it can also benefit learning agents by serving as a gradient in action space.

The correspondence metric could also have applications in a wider range of domains. For example, it is directly relevant to animation research in synthesizing believable motion. It is also relevant to physical therapy, where it can be used to automatically monitor and evaluate the progress of patients. In the domain of reconfigurable robots, it may prove useful in the transfer of action strategies from one configuration to another very different in form.

The Approach

We plan to address the correspondence problem by developing a metric that geometrically compares any two action sequences and provides a scalar measure of dissimilarity. In imitation, however, the notion of similarity is not purely geometric but also rests on the intentionality of the demonstrator. For example, in a task like reaching, only the end-point trajectory or even the end point itself, is of significance. Thus an effective similarity measure must ignore differences in all other limb and joint values between the demonstrator and the imitator. In order to make the metric comprehensive and incorporate the notion of intention, we plan to have a weighting mechanism that can be suitably instantiated to bias the metric based on what is significant in the demonstrator's action sequence. Aside from spatial variability, as in the example above, intentionality may also be reflected in temporal variability. The temporal profile of the action sequence may or may not be of significance in the demonstration. In order to address this issue, we plan to make the correspondence metric decomposable into spatial and temporal components. The temporal component can thus be selectively included in the dissimilarity computation.

In order to keep the metric sufficiently general, two additional properties are desirable, (1) reference frame independence: the two agents are not required to be in a common reference frame; and (2) scale invariance: scaling of any one agent does not affect the dissimilarity measure. The first property automatically implies translational and rotational invariance.

We are approaching the problem of developing the correspondence metric by first developing a *pose metric* that provides dissimilarity measures between static postures/poses of agents. We will then extend it to the comparison of action sequences.

In order to compare poses of agents, we require a uniform representation to encode them. We have chosen to treat agents as open kinematic chains, and therefore encode their structure in a *tree* termed *kinematic tree* or *k-tree*. We have introduced the following definitions.

Definition 1 (k-tree) *A* kinematic tree *or* k-tree *is an encoding of an open kinematic chain such that every link in the kinematic chain is represented by a unique edge in the k-tree.*

Definition 2 (Pose) *A* pose p *of a k-tree* t *is an assignment of the ordered pair* $\langle n_i, l_i \rangle$ *to every edge* e_i *of* t. n_i *is a unit normal that is the orientation of the link, represented by* e_i, *in the world coordinate frame.* l_i *is the length of the link represented by* e_i.

Definition 3 (Homeomorphic pose class) *A* homeomorphic pose class P *is a set of poses such that for any pair of poses* $p, q \in P$, *if* t_p *is the k-tree of* p *and* t_q *the k-tree of* q *then* t_p *and* t_q *are* homeomorphic*.*

We have developed a pose distance algorithm that takes a pair of poses from a homeomorphic pose class as input, and computes a distance measure between the poses. The algorithm first realigns the two poses and brings them to a common reference frame, then partitions the edges of the individual k-trees of the two poses, then uses the underlying homeomorphism between the k-trees of the two poses to find matchings between the partitions of the k-trees. Dissimilarity measures are computed between every such pair and these are summed up to obtain the dissimilarity measure for the pair of poses. The distance measure computed by the pose distance algorithm satisfies properties (1) and (2) desired of the correspondence metric. We have successfully applied the pose metric across various poses of a human, the Sony AIBO dog, and a simulated dolphin-like skeleton.

We have recently used multi-dimensional scaling (MDS) followed by principal component analysis (PCA) to project poses as distributions on a common space. We are investigating the use of transportation cost functions in order to provide measures of pose distance without the homeomorphic pose class constraint.

Related Work

Nehaniv et al. (Nehaniv & Dautenhahn 2000; 2001) have used abstract algebra as a means to formalize the correspondence problem. Their work provides an abstraction where, given elementary correspondences, one can employ a suitable metric and analyze more complex sequences. The metric is crucial to the process of determining correspondences, but their work does not address the issue of determining a metric. Alissandrakis et al. (Alissandrakis, Nehaniv, & Dautenhahn 2002; 2003) have explored some metrics for this formal framework and applied them to different agents. However these metrics are only suitable to the specific problem considered. We are interested in developing a generalized metric that can be applied to different domains.

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