– Appendix –
Proactive slip control by learned slip model and trajectory adaptation

Kiyanoush Nazari, Willow Mandil, Amir Ghalamzan E.
School of Computer Science
University of Lincoln United Kingdom

1 Overview

This Appendix includes some results we achieved supporting the results presented in the paper. What we cover in the appendix includes: (i) Sec. 2: Comments on slip constraint violation and rotations larger than 6 degrees; (ii) Sec. 3: Qualitative analysis on the role of the basis functions in the reactive system; (iii) Sec. 4: Qualitative analysis on the role of the basis functions in the proactive system; (iv) Sec. 5: An analysis on the methods of initilizing the optimization parameters for better convergence; (v) Sec. 6: Qualitative analysis on the results of novel object test cases.

2 Slip Constraint Violation For The RSC and PSC Systems

The optimization goal for both RSC and PSC is to keep close as much as possible to the reference trajectory while the object maintains rotations smaller than 6 degrees as the no-slip constraint. However, in the experimentation on the robot we observe that the slip constraint can be violated by having maximum rotations between 7 to 10 degrees in some of the test cases. There are two main reasons for observing slip constraint violation by 2-4 degrees in the test cases. The first cause is the error in the slip classification models. Although, these models showed high accuracy and f-score for the test set of the data, in real-time test cases the robot is taking novel actions (actions generated by the optimization) which are not included in data set, and the classification models are encountered with novel tactile and robot action input accordingly. The false negative cases of the classification can cause actual rotations which are larger than 6 degrees. There are two possible approaches to deal with the uncertainty of the slip detection/prediction results. The first approach is to model the uncertainty and use uncertainty-aware methods for generating new actions. For instance, the slip classification models output can be probabilistic (instead of the deterministic values here) and based on the estimated uncertainty the norm of the velocities can be fine-tuned. The second approach can be to use control methods inspired by H_∞ control to deal with the existing unmodeled uncertainties in the system.

In both cases, a solution to decrease the number of the false negative cases is to collect larger data sets with broader ranges of the reference trajectory or add Gaussian noise to the reference trajectory to cover a band around the reference profile actions. As such, the probability that the actions generated in test time belong to the training set of slip classification will increase. The second reason for slip constraint violation relates to the optimization results. This is more relevant to PSC system, since slip is added to the optimization as an equality constraint. The final solution of the optimization library may reach the maximum number of iterations by slightly violating a constraint. This is partially caused by the error in the numerical estimation of the gradient and the Hessian matrix of the slip constraint by the trust region method. To partially resolve this issue, the gradient coming from the chain rule of the slip classification neural network can be exploited in the numerical gradient estimation of the slip constraint.

Overall, the proposed slip controllers are dependent on the slip detection/prediction models. To make the slip controllers more robust, a large data set for slip classification with multiple sets of objects and robot actions can substantially decrease the slip constraint violation cases in real time tests. As we proved the effectiveness of using trajectory adaptation for slip control, we increase the size of the slip classification data set in future works.

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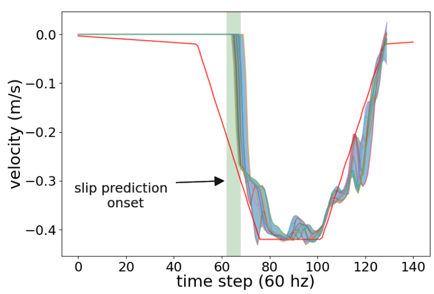
3 Qualitative Analysis of The Effect of The Number of Basis Functions On The Reactive System

Here we present the qualitative analysis for choosing the best number of basis functions for RSC and demonstrate the effect of this hyper-parameter. While Table 1 in the paper shows the quantitative results for the introduced slip control metrics, as a qualitative analysis the form of the generated velocity profiles and resulted object rotation are presented in Fig. 1. According to Figs. 1a, 1c and 1e the generated trajectories for 2, 3, and 4 basis functions can show non-smooth behaviour in the deceleration phase. This is partially for satisfying the velocity continuity constraint in equation 1 in the paper. This problem is resolved with more number of basis functions. Nonetheless, Figs. 1l and 1n show 7 and 8 basis functions can have negative effect on object slip. As such, 5 and 6 basis functions can be the best number of basis functions for RSC system. By combining the quantitative results in Table 1 and the qualitative analysis, 5 basis functions is the best value. This is in agreement with the discussion in the results section of the paper; However, since trajectory smoothness was difficult to be quantified, we analyzed it in combination with object slip qualitatively in this section.



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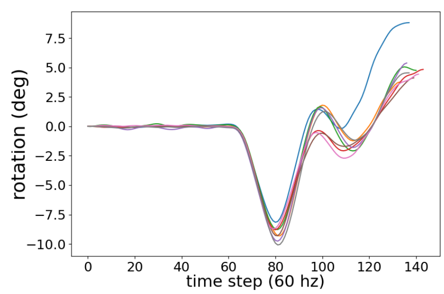

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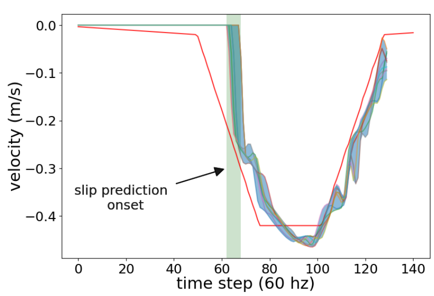

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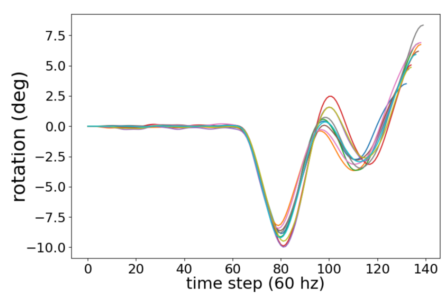

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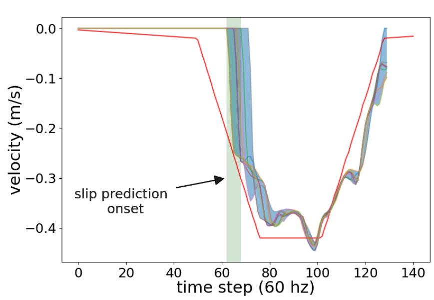

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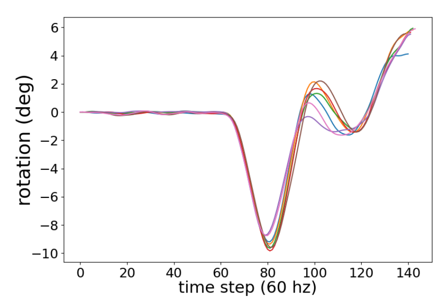

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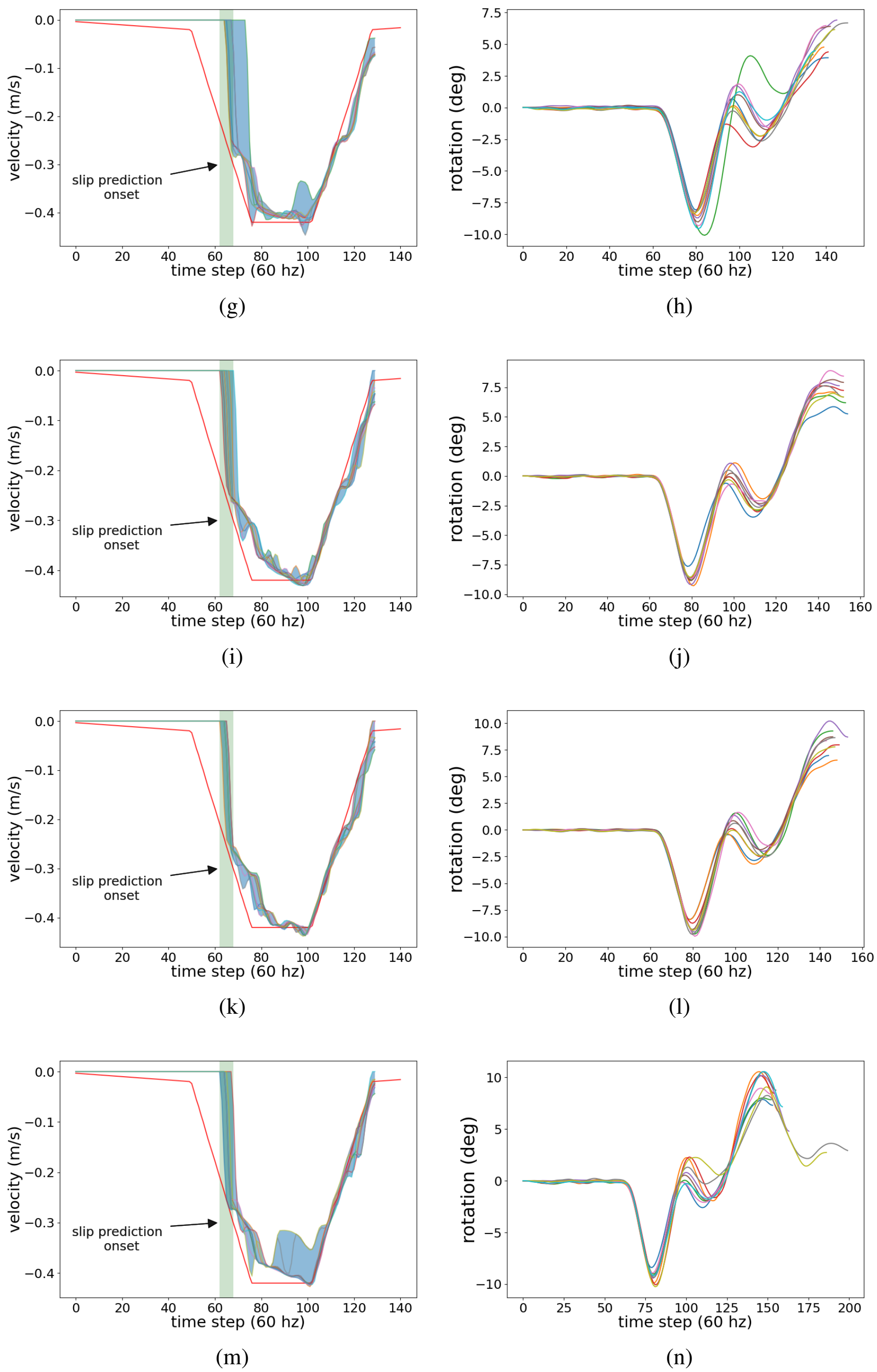


(g) (h)

(i) (j)

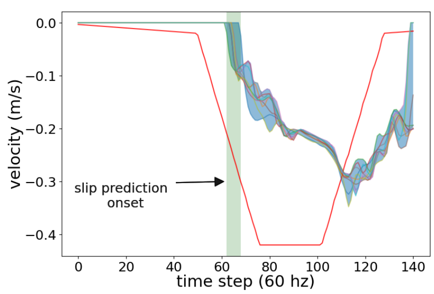
(k) (l)

(m) (n)

Figure 1: RSC system's generated velocity profiles (left column) and object rotation (right column) based on different numbers of basis functions ranging from two basis functions (first row) to eight basis functions (last row).

4 Qualitative Analysis of The Effect of The Number of Basis Functions On The Proactive System

In PSC the effect of the number of basis functions is more obvious in the complexity of the generated trajectories (see Fig. 2). Figs. 2a and 2c show the generated profiles remain very distant from the reference trajectory. This however, shows better result in object rotation according to Fig. 2b w.r.t higher number of basis functions. For 5 basis functions and more (Fig. 2g, 2i, 2k, and 2m) the generated profiles have enough complexity to capture closer behaviour to the reference trajectory. This can end up to larger deceleration values in the last phase of the motion and slip constraint violation according to Figs 2h, 2j, 2l, and 2n. Although according to the quantitative results presented in Table.1 in the paper, 2 basis functions showed the best metrics for PSC, the generated profiles remain much distant from the reference trajectory which can result in higher task completion time. As such, we consider 4 basis functions the best case for the PSC by showing better performance considering the combined quantitative and qualitative analysis.



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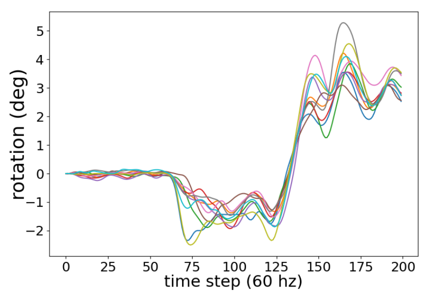

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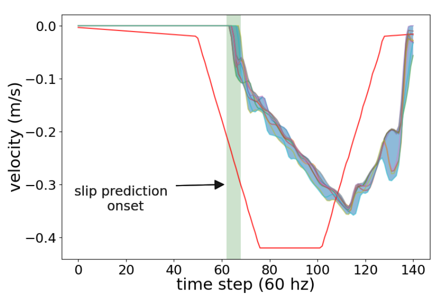

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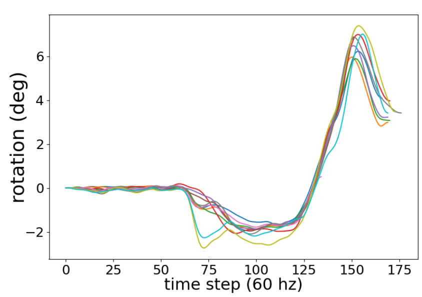

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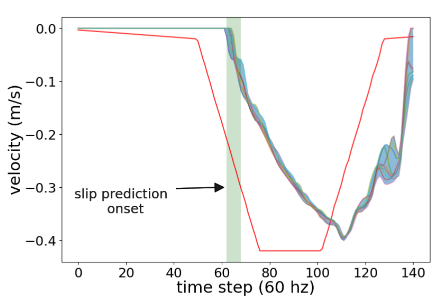

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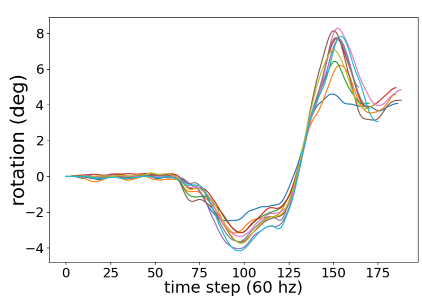

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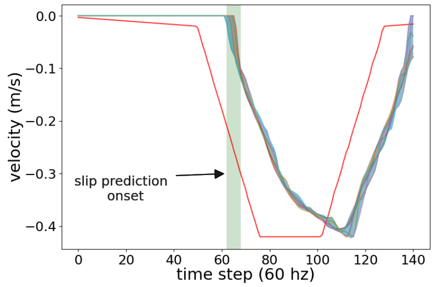

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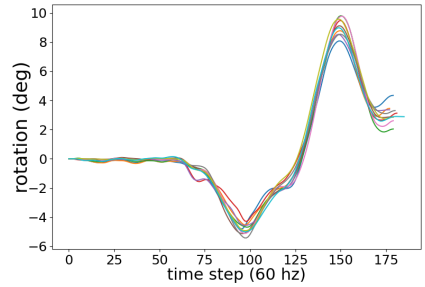

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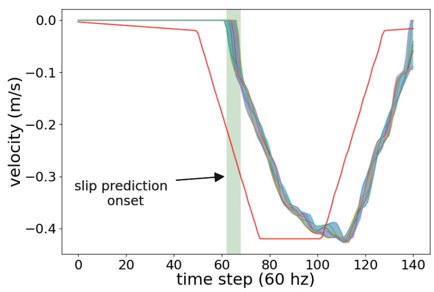
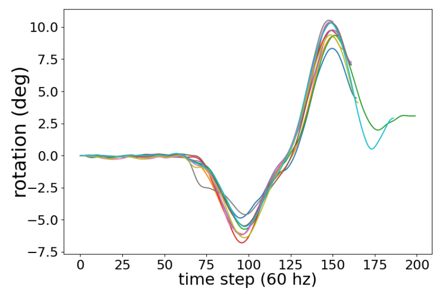


(i)



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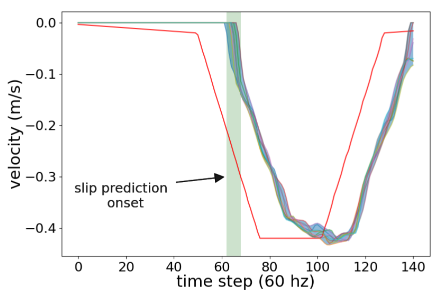

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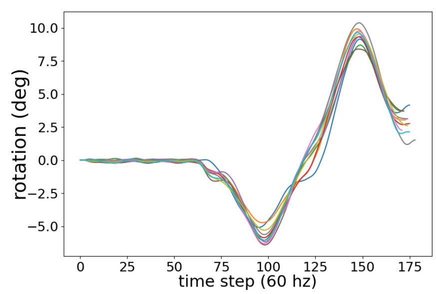

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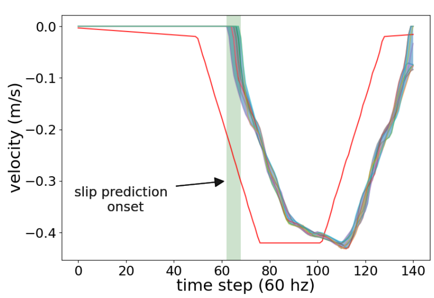

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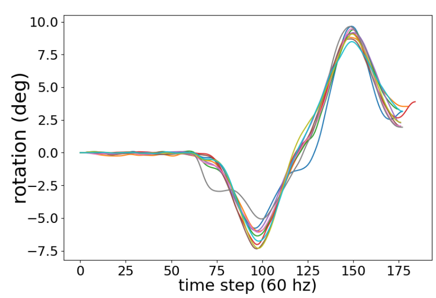


(n)

Figure 2: PSC system's generated velocity profiles (left column) and object rotation (right column) based on different numbers of basis functions ranging from two basis functions (first row) to eight basis functions (last row).

5 Optimization Parameters Initializtion Test

We used Trust Region Optimization Method [1] for optimizing the robot action for PSC and RSC from python 'Scipy' library. We used x, g and $barrier$ tollerances of 1^{-8}, 'Initial trust radius' of 1, 'Initial constraints penalty parameter' of 1, 'Initial barrier parameter' of 0.1, and 'Maximum number of algorithm iterations' of 10 to meet real-time control constraints.

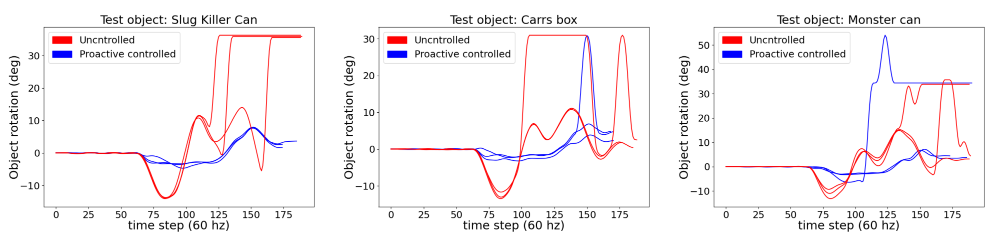
In this section we test 5 different approaches for initializing the optimization parameters. This is important to choose which initial values could help the optimization to converge to a better solution. We test five initialization methods including zero values, zero mean random values with 0.1, 0.2, 0.5, and 1 standard deviation from normal distributions, and choosing previous time step's solution as the initial values. Table1 shows the results for the tested initilization methods. Choosing random over zero values could not overally improve the performance, but the case with 0.5 standard deviation shows the best results among the tested methods.

Initialization method	Optimality	Max rotation	Customized Optimality
zero	0.46 ± 0.40	5.94 ± 1.47	2.38 ± 0.43
$\mathcal{N}(0, 0.1)$	0.47 ± 0.43	5.89 ± 1.44	2.45 ± 0.13
$\mathcal{N}(0, 0.2)$	0.46 ± 0.40	6.02 ± 1.50	2.40 ± 0.51
$\mathcal{N}(0, 0.5)$	0.43 ± 0.36	5.20 ± 1.63	2.30 ± 0.52
$\mathcal{N}(0, 1)$	0.51 ± 0.34	6.22 ± 1.89	2.58 ± 0.43
previous result	0.62 ± 0.47	6.43 ± 2.05	2.59 ± 0.33

Table 1: The impact of initial value of the controller weights on the corresponding achieved performance. Random initialization with variance of 0.5 yields the best 'optimality measure', min 'max rotation' and 'customized optimality measure'.

6 Qualitative Analysis on Novel Objects Failed Test Cases

The quantitative results in Table.2 in the paper presents the generalization for slip control for PSC system on the 5 novel objects. As a qualiative analysis for the failure cases we include marker rotations for uncontrolled and controlled cases in Fig. 3. The failure cases are usually resulted from two reasons; first, slip classification false negative cases, and second object's gained momentum in the pre-slip-detection/prediction phase is so high that even with trajectory modification the objects slips. Combined grip force and trajectory adaptation is the most effective strategy to avoid these failure cases.



(a) (b) (c)

Figure 3: Novel objects' rotations in uncontrolled (red) and proactive controlled (blue) cases for three trials. The horizontal lines correspond to the time step the object dropped of robot's hand.

References

[1] A. R. Conn, N. I. Gould, and P. L. Toint. *Trust region methods*. SIAM, 2000.