

Plug-and-Train Loss for Single View 3D Reconstruction



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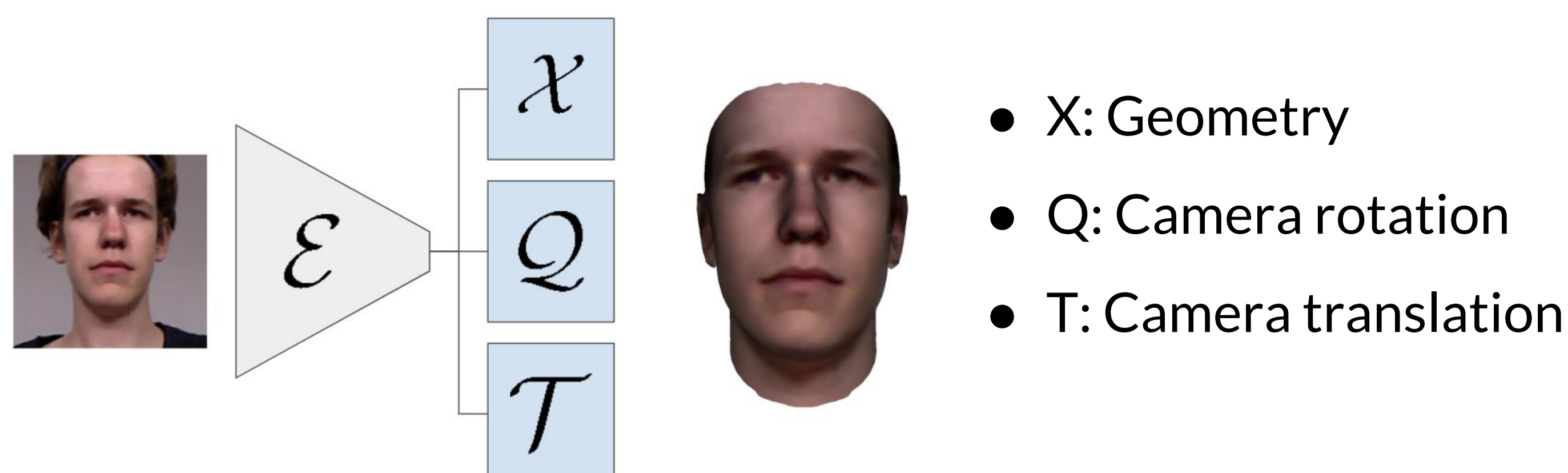


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Motivation

The single view reconstruction problem



Multi-term losses used for learning the mappings X, Q and T

$$\mathcal{L}_{data} = \mathcal{L}_x + \alpha \mathcal{L}_q + \beta \mathcal{L}_t$$

$$x = m + \Phi_{id} \alpha_{id}$$

$$\mathcal{L}_{reg} = \gamma \|\alpha_{id}\|_2^2$$

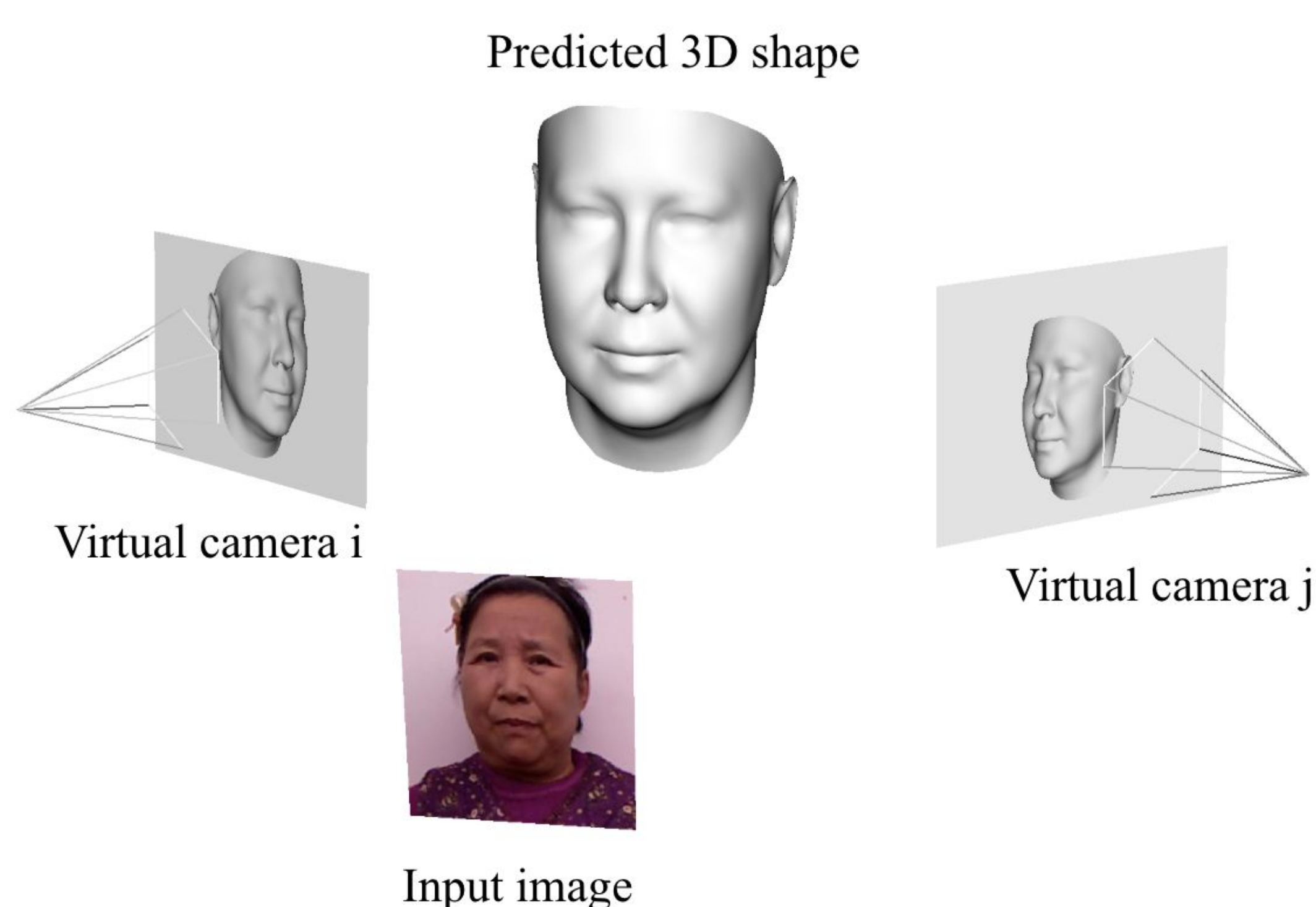
$$\mathcal{L} = \mathcal{L}_{data} + \mathcal{L}_{reg}$$

Which hyperparameters α , β and γ ?

Drawbacks:

- Problem dependent losses.
- Need of tuning a number of hyperparameters.
- Non optimal solutions.
- Waste of time and computational resources.

Multiview Reprojection Loss



$$\mathcal{L} = \sum_{v=1}^V \|\mathcal{P}_I(q_v, t_v)(x) - \mathcal{P}_D(q_v, t_v)(\hat{x})\|_1$$

$$\mathcal{P}_D(q, t) = K[R(q)|t]D$$

$$D = [R(q)|t] \cdot [R(\hat{q})|\hat{t}]^{-1}$$

Experiments

Implementation details:

- VGG16 encoder
- Training dataset with 6k facial scans and 50k images

Single term vs Multi-term losses

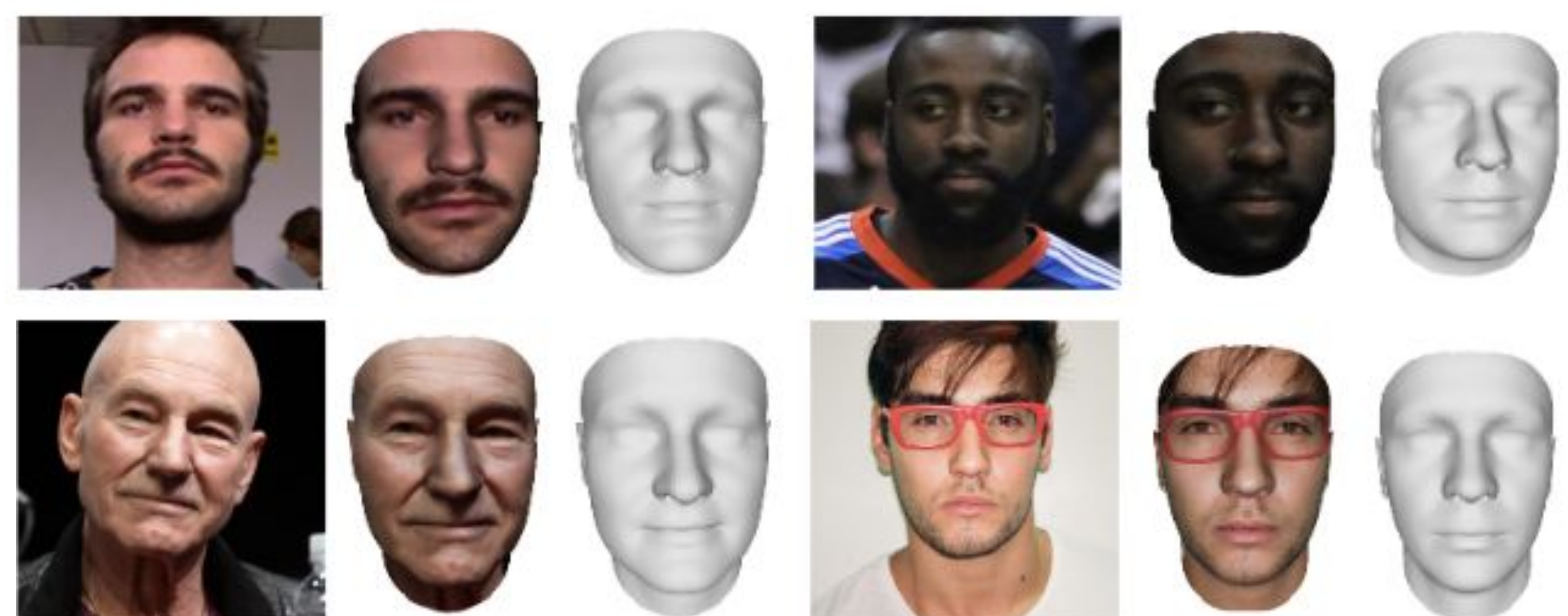
	Repro- jection (pixels)	Shape 3D (mm)	Camera position (mm)	Camera rotation (degrees)
Best pose	5.4	1.7	2.39	2.51
Best shape	8.58	1.5	2.50	2.62
MRL (ours)	3.29	1.7	2.86	3.04

Results on MICC dataset

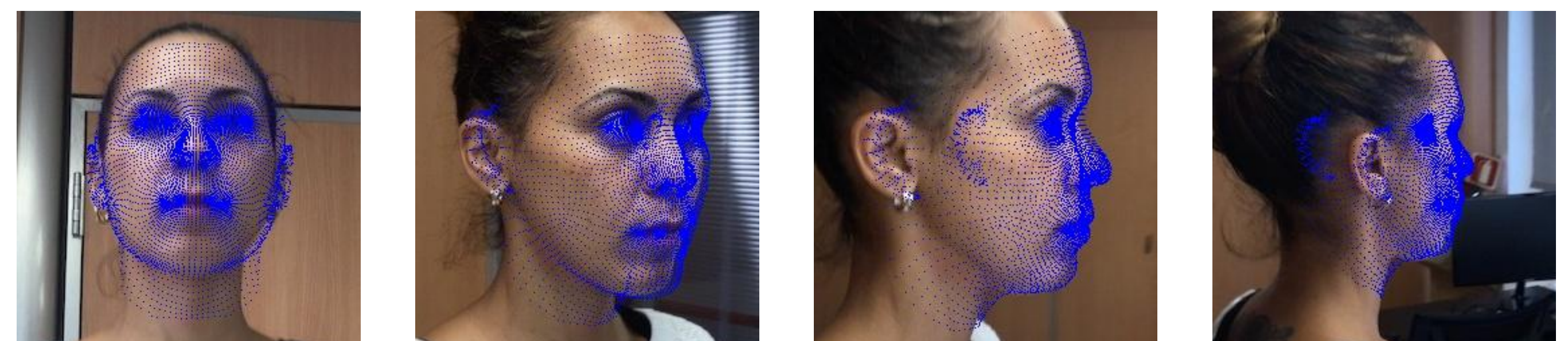
(WARNING: Our MRL results are over a subset of faces without expression)

Method	3DRMSE
3DMM [24]	1.75 ± .42
Flow-based [11]	1.83 ± .39
Discriminative [30]	1.57 ± .33
MRL (ours)	1.47 ± .30

Robustness against face diversity



Robustness against large poses



Conclusions and future work

Conclusions:

- MRL can train single view reconstruction models without adding hyperparameters.
- Comparable performance against manually tuned losses.
- Robust models against input diversity.

Future work

- Evaluation of the method with non model-based geometries.
- Evaluation of single term losses in 3D space.