

Generative Graphical Inverse Kinematics (Abstract Reprint)

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Abstract Reprint. This is an abstract reprint of the journal article by Limoyo, Mari, Giamou, Alexson, Petrovi, and Kelly (2025).

Abstract

Quickly and reliably finding accurate inverse kinematics (IK) solutions remains a challenging problem for many robot manipulators. Existing numerical solvers are broadly applicable but typically only produce a single solution and rely on local search techniques to minimize nonconvex objective functions. More recent learning-based approaches that approximate the entire feasible set of solutions have shown promise as a means to generate multiple fast and accurate IK results in parallel. However, existing learning-based techniques have a significant drawback: each robot of interest requires a specialized model that must be trained from scratch. To address this key shortcoming, we propose a novel distance-geometric robot representation coupled with a graph structure that allows us to leverage the sample efficiency of Euclidean equivariant functions and the generalizability of graph neural networks (GNNs). Our approach is generative graphical inverse kinematics (GGIK), the first learned IK solver able to accurately and efficiently produce a large number of diverse solutions in parallel while also displaying the ability to generalize – a single learned model can be used to produce IK solutions for a variety of different robots. When compared to several other learned IK methods, GGIK provides more accurate solutions with the same amount of data. GGIK can generalize reasonably well to robot manipulators unseen during training. Additionally, GGIK can learn a constrained distribution that encodes joint limits and scales efficiently to larger robots and a high number of sampled solutions. Finally, GGIK can be used to complement local IK solvers by providing reliable initializations for a local optimization process.

References

Limoyo, O.; Mari, F.; Giamou, M.; Alexson, P.; Petrovi, I.; and Kelly, J. 2025. Generative Graphical Inverse Kinematics. *IEEE Transactions on Robotics*, 41: 1002–1018.