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Intuitive Robot Arm Reach

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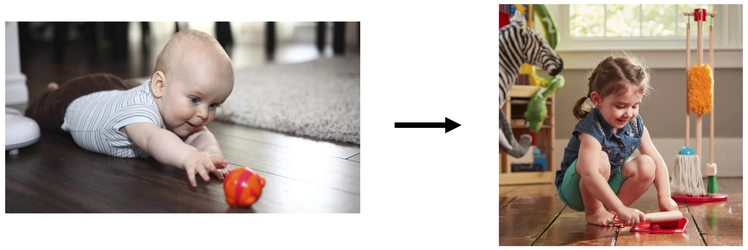
Project Goal

Demonstrate robot arm reach based on human inspired processes

Background



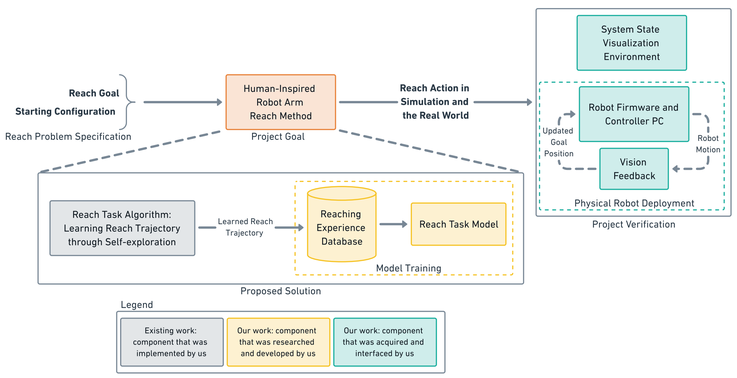
- **Proximodistal development** is the preference of using proximal (closer) joints over distal (further) joints.
- Proximodistal Freezing and Freeing of Degrees of Freedom (**PDFF**) is a computational model for planning robotic arm trajectories based on proximodistal development.

Motivation

Develop a model that:

- Is **less computationally intensive** than existing robotic arm path planning methods such as gradient descent,
- Mimics **human development**, especially proximodistal exploration.

System Context Diagram



Reach Task Algorithm

- Reach task algorithm is the implementation of PDFF, which is a human learning inspired cost-based optimization algorithm.

Reach Cost	$\|\|^W p_n(T) - {}^W p_{\text{target}}(T)\|\|^2$
Comfort Cost	$\max(\mathbf{q}(T))$
Acceleration Cost	$r_t = \frac{\sum_{i=1}^{n}(n+1-i)\ddot{q}_i(t)}{\sum_{i=1}^{n}(n+1-i)}$
Total Cost	$J(\ddot{\mathbf{q}}) = \text{reach} + \text{comfort} + \sum_{t=0}^{T} r_t \Delta t$

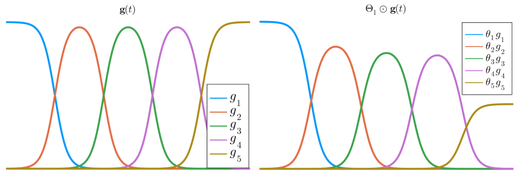
- Total cost is the sum of reach, comfort, and acceleration costs

- Joint **accelerations represent robot motion**.
- Accelerations are approximated using a set of Gaussian **basis functions**.

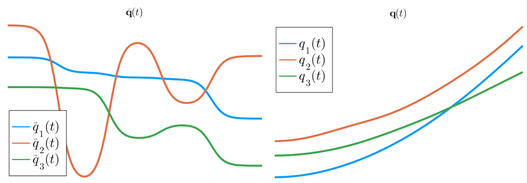
$$\psi_b(t) = \exp\left(\frac{-(t-c_b)^2}{w^2}\right)$$

$$g_b(t) = \frac{\psi_b(t)}{\sum_{b=1}^{B}\psi_b(t)}$$

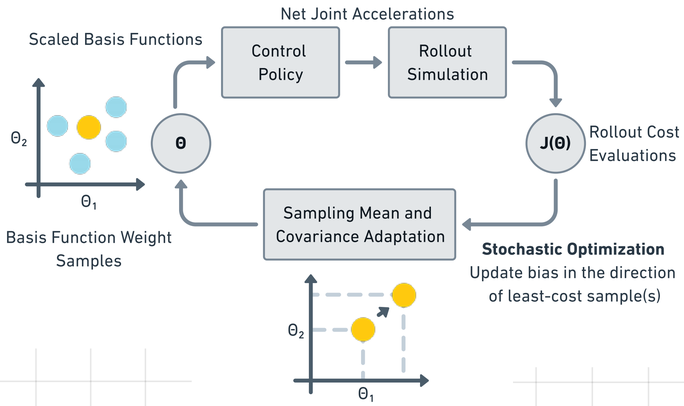
$$\ddot{\mathbf{q}}(t) = \Theta^\top \mathbf{g}(t)$$

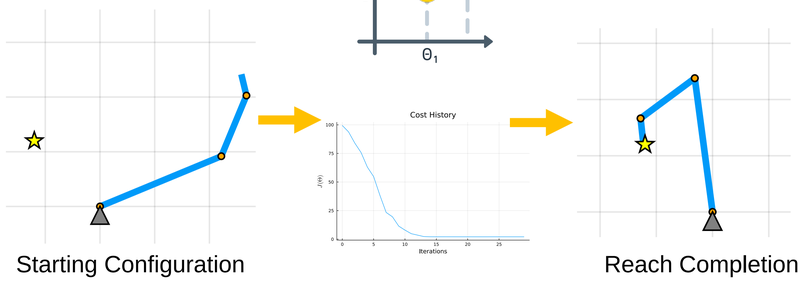


Normalized Basis Functions | Weighted Basis Functions



Joint Acceleration Profiles as Weighted Sums of Basis Functions | Joint Angle Profiles

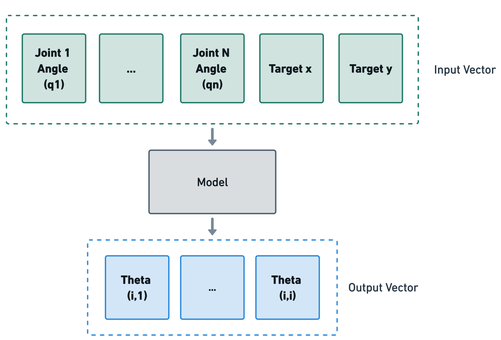


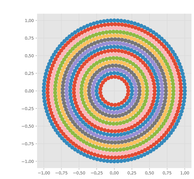


Starting Configuration | Reach Completion

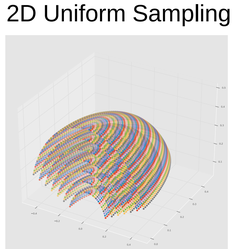
Reach Task Model

- Reach Task Model was trained with data generated from PDFF by
  - Uniform Sampling of Target Points
  - Random Sampling of Initial Joint Configurations





2D Uniform Sampling

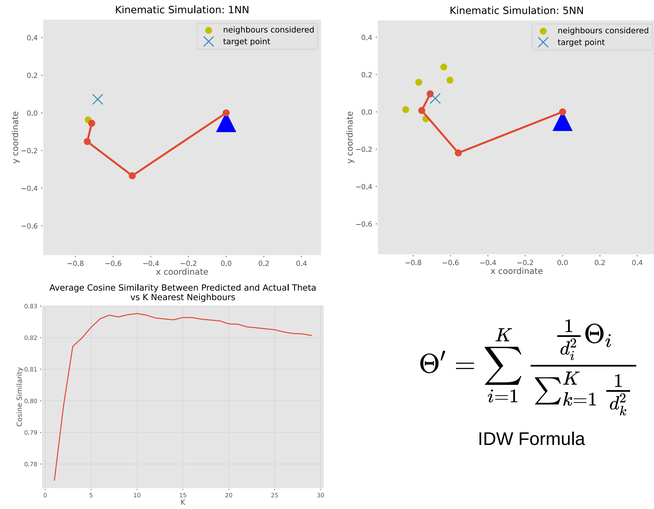


3D Uniform Sampling

Acknowledgements

Prof. Mireille Broucke for supervising; Prof. Freek Stulp and Dr. Travis DeWolf for answering our numerous questions about their research work; Daniel Lu, Kooresh Akhbari, Alex Bogdan for their work on platform set up

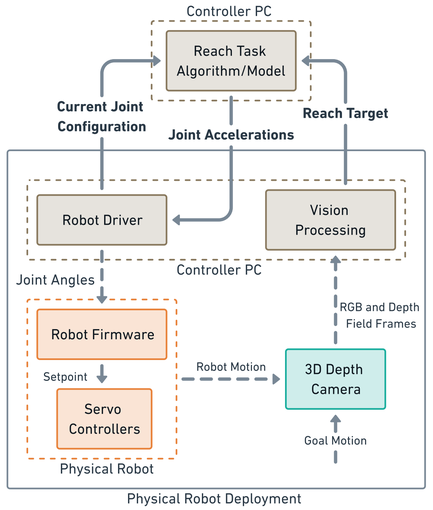
- We are using **Inverse Distance Weighted (IDW) Interpolation** for our final Reach Task Model. Neighbors refer to training points near the unexplored target points

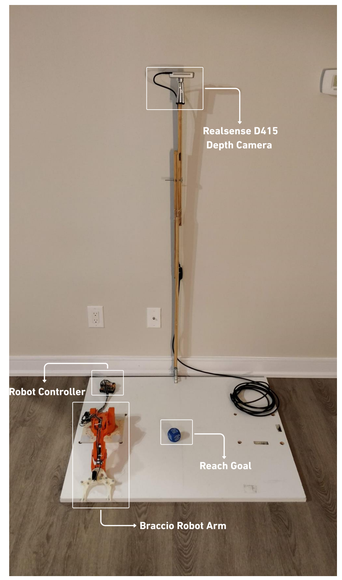


$$\Theta' = \sum_{i=1}^{K} \frac{\frac{1}{d_i^2}\Theta_i}{\sum_{k=1}^{K}\frac{1}{d_k^2}}$$

IDW Formula

Robot Platform Setup





Key Learnings

- Finding **consistent trends** to model stochastic optimization processes is hard and requires **large amounts of training data**.
- Training data generation needs to have **structured biases** to **regularize** the stochastic outputs.
- It is **unclear** which Reach Task Model **architecture** can best extract the relationship between joint movements and the reach targets from the training data.
- There are **infinite acceleration profiles** that can result in reaching the same target, and our approach for the Reach Task Model **fails** to produce different acceleration profiles and hence **generalize**
- IDW Interpolation may help inform how to normalize input data for model training.

Conclusion

We demonstrated two different methods for robot arm reach based on human inspired processes, specifically proximodistal development.