**Introduction**

In everyday life, humans often make contact with their environment at non-zero speed. In particular, we can grab and push objects without the need to stop our hands at the moment of contact, causing intentional impacts to occur between our body and the objects to be picked or moved. Learning and executing such a task comes naturally to us. Not for robots. To avoid complexity, common control approaches circumvent contact at non-zero speed by reducing the relative velocity to zero near impact in a so-called transition phase. This limits their performance, especially when time is of importance.

Learning from demonstration refers to the process used to transfer new skills to a machine through human demonstrations instead of traditional, time-consuming, robotic programming. In this research, we show that it is possible to extend state-of-the-art learning from demonstration methods to learn and execute tasks in which contact is made at non-zero speed by incorporating in the learning pipeline the key elements of an impact-aware robot control strategy recently developed at the TU/e.

Reference spreading tackles the problem of having a different time of impact than expected by defining a new tracking error. The new error, denoted as $e_{rs}(x, t, j)$, compares the actual trajectory $x$ to an extended reference trajectory $\bar{r}(t, j)$ with event counter $j$, switching on impact. To apply the reference spreading error for learning from demonstration, the data of each demonstration is split and extended about the time of impact (Figure 1a). Thereafter, ProMP are fit on the extended demonstration data, resulting in a probability distribution for each $j$. This probability distribution can then be used to define an extended reference trajectory $\bar{a}(t, j)$ (Figure 1b).

To validate the new learning approach, we consider the case where two end effectors are tasked to grab simultaneously a box, making contact at non-zero speed, for then placing it on a shelf. Figure 2 provides an illustration of the effectiveness of the impact-aware learning strategy on a 2D numerical simulation where contact is modelled using a Hunt-Crossley-type contact model and the end effectors are controlled via a task-based quadratic programming controller [3].

**Combining reference spreading and learning from demonstration**

Our proposed learning strategy is a combination of reference spreading [1] and Probabilistic Movement Primitives (ProMP) [2]. Probabilistic Movement Primitives are a way to translate demonstration data into a reference trajectory. It presents the trajectory as a probability distribution. Reference spreading tackles the problem of having a different time of impact than expected by defining a new tracking error. The new error, denoted as $e_{rs}(x, t, j)$, compares the actual trajectory $x$ to an extended reference trajectory $\bar{r}(t, j)$ with event counter $j$, switching on impact. To apply the reference spreading error for learning from demonstration, the data of each demonstration is split and extended about the time of impact (Figure 1a). Thereafter, ProMP are fit on the extended demonstration data, resulting in a probability distribution for each $j$. This probability distribution can then be used to define an extended reference trajectory $\bar{a}(t, j)$ (Figure 1b).

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**Impact-Aware Learning from Demonstration**

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**References**


Dynamics and Control