Real-time Perception meets Reactive Motion Generation

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Fig. 1: Illustration of one time step in our system. From left to right: sensory input $y$ (we overlay the position of target object [drill] at an earlier time step), perceived state $s$ of the robot and the environment (target object, obstacles), local and global policies $\pi^l$, $\pi^g$, and fused policy $\pi$.

Autonomous and robust grasping and manipulation remains a challenge in robotics. Some robots can reliably perform complex tasks in well-defined, highly-controlled and structured environments, which are typical of industrial scenarios. However, it remains unclear how they can achieve reliability and robustness in other domains, such as human-robot collaboration, household or disaster relief, towards which we would like to push robot operation in the future. These domains are characterized by a high degree of uncertainty about the spatial structure of the environment and how it may evolve over time. The sources of uncertainty are noisy sensing, inaccurate models (e.g. of the environment, robot kinematics or sensors) and hard-to-predict environment dynamics during physical interaction.

For a system exposed to these challenging circumstances, it is crucial to continuously process task-relevant feedback and to incorporate this feedback to generate adaptive motion. However, the lack of integration between perception and motion generation is persistent and has already been recognized in the 80’s \textsuperscript{2}. Since then it has been reported again by the teams who participated in the recent robotics challenges (e.g. the DARPA Robotics Challenge (DRC) \textsuperscript{3,4} or the Amazon Picking Challenge (APC) \textsuperscript{4,5}).

Our approach towards an autonomous robotic manipulation emphasizes the importance of continuous, real-time perception and its tight integration with reactive motion generation methods. We present a fully integrated system where real-time object \textsuperscript{10} and robot tracking \textsuperscript{5} as well as ambient world modeling \textsuperscript{8} provide the necessary input to feedback controllers and continuous motion optimizers. Specifically, they provide attractive and repulsive potentials based on which the reactive motion generation module can compute movement policies online at different time intervals. The motion generation module combines local feedback controllers and continuous motion optimization.

Feedback controllers compute the best action (1 kHz) for the next control cycle that simultaneously optimizes obstacle avoidance and motion towards the target object (red arrows in Fig 1). For continuous motion optimization (10 Hz) we have integrated the Riemannian Motion Optimization (RieMO) framework \textsuperscript{9}. It integrates all available information over a time horizon of three seconds, enabling anticipatory behaviors and efficient coordination of collision controllers and potentially multiple target controllers (green arrows in Fig 1).

We extensively evaluate the proposed system on a real robotic platform in four scenarios that exhibit challenging workspace geometry and/or a dynamic environment. We compare two flavours of the system with a more traditional sense-plan-act approach: locally reactive control which only uses $\pi^l$ in Fig. 1 and reactive planning which uses $\pi$ in Fig. 1. In 333 experiments, we demonstrate the robustness and accuracy of the tightly-integrated systems in the presence of uncertainty and a dynamically changing environment \textsuperscript{7}.

\section*{REFERENCES}


