Multiview Image-based Hand Geometry Refinement using Differentiable Monte Carlo Ray Tracing

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1 Evaluation on Real Data

In this work we address the problem of hand pose and shape refinement in an unsupervised manner. Our method [1] is based on differentiable rendering using the Monte Carlo ray tracer by Li et al.[2]. To evaluate our method on real data, we relied on the InterHand2.6M [3] dataset. InterHand2.6M is a large-scale dataset with real multi-view images depicting hands of various subjects performing sign language and everyday life gestures. The annotations within InterHand2.6M are partly manual (joint locations) and partly automatic (joint locations and MANO [4] poses) with reported annotation errors in the order of a few millimeters. However, when it comes to fine prediction of hand geometry, the provided annotations can mainly serve as references for the true location and geometry of the hand rather than ground truth. This is evident in the first row of the figures provided below.

As a remedy to imperfect ground truth annotations in InterHand2.6M, we resorted to experiments with synthetic data that closely simulate the capture environment in InterHand2.6M and come with perfect and known ground truth. As described in section 4.2.1 of the main paper, we evidenced the correlation between the improvement in 3D hand geometry estimation and the backprojection error. Specifically, we found a monotonic relation where the error on the estimated 3D geometry decreases as the back-projection error decreases. To further show how the per-camera backprojection improvement actually yields a true amelioration in 3D hand geometry, we conducted extensive qualitative experiments that demonstrate visually consistent and significant improvement in both metrics. Indicative results, in enough detail to highlight the improvements, are presented below.

In addition, we show the impact of our method on the estimated variable c (color map), which implements the hard constraint of color constancy during optimization. The sharpness and definition of the visible parts of the color maps can only be attained through an accurate estimation of the 3D geometry and a proper method (see our discussion on ray tracing in the introduction of the main text [1]) to correctly connect the 2D backprojection error with 3D information (surface color). If the geometry had not been estimated with enough accuracy, the color maps would have been less sharp, due to the positional (on the 3D surface) inconsistencies of the color updates during backpropagation.

In the following figures, we show representative results of hand geometry refinement on InterHand2.6M. In each figure, the first row corresponds to the MANO annotation provided in the dataset that we use as an initialization to our method. The second row shows the result of our method. The third and fourth rows depict the estimated hand appearance before and after refinement. The improvement on the estimated hand geometry as well as the estimated appearance of the hand are evident.

Acknowledgements

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References

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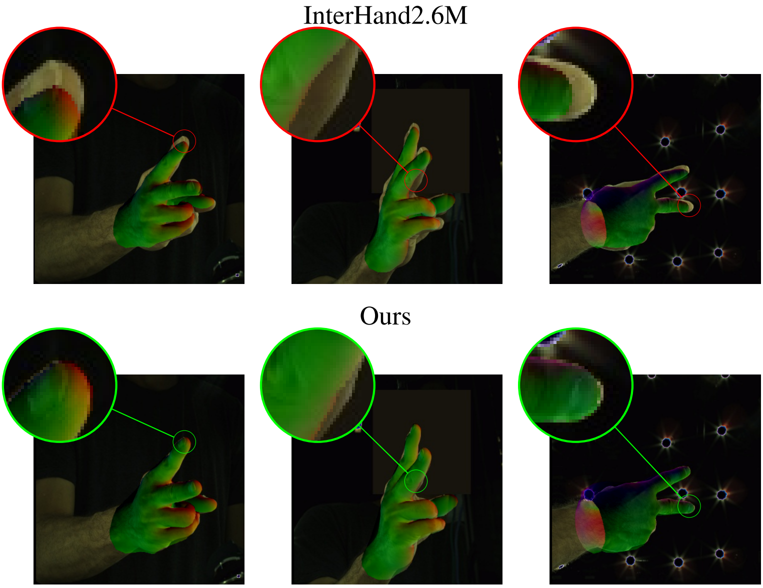
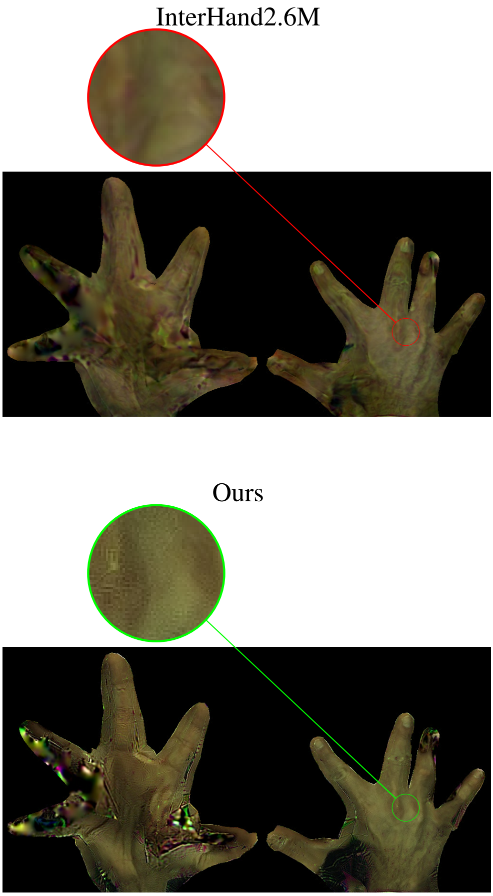

InterHand2.6M
Ours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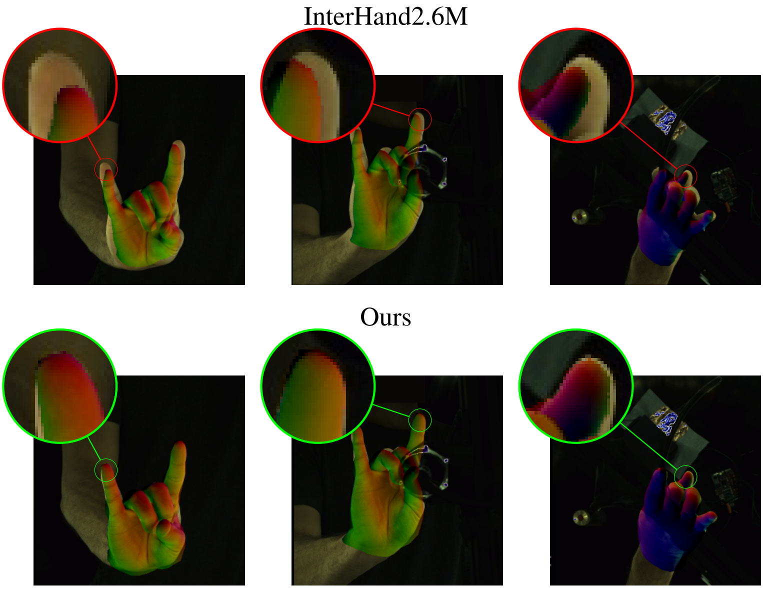
Ours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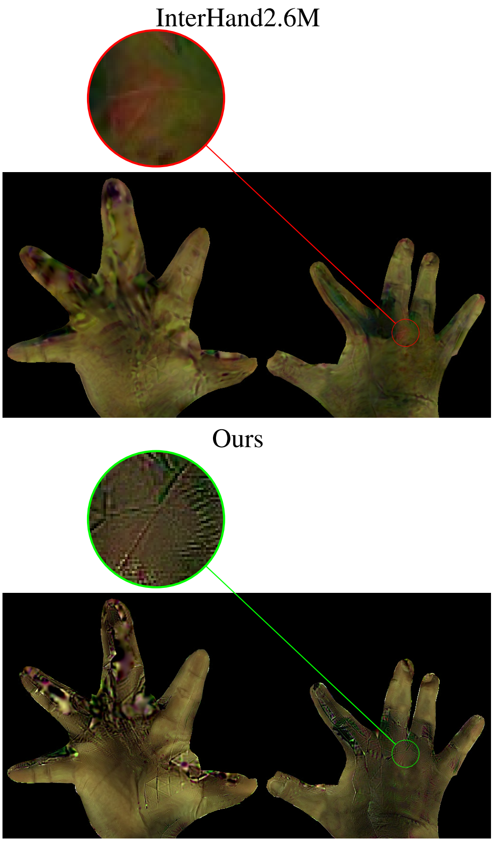
Ours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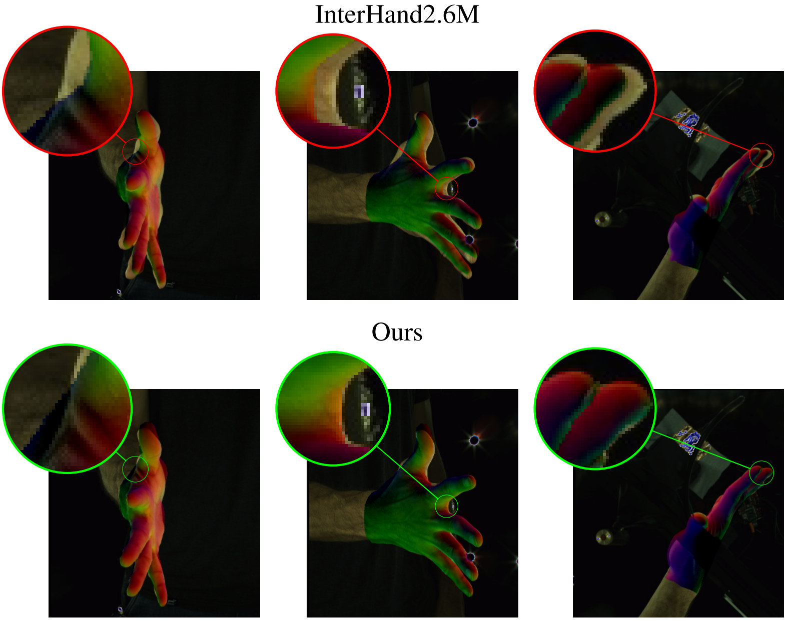
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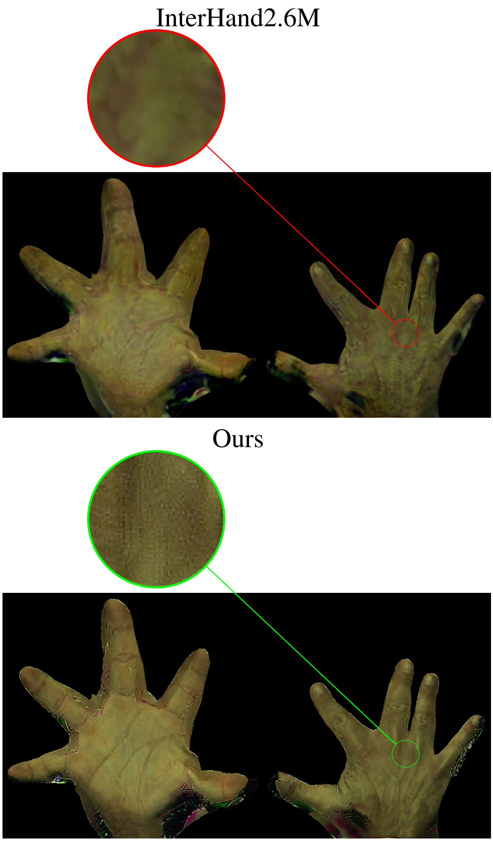
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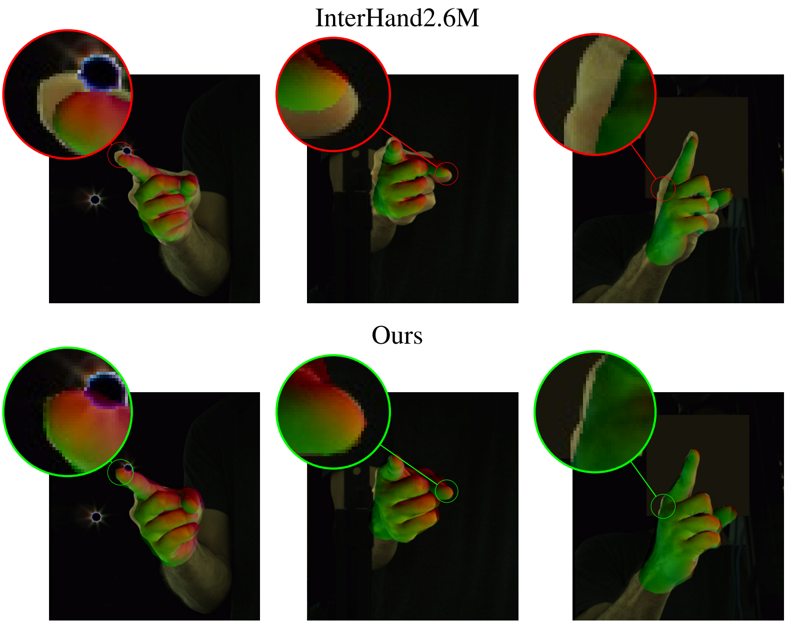
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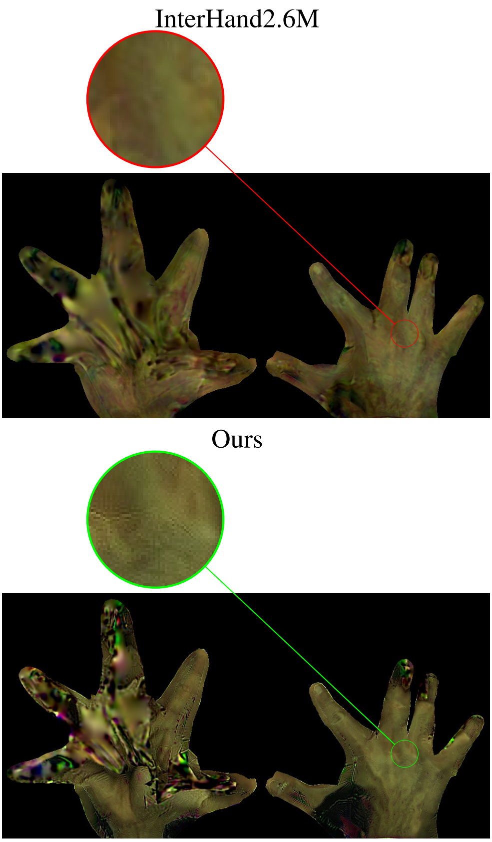
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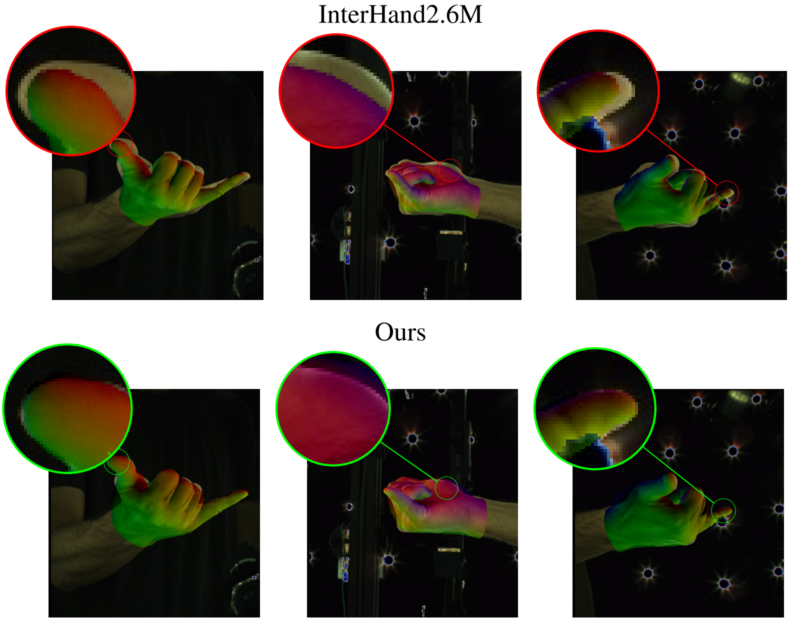
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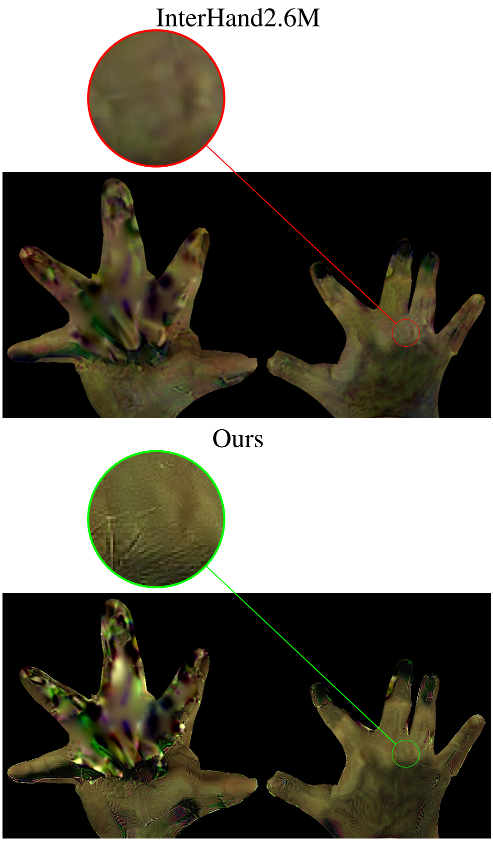
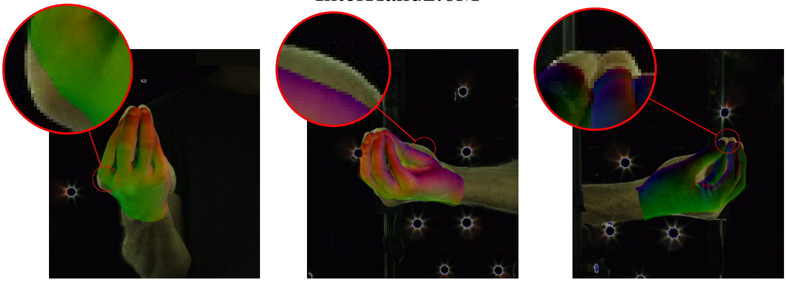

InterHand2.6M
Ours

InterHand2.6M



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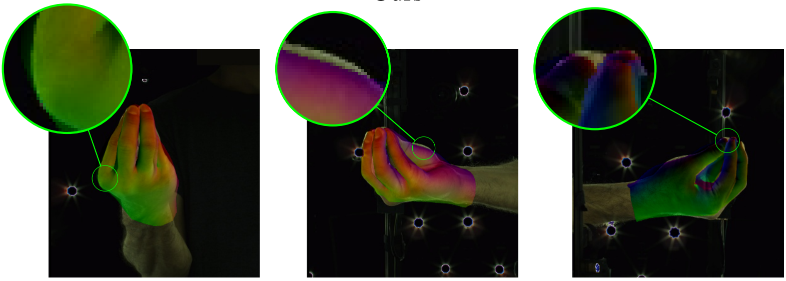

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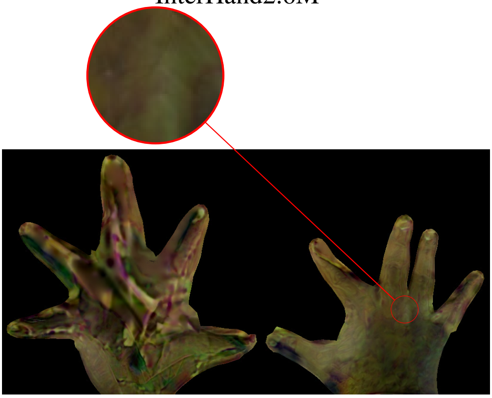

Ours