Application of Machine Learning in Logistics Systems

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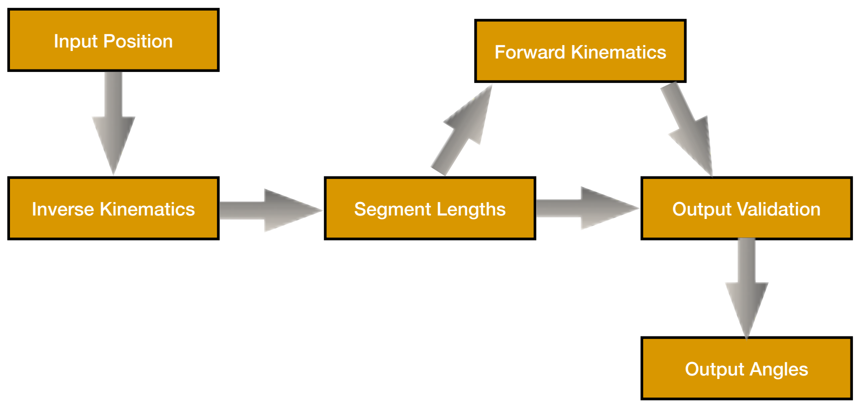
Problem Motivation

- Traditional inverse kinematics systems used to manipulate robotics in logistics applications offer low flexibility and require high computational overhead
- The motions of traditional inverse kinematics systems can result in abrupt or inaccurate motion

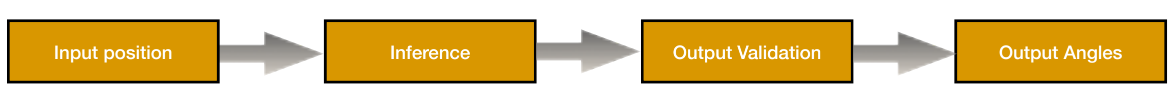


- **Figure 1:** Traditional Inverse Kinematics approach using iterative gradient descent

- **Challenge**: Create a flexible, accurate system to find solutions for complex inverse kinematics problems that arise in logistics systems

Solution and Novelty

- We design and implement a novel framework for performing inverse kinematics to facilitate logistics systems
- We present a comparison of this framework to an industry standard algorithm
- We utilize fully open source tools for simulation and training.



- **Figure 2:** Proposed model using Inference to perform inverse kinematics

Model Implementation

- **Model Input:** During training the model takes into account the angles of all six axes, the relative position of the end effector, the distance to the goal, and the current step count.
- **Reward Structure:** Small positive rewards are given in order to optimize for speed, accuracy, and natural movements. At the end of each episode, larger positive rewards are given for each goal achieved with a multiplier for solutions found in less than 1000 steps. Large negative rewards are given for any movements that lead the end effector away from the target or violate a constraint.
- **Parameter Selection:** 10 hyper parameters were selected for this model via a grid search method. 5 values were selected for each parameter. Each value was allowed to run for 5,000 steps. The values that showed a negative correlation between entropy and standard of reward and a high cumulative reward were selected for the final model.

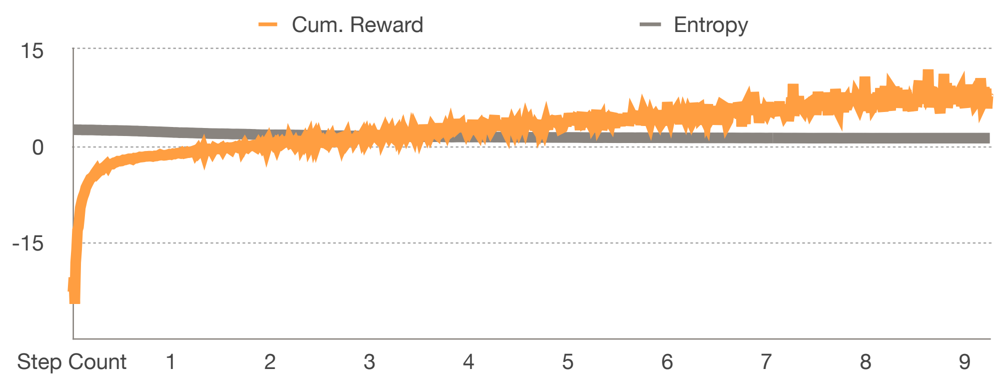
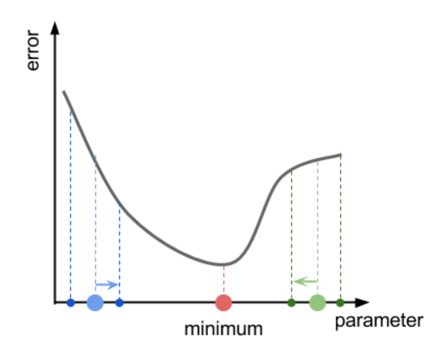


Figure 3: Cumulative Reward and Entropy of the final model during training. Steps are shown in millions of steps.

Inverse Kinematics Implementation

- Taking an input target position and the angles of each axis, our IK algorithm iteratively calculates a gradient for each axis that is used to determine the amount that each angle must move in order to minimize our error function.

- **Figure 4:** Showing the sampling process that is used to approximate a solution



- **Constraints:** Limits are imposed on the travel of each axis to prevent the model from finding non-real solutions

Validation

- **Goal:** To compare our ML model with a traditional IK model in a common logistics situation and show the effectiveness of our solution.
  - We used a Picking/Stocking scenario with randomly generated picking locations and stocking destinations
  - We simulated a robotic arm with 6 degrees of freedom
  - We ran a series of trials and compared the rate at which solutions were produced
  - We rejected solutions that resulted in unnatural poses or inaccurate results

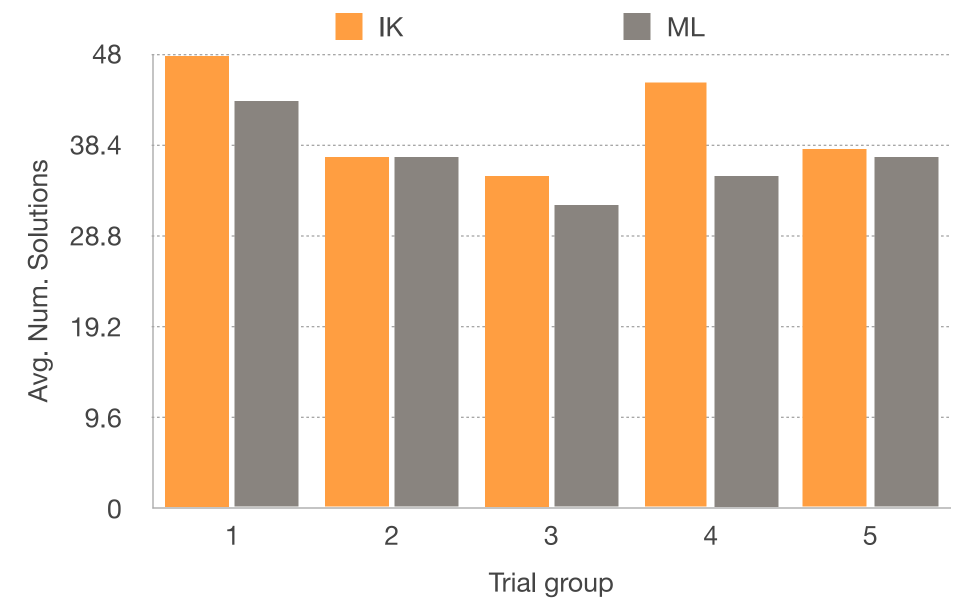


Figure 5: Validation data collected over 5 ten minute trials

Conclusion and Future Work

- We concluded that our model could achieve similar performance to traditional methods
- We demonstrated that reinforcement learning is a viable tool for use in logistics applications
- **Future Work:**
  - Experiments can be conducted to test the efficacy of our model with more complex tasks and environments, such as tasks in proximity to humans as well as tasks requiring complex action sequences