Human Motion Prediction in a Human-Robot Joint Task

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A collaborative transportation task in which a human physically interacts with a robot, is a fundamental task that requires coordination between agents and prediction of intent of a collaborator. Teaching a robot to participate in such a task can be considered as a twofold problem: teaching a task as a set of constraints and teaching to predict motion of a collaborator for proper adaptation.

While the former question has been addressed in Robot Learning by Imitation research ([1], [2]), learning to predict a human has received less attention in this context; in ongoing work we address this problem to extend robotic capabilities for natural interaction.

In our previous work on robotic bimanual coordination [2] we discussed a hypothesis that for a certain type of bimanual tasks, constraints can be extracted from variables expressing mutual relations between the two arms. To validate our approach we performed experiments where we chose the relative position between the arms as such a variable: the robot successfully learned coordination tasks. Currently we are extending this approach to teach a robot a coordination task with a user "in a loop" acting as a collaborator in a joint transportation task. The principal difference here in comparison with "intra-agent" bimanual coordination consists in the fact that a robot has to predict human motion in order to adapt its next step satisfying the constraints.

To endow a robot with such an ability we use the methodology of *Hidden Markov Models* (HMMs). The prediction with HMMs in some fields is a well-established approach, however its applicability to the prediction of human motion in the context of *Learning by Imitation* is much less researched. Elaborating the problem, we came to the requirements that the framework of human motion prediction for collaboration should satisfy: 1) a model should have predictive power; 2) a model should evolve on-line as soon as a new demonstration arrives; 3) a model should be reliable even if built from a small data set; 4) the framework should asses informativeness of demonstrations and requests for additional guidance, if necessary. Further we briefly discuss these points and the ways we address them.

Fig. 1. In a scenario used for collecting data and preliminary experiments, a robotic arm (KATANA from Neuronics) assists a human collaborator to transport an object. The human wears a motion suit that captures motion of her joints, thus a robot knows the posture of the human arm at each time step. Another person kinesthetically guides the robot demonstrating its part of the task.

For motion prediction we encode trajectory data collected with the motion suit into continuous HMMs with emission probabilities in the form of normal Gaussian distributions. For on-line training we have to resolve a problem of a choice of a HMMs structure: most HMMs estimation techniques (such as e.g. conventional *Baum-Welch*) assume knowledge of the model topology. However, if we start with a one demonstration, it does not seem possible to choose in advance a structure that describes all potential observations. Therefore, the topology should be learned iteratively along with parameters. We follow an approach where the topological map of data is being iteratively built from training sequences using *Instantaneous Topological Maps*[4].

On-line training of HMMs parameters is still an open issue, few existing approaches are based on the iterative version of the *Expectation Maximization* (EM) method. The iterative treatment is particularly attractive, as it does not require data to be identically distributed as does the batch Baum-Welch method. For our application this property allows using a unique HMMs for representing different motions, therefore the model becomes more compact as there is no need to duplicate states shared among several types of motion. This also increases generalization abilities of the model.

A mentioned above problem of assessing informativeness of demonstrations is highly relevant for Learning by Imitation. The data acquisition is a time-consuming and difficult process due to the limited human capacity to repeat a motion multiple times. Therefore, we want to be sure that the small number of demonstrations that we manage to collect, give a robot a consistent representation of a task. In some cases it needs to discard observational outliers that harm the consistency of a model or, on the contrary, needs to ask a human about providing additional demonstrations for improving a too particular model. This problem relates to *Active Learning* that has been a focus of significant research in *Machine Learning*. We are applying the *pool-based* approach [3] for estimating demonstrations: after observing several sequences and building an initial model of motion, a robot continues to obtain demonstrations from a collaborator and asses whether they are consistent with the learned model using information theory measures.

References

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