Learned Minimal Intervention Control Synthesis based on Hidden Semi-Markov Models

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Fullfilling the prospect of robots leaving factory floors, to enter the human world and act among us, could lie decades away. However, the move of robots from the large scale factory plants as in the car manufacturing industry towards smaller manufacturers might lie around the corner. Funding agencies are pushing robotics research in manufacturing through projects such as SMART-E [1]. This, combined with the recent development of light weight robots for industrial applications, e.g. KUKA's LBR and ReThink Robotics' Baxter, create an optimal climate to advance industrial robotics.

Medium and small scale manufacturing companies represent the largest number of entities in the manufacturing sector in Europe. Such companies could benefit greatly from robotic automation solutions, but they generally have different needs than large scale manufacturers.

In large scale companies most robots are programmed to do one specific task for their complete lifetime. Smaller scale companies robots are likely to perform a wide variety of tasks. To make this viable, robots need to be easily (re)programmable. Programming by Demonstration (PbD) [2] provides suitable solution to this problem. PbD allows easy (re)programming of a robot by providing a small number of demonstrations of the task to be learned.

The types of tasks that performed in industrial environments can have different temporal variance. When a robot has to synchronize with other systems, exact temporal execution might be critical. On the other hand, when interacting with a human co-worker the robot should be able to cope with high temporal variance. This temporal variability needs to be taken into acocunt in the representation of movements.

Encoding of movements can effectively be achieved using movement primitives acting as building blocks that can be assembled in parallel and series to form complex movements. Within the literature of movement primitives encoding we can distinguish autonomous, and non-autonomous systems. The system evolution of non-autonomous systems only depends on the state of the system (e.g. [3]). Such systems form an attractor landscape with a unique global minimum, guaranteeing that the system state will converge to the final state. The fact that their system evolution only depends on the system state, makes them ideal for situations in which high temporal variability can be expected. However, such systems are less suitable in situations where more importance should be given to correct movement duration. In non autonomous systems, the state evolution does not solely depend on the system state, but also on a temporal signal or phase variable. These additional signals, basically acting as an external clock, achieve a more exact temporal evolution. A common approach is to model the movement dynamics as a system of linear spring-damper systems [4] [5].

We propose a non-autonomous movement encoding based on a Hidden Semi-Markov Model (HSMM). The model encodes local movement dynamics in Gaussian kernels with full covariance matrices covering all the synergies among the dynamics and different degrees of freedom. The switching between the local-linear models is handled by the HSMM. This temporal modeling of the HSMM can be seen as the phase term used in e.g. Dynamic Movement Primitives (DMP). However, in contrast to the phase term, which is usually a deterministic heuristic, HSMM provides a way to learn and represent in a probabilisitc form the temporal behavior. An adaptive compliant controller is obtained by combining HSMM with Model Predictive Control (MPC). At each timestep HSMM is used synthesize desired attractors with their alloted variability on a given time horizon. A control command is then obtained by minimizing an objective function based on the synthesized information. Effectively, this leads to a minimal intervention control strategy [6].

We succesfully tested this approach in a pick&place experiment. The robot is shown a small number of demonstrations of a pick-up task. During reproduction the robot, is able to succesfully reproduce the task and react to perturbations in a compliant way.

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