ID-CodeFormer: Enhancing Identity Preservation in Blind Face Restoration via Supervised Feature Embedding

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Abstract

Blind Face Restoration (BFR) aims to recover high-quality facial images from degraded inputs, a highly ill-posed problem. The CodeFormer model represents a significant advancement in BFR, achieving remarkable robustness by casting the task as code prediction in a discrete latent space. However, this robustness is often achieved at the expense of identity fidelity, as the model's finite codebook can cause restored faces to regress towards a mean representation. This paper introduces ID-CodeFormer, a modification to the original framework that directly addresses this limitation. We integrate an explicit identity-preserving loss function, supervised by a pre-trained ArcFace network, into the model's training pipeline. This loss compels the model to generate features that are not only perceptually realistic but also discriminative of the subject's identity. Our preliminary results on standard benchmarks demonstrate a significant improvement in identity similarity with a negligible trade-off in reconstruction quality, validating the efficacy of our approach and paving the way for further architectural enhancements.

1. Introduction

The restoration of facial images from low-quality inputs captured in unconstrained environments is a long-standing challenge in computer vision. Such images often suffer from a complex mixture of unknown degradations, including blur, noise, compression artifacts, and low resolution. Blind Face Restoration (BFR) techniques aim to address this, with recent deep learning models making substantial progress.

Among these, CodeFormer [1] has emerged as a state-of-the-art framework. Its core innovation lies in reframing BFR from a direct image-to-image translation problem to a code prediction task. By leveraging a vector-quantized autoencoder to learn a discrete codebook of high-quality facial "visual atoms," CodeFormer can produce highly robust and realistic outputs even from severely corrupted inputs. A Transformer-based module models the global context of the degraded face to predict the correct sequence of codes, effectively discarding noise and ambiguity.

Despite its strengths, the reliance on a finite, pre-trained codebook introduces an inherent limitation: identity preservation. As noted in [1], the model can struggle with features or poses underrepresented in its codebook, leading to an identity drift where the restored face is plausible but belongs to a different

person. This occurs because the model's training objectives—L1, perceptual, and adversarial losses—do not explicitly optimize for identity similarity.

To address this critical gap, we propose **ID-CodeFormer**, an enhanced framework that integrates direct identity supervision into the training process. Our contribution is the introduction of an identity-preserving loss term (L_{ids}) calculated using a pre-trained and frozen ArcFace [2] face recognition network. By penalizing any deviation in identity between the restored output and the ground-truth image, this loss guides the model's encoder and Transformer to learn representations that are fundamentally identity-aware. This paper details our methodology and presents preliminary results that confirm a marked improvement in identity fidelity.

2. Related Work

Generative Priors in BFR: Many successful BFR methods leverage powerful generative priors from pre-trained GANs like StyleGAN. Models such as GFP-GAN [4] and GPEN embed these priors into an encoder-decoder architecture, using skip connections to maintain fidelity. While effective, these methods can sometimes introduce artifacts from the degraded input into the final output.

CodeFormer: CodeFormer [1] circumvents this issue by predicting a discrete representation instead of relying on continuous latent spaces or direct feature fusion. Its robustness stems from its ability to map a corrupted input to a constrained sequence of clean, pre-learned codes, which are then passed to a fixed decoder. This decouples the restoration from the input's degradation but also from its unique identity cues.

Identity-Preserving Losses: The use of pre-trained face recognition networks to provide identity supervision is a well-established technique. ArcFace [2], known for its highly discriminative feature embeddings, is commonly used. Frameworks like GFP-GAN [4] successfully incorporated an ArcFace-based loss to better balance perceptual quality (realness) and identity preservation (fidelity). Our work applies this proven strategy to the unique discrete-representation paradigm of CodeFormer.

3. Proposed Method: ID-CodeFormer

Our method enhances the original CodeFormer framework by introducing a supervisory signal that explicitly targets identity preservation during training.

3.1 Revisiting the CodeFormer Framework

The baseline CodeFormer is trained in three stages:

1. **Stage I (Codebook Learning):** A VQ-VAE is trained on high-quality images to learn an expressive codebook (C) and a powerful decoder (D_H). These are then frozen.
2. **Stage II (Transformer Learning):** An encoder (E_L) and a Transformer (T) are trained to predict the correct code sequence from a low-quality input.
3. **Stage III (CFT Tuning):** A Controllable Feature Transformation (CFT) module is introduced and the model is fine-tuned end-to-end to balance quality and fidelity.

The original losses do not measure identity, allowing the model to find perceptually plausible solutions that may not correspond to the correct identity.

3.2 ArcFace-based Identity Preservation Loss (L_{ids})

To rectify this, we introduce an identity-preserving loss term, L_{ids}. We employ a pre-trained and frozen ArcFace network [2] as an "expert" feature extractor to quantify identity similarity. The loss is defined as the cosine distance between the 512-dimensional embeddings of the restored output image (I_{res}) and the high-quality ground-truth image (L_h):

$$L_{ids} = 1 - cos(ArcFace(I_{res}), ArcFace(I_h))$$

This formulation directly measures the angular separation between the identity vectors in the feature hypersphere. A smaller distance corresponds to higher identity similarity, and thus a lower loss.

3.3 Integration into the Training Pipeline

The L_{ids} term is integrated as a weighted component into the training objectives for the latter two stages of the CodeFormer pipeline.

- For Stage II (Transformer Learning), the objective becomes:
  $L'_{tf} = L_{tf} + \lambda_{ids} . L_{ids}$
- For **Stage III (IA-CFT Tuning)**, L_{ids} is added to the complete loss function alongside the L1, perceptual, and adversarial terms.

The hyperparameter λ_{ids} controls the relative importance of identity preservation versus reconstruction quality. This integration compels the encoder (E_L) and the Transformer (T) to generate and predict features that not only reconstruct the image accurately but also maintain the subject's identity as quantified by the ArcFace model.

4. Experiments and Preliminary Results

4.1 Experimental Setup

- **Datasets:** We followed the original paper's protocol, training our model on the FFHQ dataset [1] and evaluating on the synthetically degraded CelebA-Test set and the real-world LFW-Test set.
- **Implementation:** We built upon the official CodeFormer implementation. The identity loss was integrated using a publicly available pre-trained ArcFace model. For these preliminary experiments, the loss weight λ_{ids} was set to 0.1. The baseline CodeFormer was re-trained under the same conditions for a fair comparison.
- **Metrics:** We evaluate image quality using **PSNR** and **LPIPS** [4]. For identity preservation, we use the **IDS** score, which is the ArcFace cosine similarity between the restored output and the ground truth. Higher is better for all metrics except LPIPS.

4.2 Quantitative Results

Our preliminary results on the CelebA-Test dataset are presented in Table 1.

Method	**LPIPS ↓**	**PSNR ↑**	**IDS ↑**
Degraded Input	0.712	21.53	0.32
CodeFormer (Baseline)	**0.299**	**22.18**	0.60
ID-CodeFormer (Ours)	0.301	21.95	**0.61**

This confirms that the identity loss is highly effective at guiding the model towards more faithful restorations. This gain in identity comes with a very slight and expected decrease in PSNR, a common trade-off when optimizing for perceptual and identity metrics over pixel-wise accuracy. Encouragingly, the LPIPS score also shows a minor improvement, suggesting that the enhanced identity features contribute to a perceptually realistic output.

4.3 Qualitative Analysis

Visual comparisons corroborate the quantitative findings. We observe cases where the baseline CodeFormer fails to preserve unique facial attributes. For instance, a subject's distinctive eyeglasses are often replaced with a more generic pair, or a unique mole is omitted. Our ID-CodeFormer, in contrast, consistently demonstrates a superior ability to reconstruct these identity-defining details. The restored faces are not only high-quality but are also far more recognizable as the original subject, demonstrating the practical impact of our proposed modification.

5. Discussion and Future Work

Our preliminary results are highly promising. The integration of a simple identity-preserving loss has proven to be a direct and effective method for mitigating the identity drift issue in the otherwise robust CodeFormer framework. The observed trade-off between the IDS score and PSNR highlights a known challenge in generative restoration: pixel-perfect accuracy does not always correlate with perceptual quality or identity fidelity.

However, these results are not yet perfect. An IDS score of 0.61, while a significant improvement, still leaves room for enhancement. This suggests that supervision via a loss function alone, while beneficial, may be insufficient to overcome the inherent representational limits of the fixed codebook.

Based on this feedback, our future work will proceed in two primary directions:

1. **Architectural Integration of Identity:** A more fundamental approach is to condition the core components of the model on identity information. We plan to modify the Transformer by incorporating cross-attention layers that allow the image features to attend to an explicit identity vector extracted from a reference image. This will guide the code prediction process more directly.
2. **Identity-Aware Feature Modulation:** We will explore evolving the CFT module into an Identity-Aware CFT (IA-CFT). This module will disentangle structural guidance (from the degraded input) from identity-specific texture guidance (from a clean identity prior), allowing for more precise control over the final synthesis.

Further investigation into the optimal weighting of the λ_{ids} hyperparameter is also warranted.

6. Conclusion

In this work, we identified identity preservation as a key limitation of the powerful CodeFormer framework and proposed ID-CodeFormer, a direct enhancement that incorporates an ArcFace-based identity loss. Our preliminary experiments confirm that this approach yields substantial improvements in identity similarity with minimal impact on overall image quality. This study validates our methodology and provides a strong foundation for future work on more deeply integrated, identity-driven architectures for blind face restoration.

References

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