Learning robot manipulation tasks from human demonstrations

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Schlüsselwörter: Robot learning, Human Robot Cooperation, Machine learning.

Traditionally, robots are caged off from humans; however, improvements in robotic technology enable human-robot collaboration [1]. The human and the robot work together as a team in the same workspace, where each member can contribute towards solving a task based on their capabilities. In this work, a framework is presented which enables robots: ***A.*** to learn new tasks by human demonstrations without the need of programming and, ***B.*** to reproduce the learned task even if there are environmental changes due to the human robot collaboration without the need of additional teaching from the human.

The human-“teacher” guides the robot’s end effector through the manipulation task via kinesthetic teaching. From those demonstrations the robot learns offline the sequence of actions (high-level learning), the demonstrated paths in order to achieve those actions (low-level learning) and reproduces successfully the task in real-time, even if the pose of involved objects change with respect to the pose during the teaching. The robot learning framework is illustrated in fig. 1 and it contains two major phases: learning (offline) phase and working (online) phase. The industrial dual-arm *Pi4 Workerbot 3* is used as robotic platform and a Vacuum gripper is connected in each arm as end-effector in the presented work.

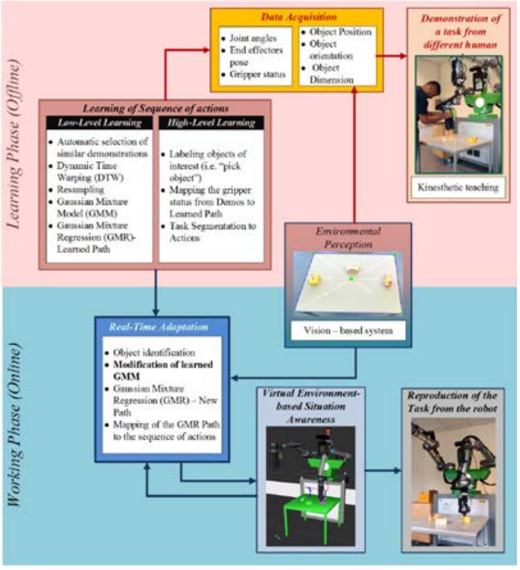

Figure 1: Overview of the Robot Learning Framework

The *offline learning phase* consists of the “*Data Acquisition*” and the “*Learning of Sequence of Actions*” modules. The “*Data Acquisition*” module stores in database the joint angles, the end effector pose (position: X, Y, Z and orientation: in quaternions) of the robotic arms and the gripper actuation status (On/Off) during the human demonstrations of the task. Moreover, the “*Data Acquisition*” module stores the following data from the “*Environmental Perception*” module: the position, orientation and dimensions of every object in the view of the vision-based system. In the presented work, a table with the objects placed on it is in the view of the vision-based system using the *Kinect for Xbox One* camera. The "*Learning of Sequence of Actions*" module uses as input the end effector pose *ee.pose = {X, Y, Z, qx, qy, qz, qw}* of both robotic arms during demonstrations and consists of the following steps for *low-level learning*: the automatic selection of similar demonstrations [2] based on similarity measurement, the Dynamic Time Warping (DTW) [3] for alignment of the selected demonstrations, the unsupervised machine learning technique Gaussian Mixture Model (GMM) [4] which provides the mean (*Mu*) and covariance (*Sigma*) matrix of the Gaussians for the 7-dimensions, Gaussian Mixture Regression (GMR) [4] which provides the learned path ζ^N (where N=7 dimensions) and for *high-level learning*: the labelling of the involved objects in a generic matter, the mapping of the gripper status to the learned path and the Task Segmentation to Actions (*A*).The output of this module includes the demonstrated task presented as the mean (*Mu*) and covariance (*Sigma*) matrix from Gaussian Mixture Model (GMM), the actions (*A*) of moving, grasping and releasing objects and also the description of the involved objects (*obj*).

In the online working phase, a novel real-time robust algorithm for modification of the learned GMM is developed, giving the ability to the robot to adapt the learned sequence of actions to the new positions and orientations of the identified objects within the workspace of the robot, to avoid obstacles that did not exist during the teaching phase and to successfully perform the task without programming or additional teaching. The input of the proposed algorithm is the *Mu* matrix from the learned Gaussian Mixture Model (GMM), the actions (*A*) and the description of the involved objects (*obj*) during the learning phase. The algorithm first identifies the objects of interest in order to perform the learned task. All other objects are treated as obstacles. Second, the proposed algorithm modifies the *Mu* values of the learned GMM based on the new poses of the involved objects and obstacles. At last, the Gaussian Mixture Regression (GMR) method is used to produce the new path $\zeta^{N'}$ for the current environment. The new path $\zeta^{N'}$ is mapped to the learned actions (*A*) for the reproduction of the task by the robot.

The proposed framework has been tested with the *Pi4 Workerbot 3* in two different manipulation tasks and the results are presented.

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