# ShowFace: Coordinated Face Inpainting with Memory-Disentangled Refinement Networks


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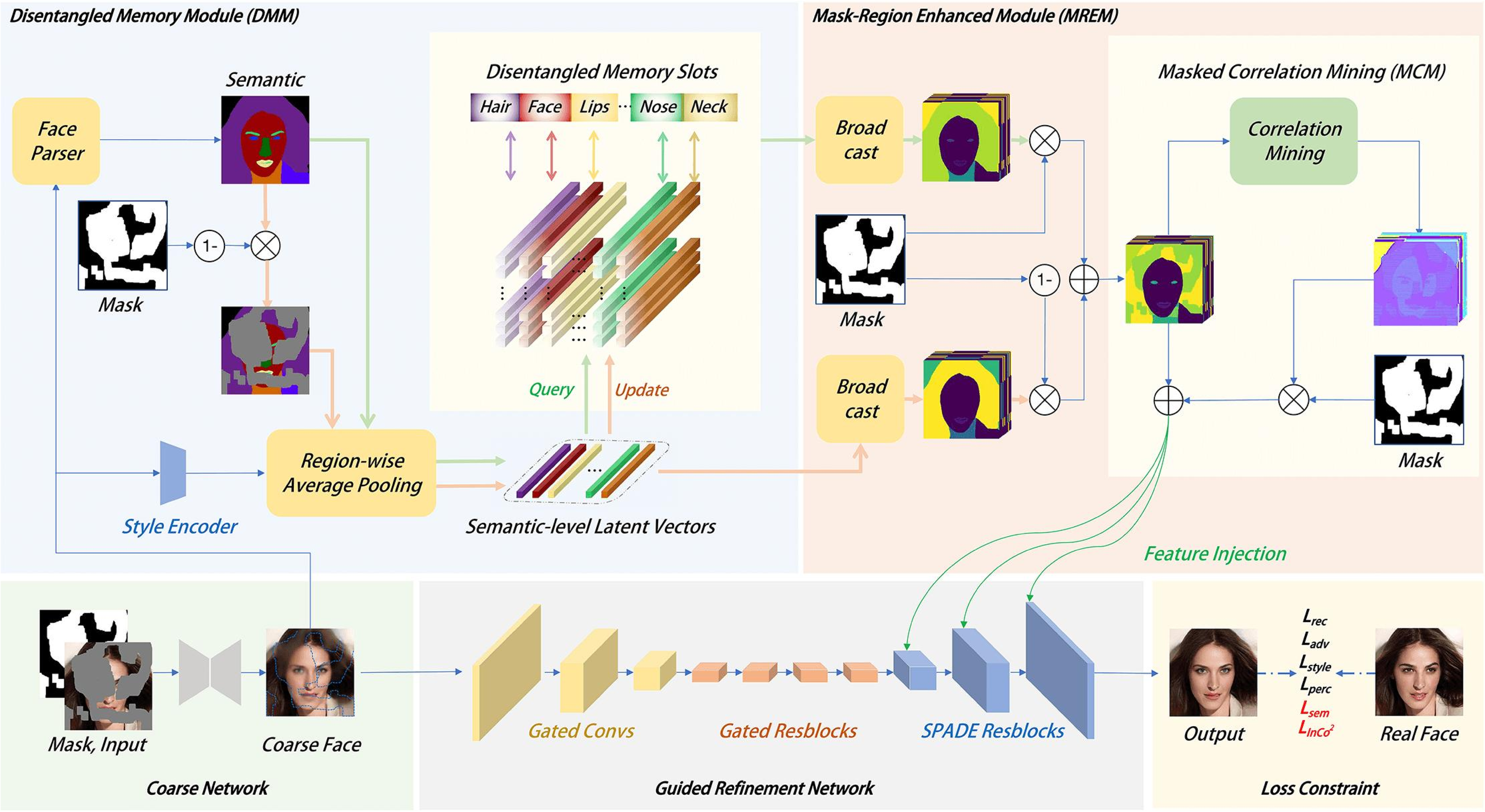
## Motivation

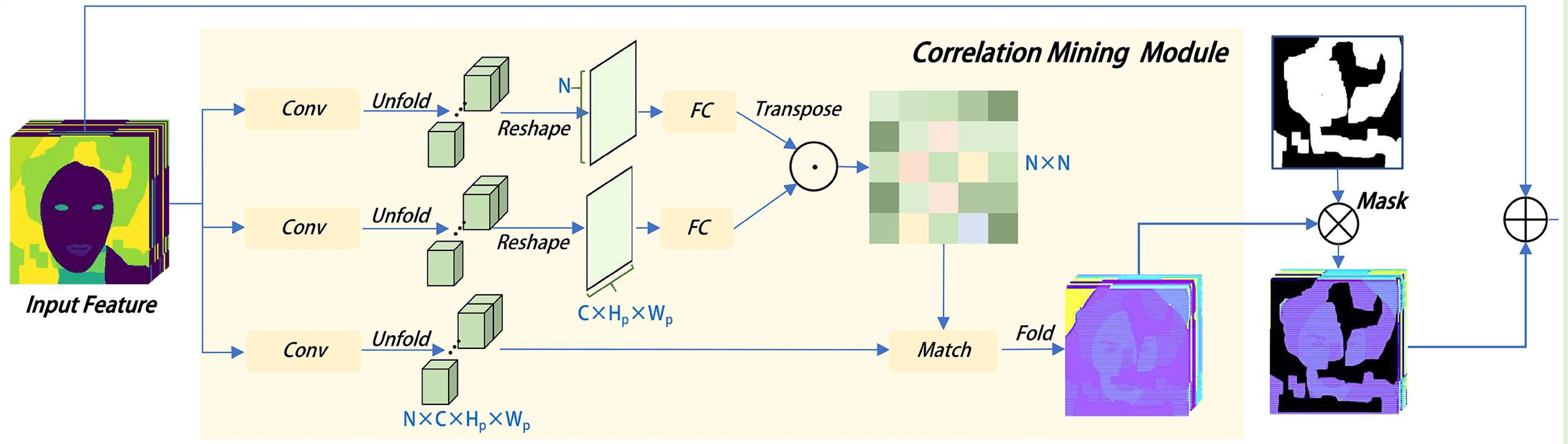
- **Face inpainting aims to complete the corrupted regions of the face images, which requires coordination between the completed areas and the non-corrupted areas.**
- **Recently, memory-oriented methods illustrate great prospects in the generation related tasks by introducing an external memory module to improve image coordination.**

## Proposed Method

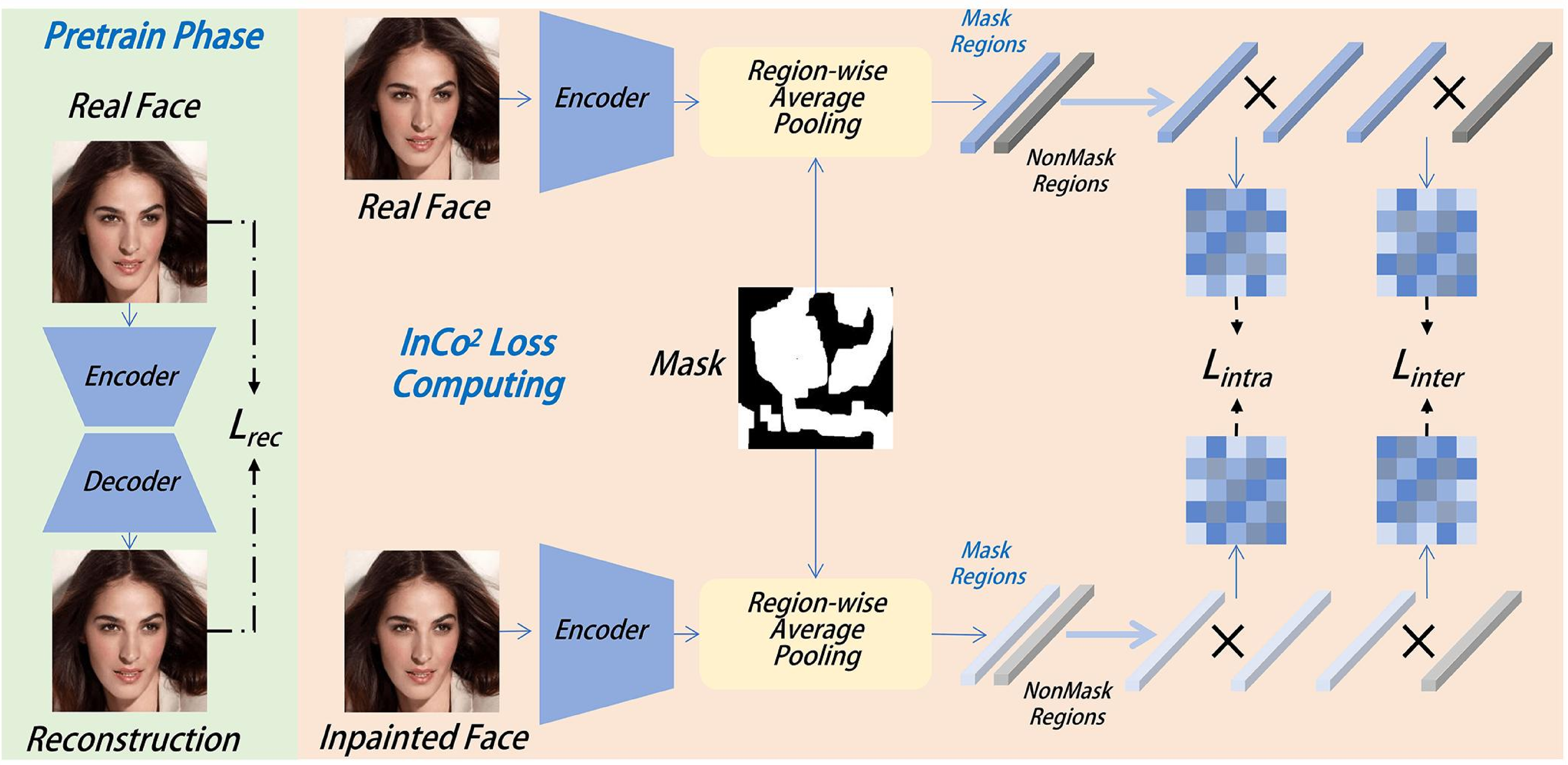
- **We propose the coarse-to-fine Memory-Disentangled Refinement Networks (MDRNets) for coordinated face inpainting, in which two collaborative modules are integrated, Disentangled Memory Module (DMM) and Mask-Region Enhanced Module (MREM).**
- **The DMM establishes a group of disentangled memory blocks to store the semantic-decoupled face representations. The MREM involves a masked correlation mining mechanism (MCM) to enhance the feature relationships into the corrupted regions.**
- **Furthermore, to better improve the inter coordination between the corrupted and non-corrupted regions and enhance the intra coordination in corrupted regions, we design InCo² Loss to constrain the feature consistency.**




*An overview of MDRNets. The MDRNets mainly consists of four steps: 1) Generate the coarse face. 2) DMM stores the semantic-level latent vectors. 3) MREM fuses the features from the DMM and constructs a correlation map to enhance the correlations into the corrupted regions. 4) The fused features after MREM are injected into the Guided Refinement Network. Furthermore, InCo2 Loss is designed to constrain the feature consistency.*




*Detailed illustration of Masked Correlation Mining.*




*Detailed illustration of InCo² Loss.*

## Fundings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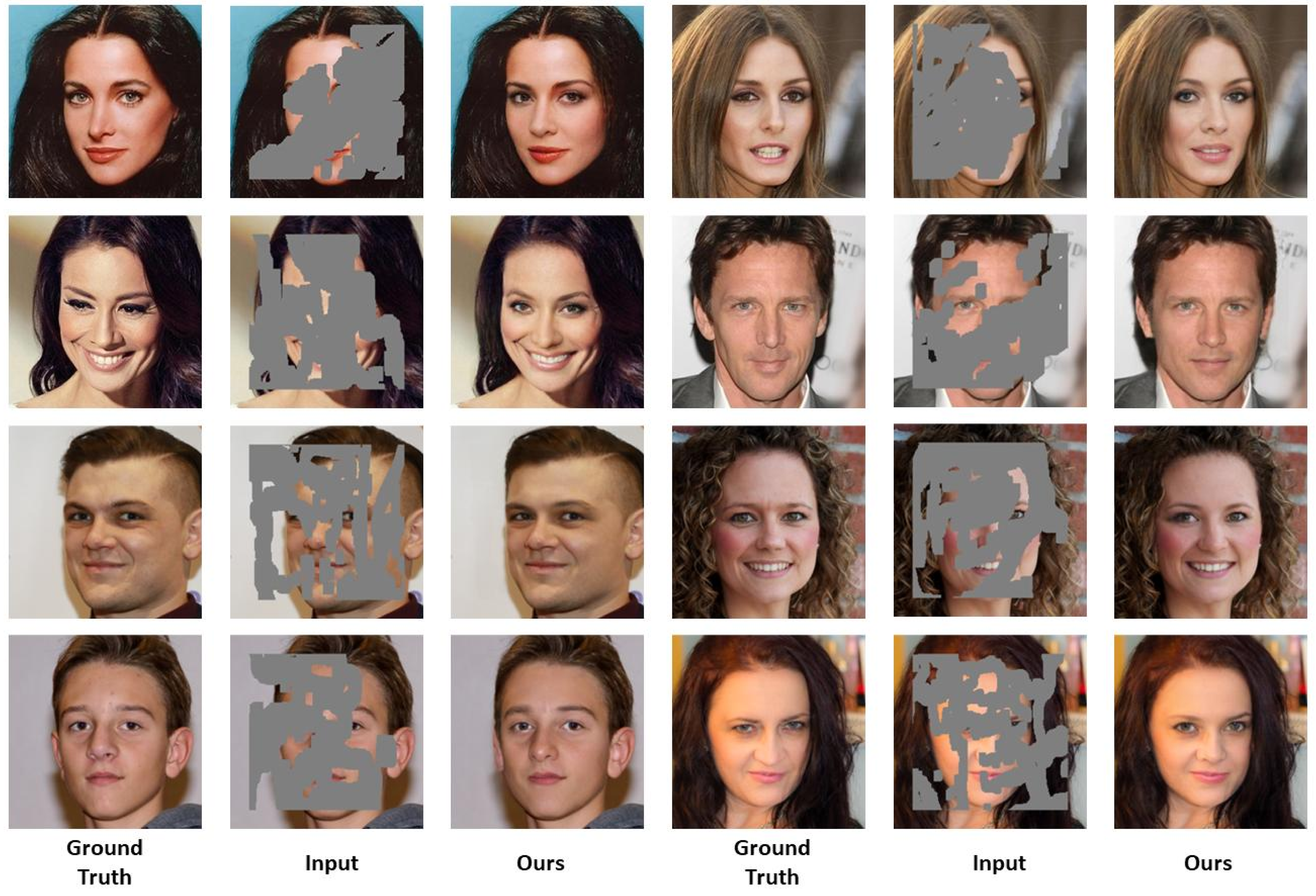
## Results




*Face inpainting results from our proposed method.*

| Methods | Dataset | L1(%)↓ | | | FID↓ | | | PSNR↑ | | | SSIM↑ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1-20% | 20-40% | 40-60% | 1-20% | 20-40% | 40-60% | 1-20% | 20-40% | 40-60% | 1-20% | 20-40% | 40-60% |
| PConv [15] | CelebA-HQ [11] | 1.131 | 2.311 | 4.363 | 12.716 | 27.957 | 42.594 | 32.240 | 26.085 | 21.900 | 0.941 | 0.862 | 0.762 |
| DeepFillv2 [37] | | 0.788 | 2.066 | 3.968 | 9.766 | 22.793 | 29.243 | 32.700 | 25.998 | 21.943 | 0.944 | 0.848 | 0.736 |
| PIC [39] | | 0.780 | 2.036 | 4.311 | 4.190 | 11.035 | 21.360 | 33.006 | 25.961 | 21.263 | 0.951 | 0.859 | 0.730 |
| CTSDG [4] | | 1.350 | 2.213 | 3.900 | 9.171 | 14.324 | 22.889 | 32.198 | 26.823 | 22.490 | 0.927 | 0.856 | 0.747 |
| DSI [22] | | 0.820 | 2.077 | 4.149 | 9.037 | 20.327 | 29.040 | 32.699 | 26.107 | 21.708 | 0.938 | 0.831 | 0.704 |
| ICT [26] | | 0.949 | 2.004 | 3.901 | 3.136 | 8.715 | 16.747 | 33.416 | 26.639 | 22.013 | 0.959 | 0.879 | 0.765 |
| Ours | | **0.585** | **1.451** | **2.937** | **2.369** | **6.410** | **12.086** | **35.772** | **28.669** | **24.177** | **0.968** | **0.900** | **0.800** |
| PConv [15] | FFHQ [12] | 0.720 | 2.178 | 4.411 | 12.208 | 30.403 | 45.709 | 32.592 | 25.422 | 21.237 | 0.955 | 0.867 | 0.761 |
| DeepFillv2 [37] | | 0.715 | 2.104 | 4.250 | 12.062 | 29.276 | 40.295 | 32.428 | 25.470 | 21.301 | 0.946 | 0.845 | 0.725 |
| PIC [39] | | 0.709 | 2.099 | 4.573 | 5.411 | 14.344 | 27.334 | 32.640 | 25.490 | 20.819 | 0.952 | 0.854 | 0.719 |
| CTSDG [4] | | **0.419** | 1.532 | 3.569 | 3.916 | 13.477 | 28.495 | 34.946 | 27.044 | 22.272 | 0.968 | 0.888 | 0.765 |
| DSI [22] | | 0.746 | 2.067 | 4.340 | 10.483 | 25.772 | 39.127 | 32.659 | 25.780 | 21.241 | 0.941 | 0.834 | 0.702 |
| ICT [26] | | 0.982 | 2.085 | 4.036 | 3.244 | 8.360 | 14.149 | 33.172 | 26.373 | 21.809 | 0.959 | 0.877 | 0.762 |
| Ours | | 0.470 | **1.395** | **3.068** | **2.473** | **7.170** | **13.748** | **36.046** | **28.333** | **23.575** | **0.972** | **0.903** | **0.797** |

*Quantitative comparisons with SOTA methods*