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Improving self-supervised 3D face reconstruction with few-shot transfer learning

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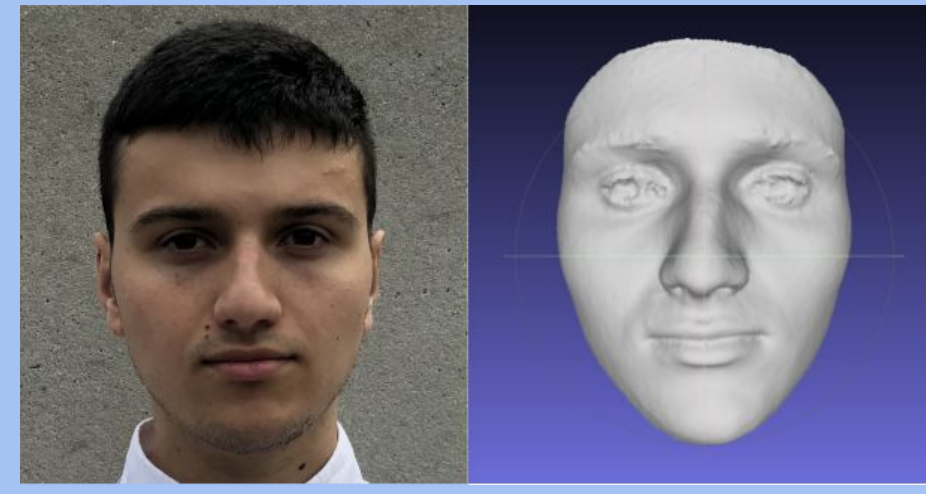
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1. INTRODUCTION

1.1 3D face reconstruction

Principle: Get a face 3D mesh from a monocular face image



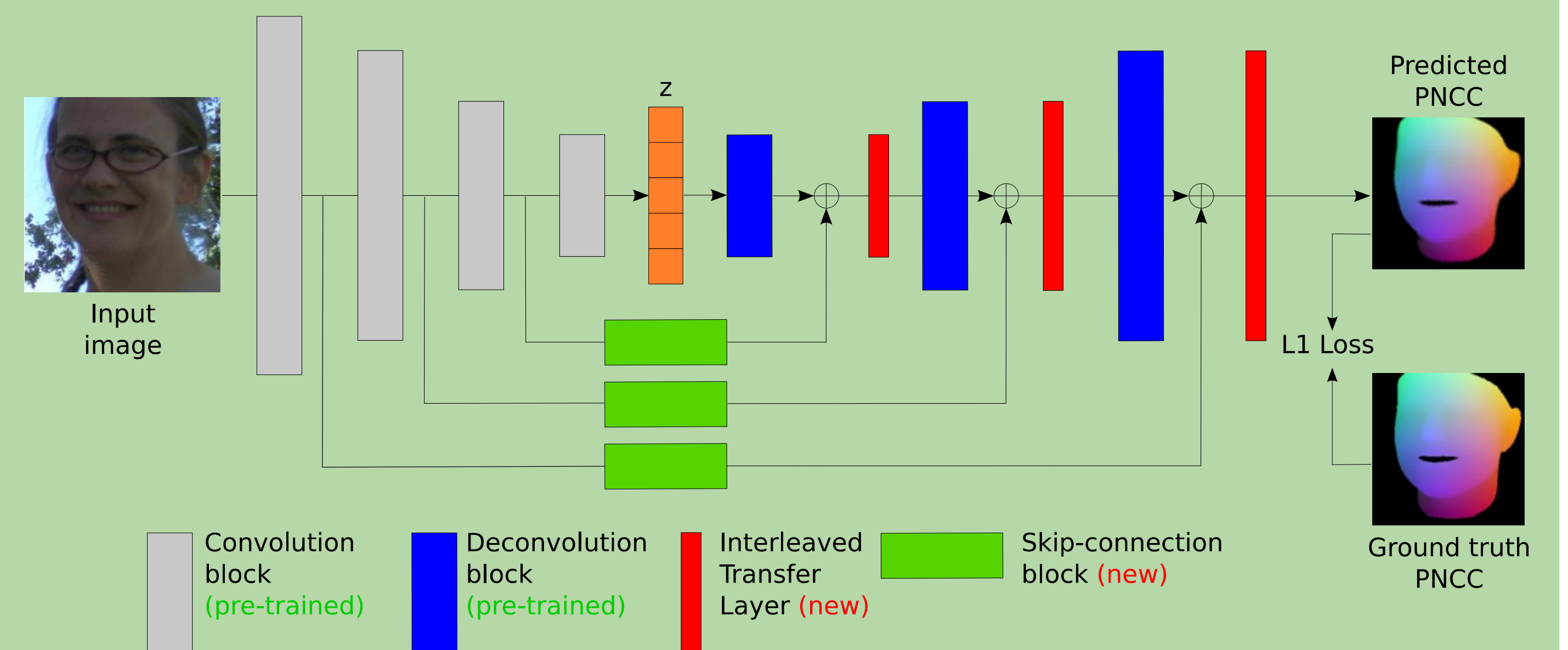
1.2 Problem: lack of annotated data

- **Supervised methods:**
 - Need annotated data to train
 - **3D annotations are hard to obtain**
- **Self-supervised methods:**
 - Do not need annotated data
 - **But tend to predict wrong head pose and scale**

1.3 Goal: Improve self-supervised methods predicted head pose and scale

- Add **supervised 3D** information
- But use **as few as possible** annotated 3D samples

2.2 PNCC predictor

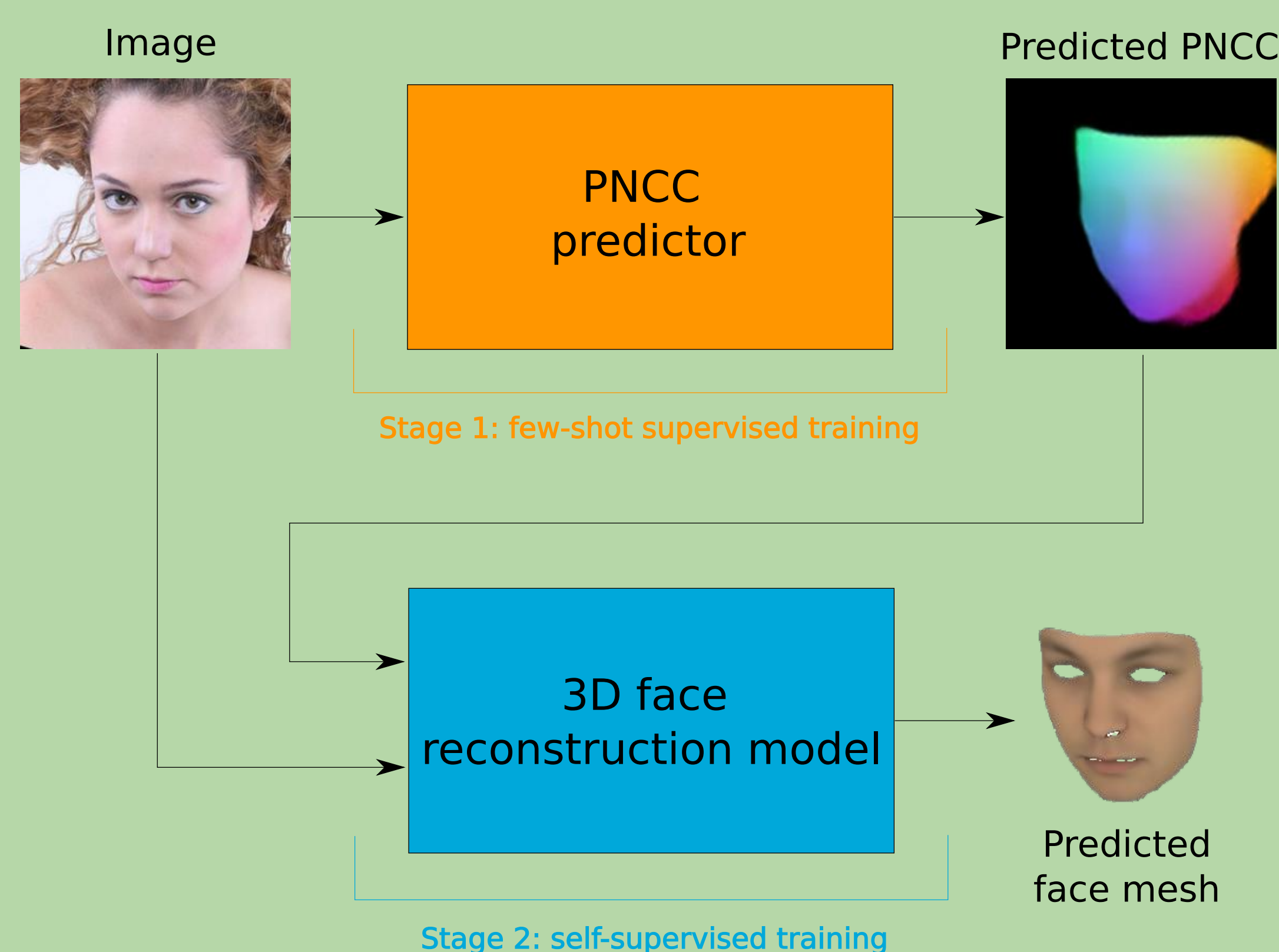


- Architecture based on SCAF [4]
 - **Pre-trained face autoencoder** adapted to the PNCC prediction task
 - **Interleaved Transfer Layers (ITLs)** [3] and **skip-connections** are added for the supervised PNCC prediction task
 - ITLs adapt the decoder flow to the PNCC prediction task
 - Skip-connections improve the quality of the generated PNCCs
 - Can be trained with **limited annotated data**

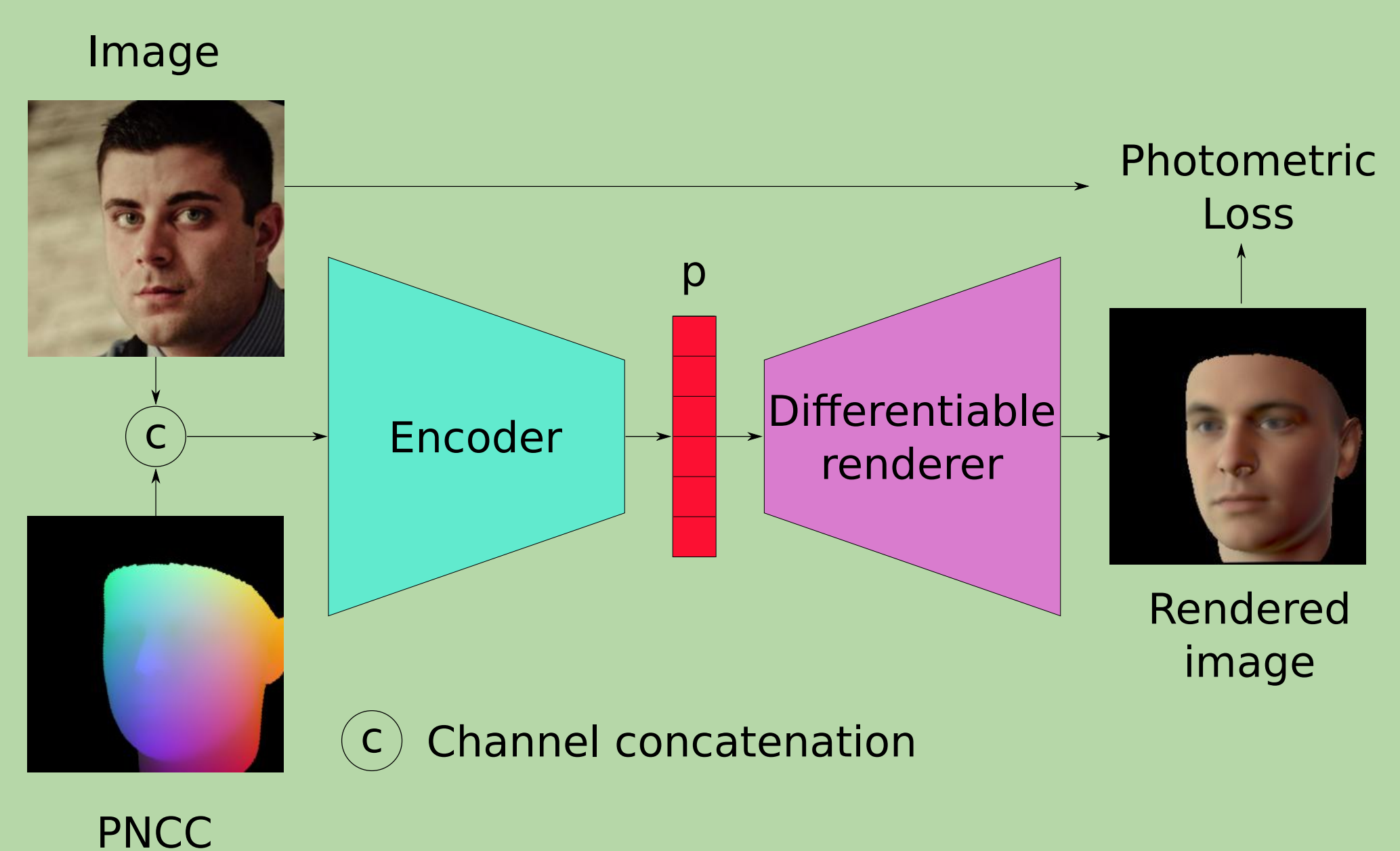
2. Method

2.1 Principle

- Use the **Projected Normalized Coordinate Code (PNCC)** [1] as supervised information
- **2-stage** pipeline
 - **Stage 1:** Train a PNCC predictor with **a few annotated 3D samples**
 - **Stage 2:** Add the **PNCC as additional input** to a self-supervised 3D face reconstruction model



2.3 Enhanced 3D face reconstruction model



- 3D face reconstruction model based on the **self-supervised model MoFa** [2]
- The encoder predicts the 3D face parameter vector (3D face reconstruction goal)
- The decoder renders the face from the parameter vector
 - Only used for training
- We enhance MoFa [2] with an **additional PNCC input** to help it **predict better head pose and scale**
- The **face image is concatenated** with the **PNCC** predicted with our PNCC predictor

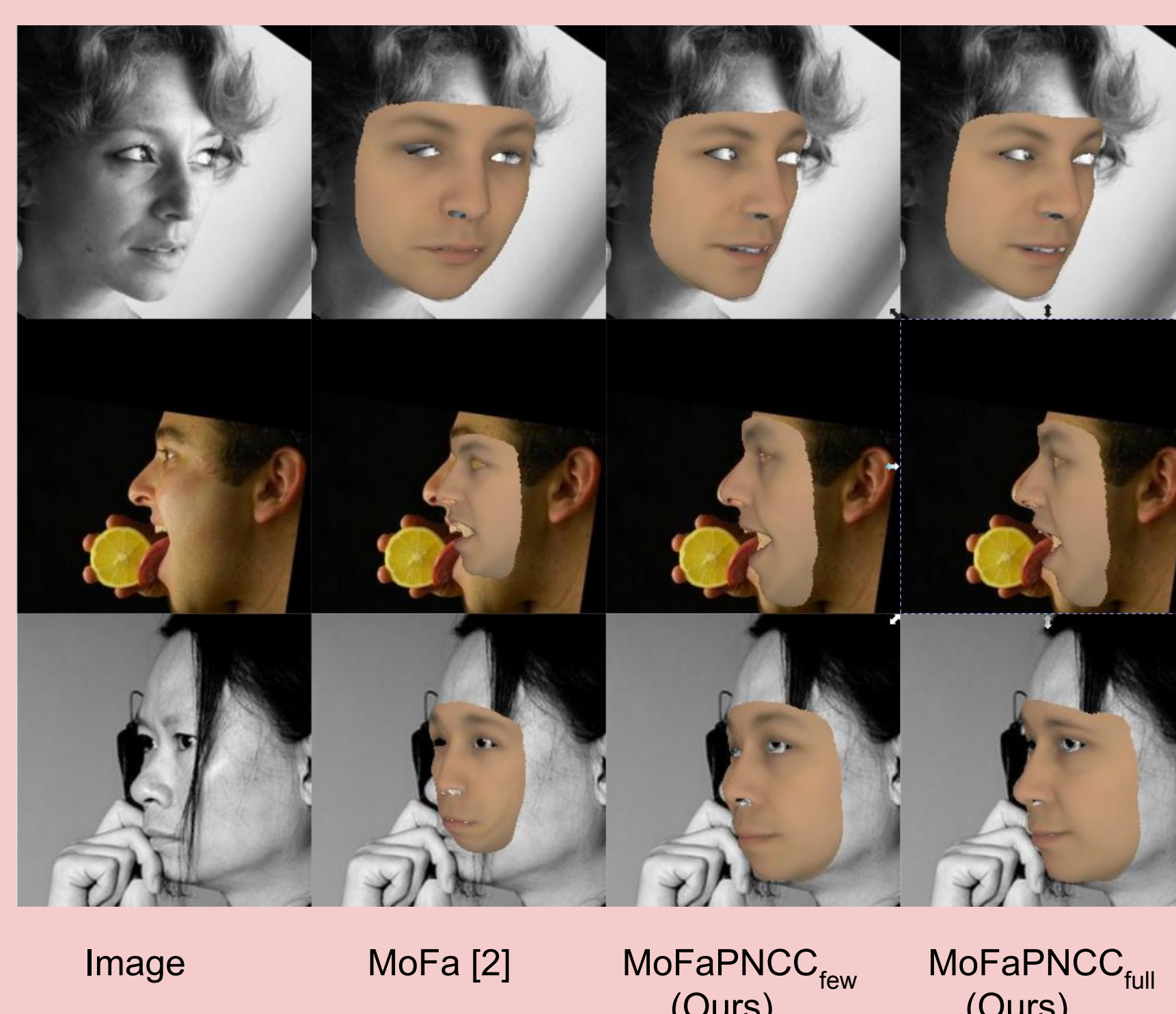
3. Results

3.1 Quantitative results

| Method | Dense 2D ↓ | Dense 3D ↓ | Yaw MAE ↓ |
|---------------------------------|------------|------------|-----------|
| MoFa [2] | 4.31 | 5.85 | 4.97 |
| MoFaPNCC _{few} (Ours) | 4.20 | 5.66 | 4.95 |
| MoFaPNCC _{full} (Ours) | 4.12 | 5.48 | 4.66 |

- MoFaPNCC_{few} uses PNCC predictions from our PNCC predictor trained with **only 50 annotated samples** of 300W-LP [1] dataset
- MoFaPNCC_{full} uses PNCC predictions from our PNCC predictor trained on the whole 300W-LP
- Both models **improve over MoFa** [2] for the **dense alignment** (Dense 2D and 3D) and **head pose** (Yaw MAE) error metrics

3.1 Qualitative results



- Our models predict better head pose and face scale

4. Conclusion

- Proposed method for 3D face reconstruction
 - **Goal: improve** the predicted **head pose** and **face scale** of self-supervised methods
 - **Context:** use **limited annotated data** (50 examples)
 - **Principle:** use the **PNCC** [1] to help the 3D face reconstruction model
- **Implementation: 2-stage pipeline**
 - **Stage 1: PNCC predictor training**
 - Based on a **pre-trained generative model**
 - Adapted to the PNCC task via the addition of **ITLs and skip-connections**.
 - Trained with **limited annotated data**
 - **Stage 2: Self-supervised 3D face reconstruction model training**
 - Predicted **PNCCs** as **additional input**
 - **Results: improved predicted head pose and face scale** compared to baseline

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References

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- [2] Ayush Tewari, Michael Zollhofer, Hyeonwoo Kim, Pablo Garrido, Florian Bernard, Patrick Perez, and Christian Theobalt. 2017. MoFa: Model-based deep convolutional face autoencoder for unsupervised monocular reconstruction. In Proceedings of the IEEE International Conference on Computer Vision Workshops. 1274–1283
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