TU Graz
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Project page:
poier.github.io/murauer

MURAUER: Mapping Unlabeled Real Data for Label AUstERity

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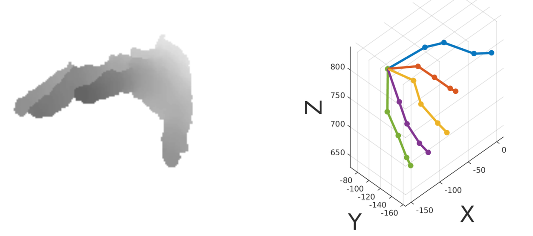
Motivation

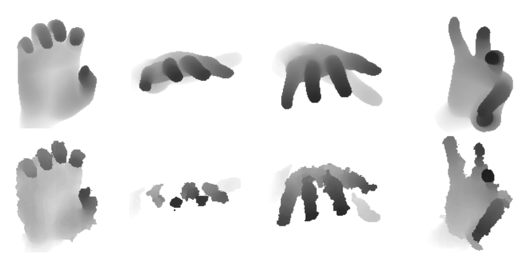
- Learning accurate models requires a large amount of labeled data
- Accurate labeling vital
- Synthetic data can help

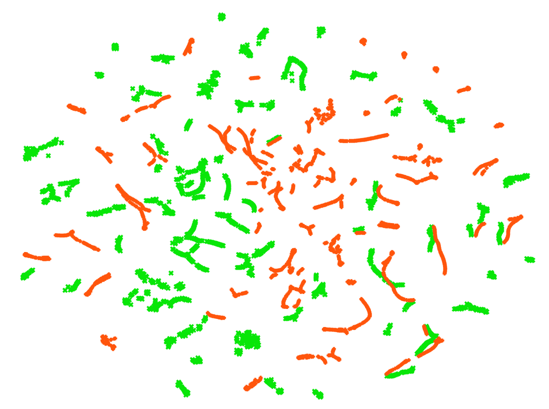
➔ **But: domain gap**

- Mitigated using corresponding real ↔ synthetic data [1,2]

➔ **But: using correspondence required labeling**







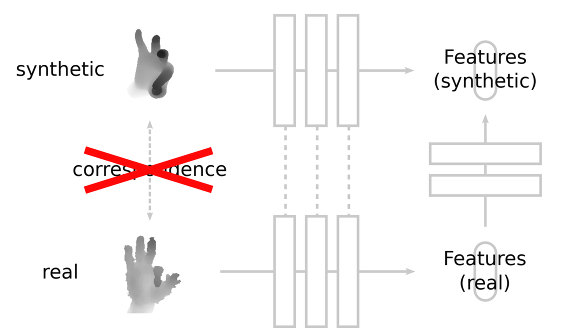
Train with synthetic data only
➔ real and synthetic representations are separated

Idea

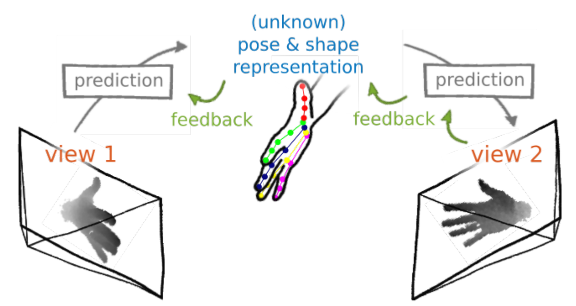
- Map features real to synthetic without labels/correspondence
- Using two auxilliary objectives computed from unlabeled data:

  (i) enforcing pose specifity [3] (use 2 views, predict one from the other)

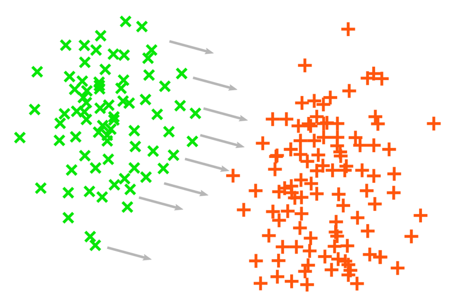
  (ii) enforcing to align real and synthetic samples (make distributions indistinguishable)



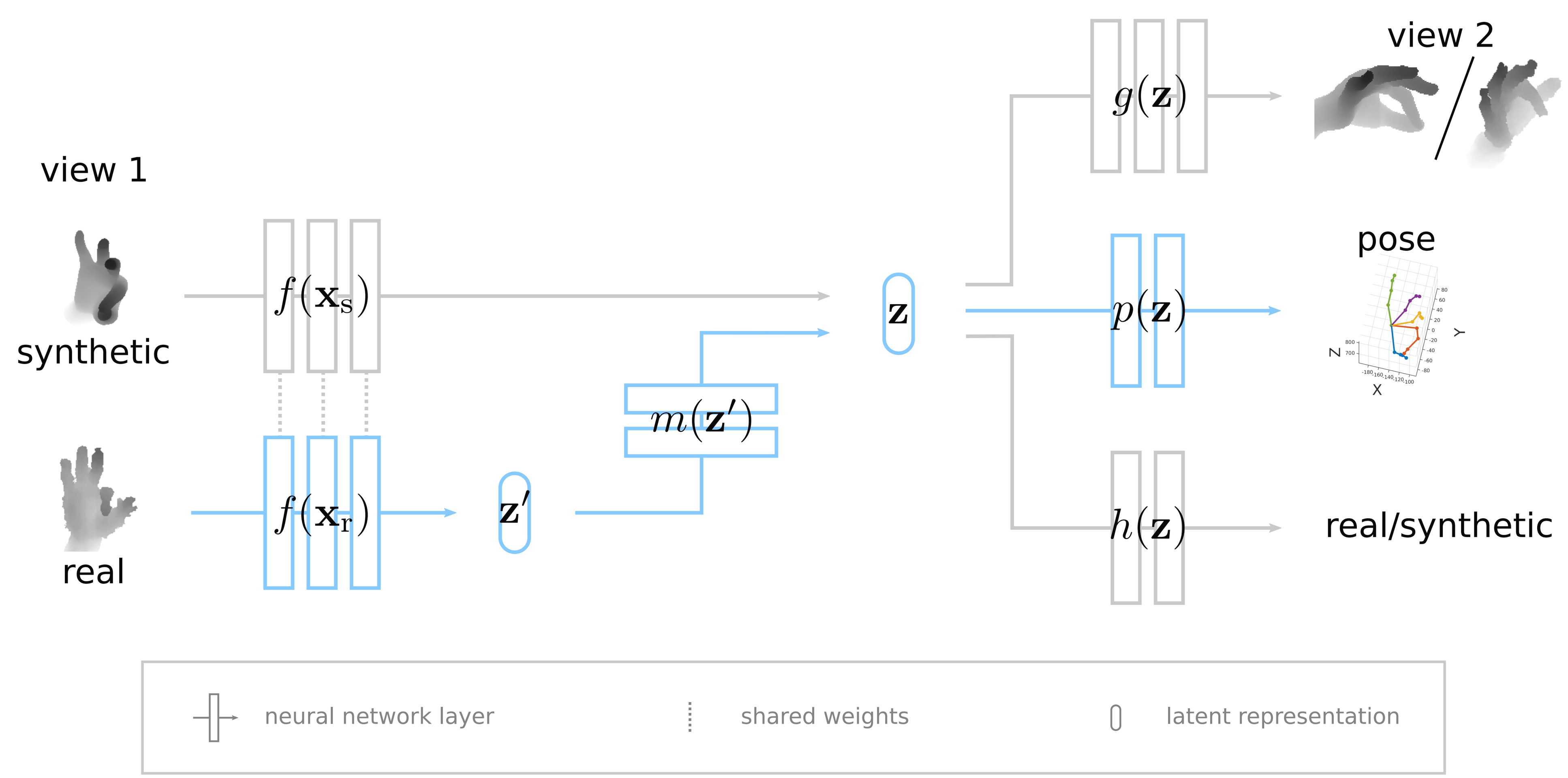
(i)



(ii)



Implementation



- Overall loss: $$\ell = \underbrace{\ell_p + \lambda_c \ell_c}_{\text{labeled}} + \underbrace{\boxed{\lambda_g \ell_g} + \boxed{\lambda_m \ell_m}}_{\text{unlabeled}}$$

  Enforce pose specifity

  Enforce distribution alignment

- Enforce pose specifity (by learning to predict/reconstruct other view [3]):

$$\ell_g = \sum_k \left\| \mathbf{x}_k^{(j)} - \hat{\mathbf{x}}_k^{(j)} \right\|_1$$

- Enforce feature distribution alignment (adversarial; LS-GAN [4]):

$$\hat{l} = h(\mathbf{z}), \quad \hat{l} \in \mathbb{R}$$

Discriminator output: real valued label

$$\ell_h = \frac{1}{2} \sum_{k \in \mathcal{R}} \left(\hat{l}_k - l_{\mathrm{r}} \right)^2 + \frac{1}{2} \sum_{k \in \mathcal{S}} \left(\hat{l}_k - l_{\mathrm{s}} \right)^2$$

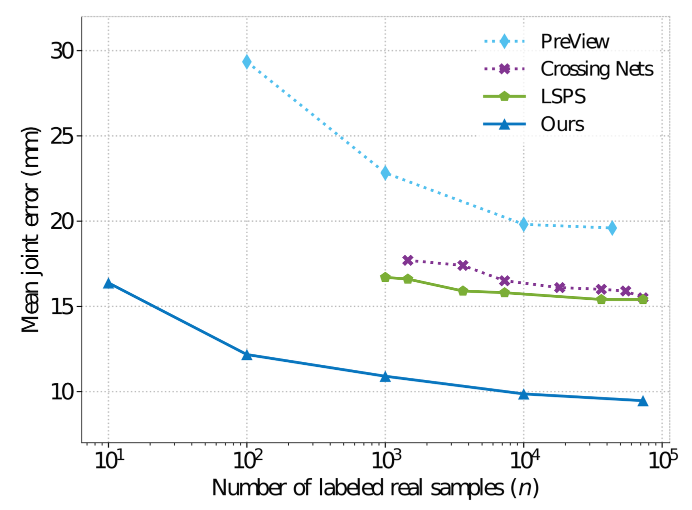
Discriminator between real and synthetic

$$\ell_m = \frac{1}{2} \sum_{k \in \mathcal{R}} \left(\hat{l}_k - l_{\mathrm{s}} \right)^2$$

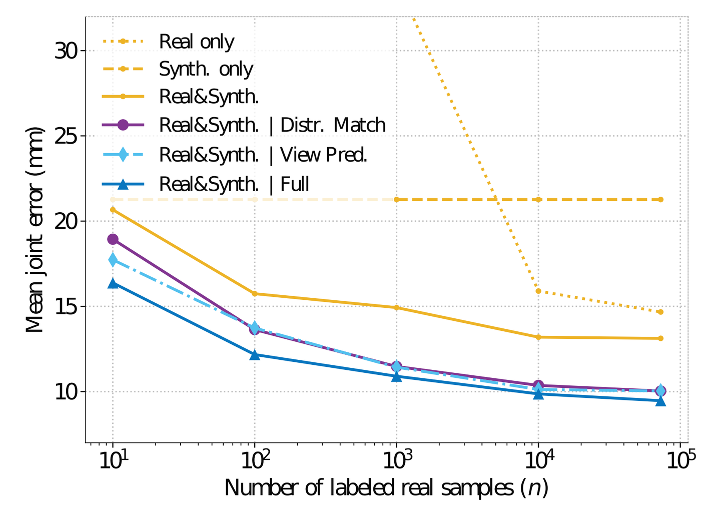
Mapping tries to make real indistinguishable from synthetic

Findings

Comp. to state-of-the-art



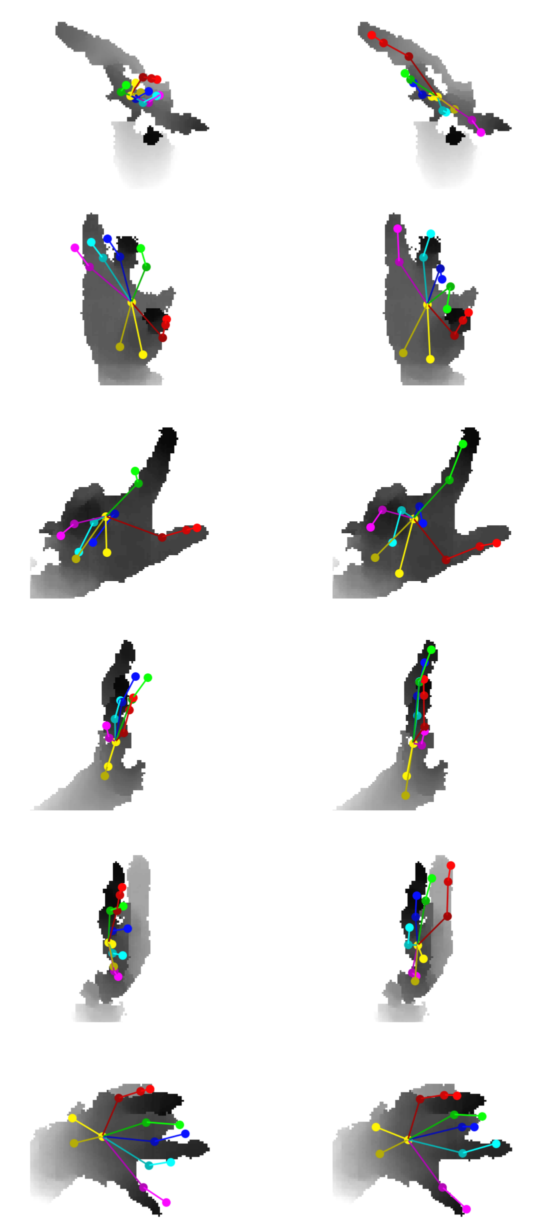
Ablation



Qualitative results

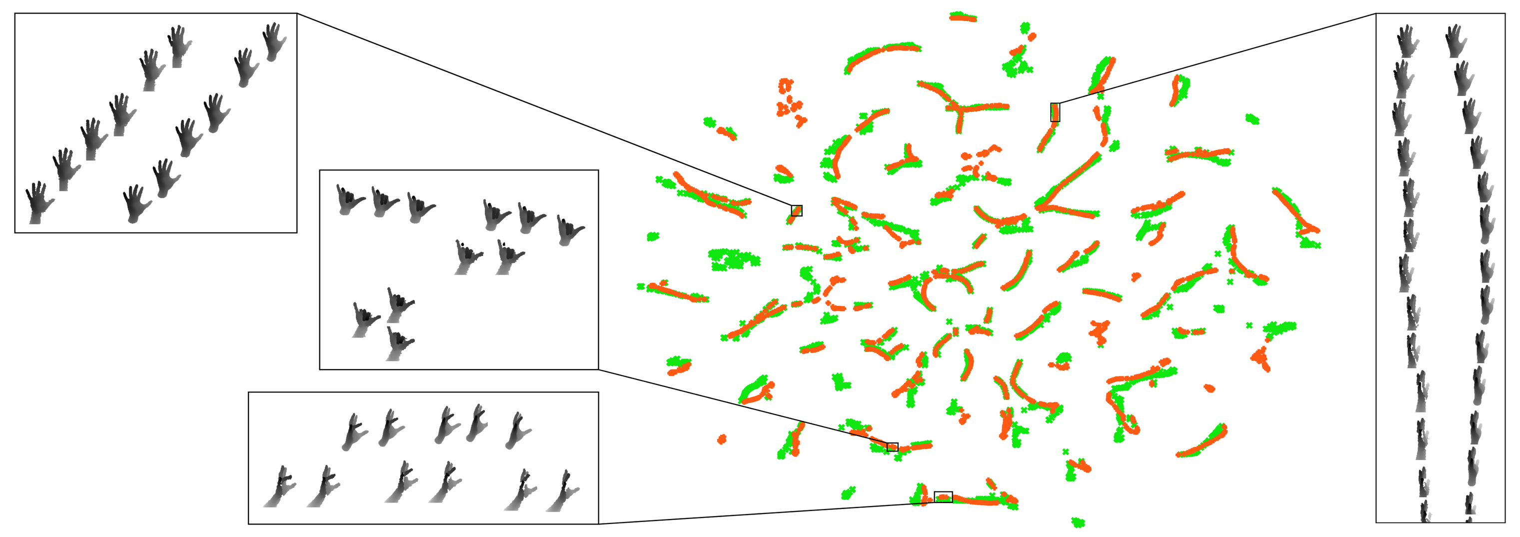
Baseline trained with real & synth.

Ours trained with real & synth. *& unlabeled*



Mapped latent representation

well aligned real and synthetic samples
trained with only 100 labeled real & unlabeled & synthetic samples



References

[1] F. Massa, B. C. Russell, and M. Aubry. Deep exemplar 2d-3d detection by adapting from real to rendered views. In Proc. CVPR, 2016.
[2] M. Rad, M. Oberweger, and V. Lepetit. Feature mapping for learning fast and accurate 3d pose inference from synthetic images. In Proc. CVPR, 2018.
[3] G. Poier, D. Schinagl, and H. Bischof. Learning pose specific representations by predicting different views. In Proc. CVPR, 2018.
[4] X. Mao, Q. Li, H. Xie, R. Y. Lau, Z. Wang, and S. P. Smolley. Least squares generative adversarial networks. In Proc. ICCV, 2017.