Efficient Learning from Demonstration for Manufacturing Tasks

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I. Introduction and Motivation

The manufacturing industry's recent paradigm shift from mass production to mass customization necessitates frequent reconfiguration and reprogramming of tasks based on market demand. These tasks are evaluated by the key metrics of time, accuracy, and energy efficiency. However, traditional programming methods, demanding an on-site robot expert and significant time and resource investment, increase production downtime and costs. Learning from Demonstration (LfD) emerges as a potential alternative, which empowers robots to acquire tasks through human demonstrations [1].

Yet, the efficiency of existing LfD methods is often hampered by the quality of the demonstration, typically failing to satisfy the key metrics. These demonstrations are usually slower and cannot be uniformly sped up due to variable velocity requirements across different task phases [2]. Moreover, the inherent noise in these demonstrations directly affects the encoded accuracy intended by the human teacher. Consequently, filtering this noise without compromising accuracy becomes nontrivial. Existing LfD approaches might resort to suboptimal trade-offs between accuracy and time. Further, high-jerk trajectories, indicative of high energy consumption, are a frequent outcome of noisy demonstrations. Although learning algorithms can mitigate these jerk spikes to some extent, it hinders learning efficiency. Balancing jerk minimization and complying with the original demonstration path is an intricate task that current LfD methods struggle to tackle effectively.

II. Problem Statement

Motivated by the above-mentioned considerations, in this work, we introduce a novel optimization-based smoothing algorithm to refine noisy demonstrations in terms of time, accuracy, and energy efficiency. By adjusting the demonstration path within user-specified tolerances, our method achieves minimal cycle time and jerk. We extract the tolerances through an intuitive velocity correction procedure, i.e. a high-velocity feedback is associated with a high tolerance and vice versa [3]. The main novelties of this work are as follows:

- A new hierarchical optimization scheme is introduced, prevailing one-shot optimization approaches, which often suffer from infeasibility issue. This scheme mitigates the noise in demonstrations while optimizing for key metrics of industrial tasks.
- An intuitive velocity feedback procedure is introduced to let human demonstrators provide meaningful velocity inputs. This leverages the inverse relationship between velocity and accuracy.
- By incorporation of a smooth function within the smoothing algorithm, a trade-off between velocity and accuracy is achieved and the value of tolerances is extracted for each segment of the demonstration.

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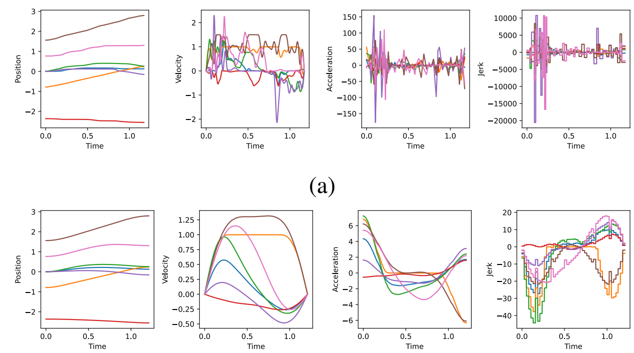

(a)

(b)

Fig. 1: Result of each phase of the proposed optimization

III. Results

Fig. 1 visualizes each phase of the proposed hierarchical optimization process. We employ kinesthetic teaching [1] using a 7 DOF Franka Emika Research 3 (FR3) robot to capture the original demostration. Fig. 1a depicts the joint trajectory of a reaching task, optimizing to closely follow the demonstration while minimizing time. The subsequent optimization stage incorporates the timings computed from the first phase, with the task of locating the minimum jerk solution within the established tolerance from the original demonstration in the end-effector space. As demonstrated, the initial noisy trajectory transforms into a smooth velocity profile, featuring significantly lower acceleration and jerk values (Fig. 1b).

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