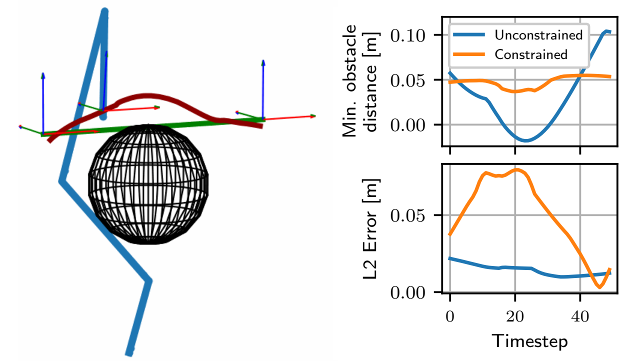

Fig. 6. Example results of 10 DoF arm (blue line) with a sphere as static obstacle; Green: target trajectory; Red: actual trajectory by IK network; On the right the minimum obstacle distance to all joints of the robot and the actual L2 error to the target trajectory are given over time. The training without additional loss functions (blue graph) is compared to the model with obstacle distance loss L_{obs} (orange graph).

The 0.1m here is a safety margin, the robot should keep to the obstacle when possible.

The resulting behavior of the IK model is exemplary shown in Fig. 6. The comparison of the minimum joint to obstacle distance over the pass along the green trajectory (see right side of the figure) shows, that the extended model finds a trade-off between the distance to the target trajectory and the distance to the obstacle inside the safety margin and avoids the obstacle completely otherwise. Therefore, the L2 error (orange curve lower diagram) is increased in the region where the sphere comes close to the target trajectory. The model without the L_{obs} term (blue plots) completely ignores the sphere causing collisions even if the actual trajectory is outside the sphere.

This behavior demonstrates the claimed ability to consider collision avoidance in static scenes during the training of the redundant IK model. In order to extend the obstacle awareness to dynamic objects, the network needs an additional input describing the current scene. As there are multiple approaches to represent the environment of a robot, e.g. though point clouds or voxel based approaches, which can also be used as an input to a neural network (e.g. PointNet[15]), it would be promising to train a network capable of handling dynamic environments in future.

IV. Conclusion and Future Work

We could show that the lack of performance of simple feed forward neural networks (MLPs) for the inverse kinematic task is related to the contradictory data samples when using supervised training. The proposed unsupervised training proved to be insensitive to ambiguity and even performed better for highly redundant robots. We also showed that learning to solve the orientation of a robot's end effector is possible but harder than using only a target position.

An analysis of the distribution of the remaining errors showed a correlation to the sample density. Therefore, in future work we will concentrate on improving the sampling strategy. Also the ability to consider additional constraints gives rise to further investigations. We plan to train obstacle sensitive inverse kinematic models by adding an abstract encoding of a dynamic collision scene at the network input while using the distance of the robots limbs to the scene as additional loss during training. Despite the remaining error and the lack of redundant solutions for a single target pose, the IK network with obstacle avoidance can therefore be helpful as a fast sampler for motion planning approaches like [16]. By means of such a model, the planning time in cluttered environments might be drastically reduced, as it can provide an initial guess for the required joint configuration. While this initial guess might not reach the target pose exactly, subsequent optimization steps can reduce the remaining error.

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