DNBP: Differentiable Nonparametric Belief Propagation

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PROBLEM STATEMENT

Nonparametric belief propagation (NBP) algorithms are a form of generative probabilistic inference that have proven effective for inference in visual perception tasks such as human pose tracking and articulated object tracking in robotic perception. The adaptability of NBP algorithms to new applications, however, is limited by the need to define hand-crafted functions that describe the distinct statistical relationships in a particular dataset. Current methods that utilize NBP rely on extensive domain knowledge to parameterize these relationships. Reducing the domain knowledge required by NBP methods would enable their use in a broader range of applications.

METHODS

A method is developed that combines the robustness of generative probabilistic inference with the speed, recall power, and general adaptability of discriminative neural networks. Inspired by differentiable Bayesian filters and the pull message passing for nonparametric belief propagation algorithm, a differentiable nonparametric belief propagation algorithm is proposed that performs end-to-end learning of each probabilistic factor required for graphical model inference.

RESULTS

The effectiveness of DNBP is demonstrated on two simulated articulated tracking tasks and on a real-world hand pose tracking task in noisy environments. An analysis of the learned probabilistic factors and resulting tracking performance is used to validate the approach.

SIGNIFICANCE

The results show that DNBP can leverage the graph structure to report uncertainty about its estimates while significantly reducing the need for prior domain knowledge required by previous NBP methods. This indicates that DNBP has the potential to be successfully applied to robotic perception tasks, where maintaining a notion of uncertainty throughout the inference is beneficial.

Code and data links:
https://github.com/opipari/diffBP
https://drive.google.com/drive/folders/10uiGUYoLM1B-jwoS8fUzLbfwId62hE_y?usp=share_link

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