





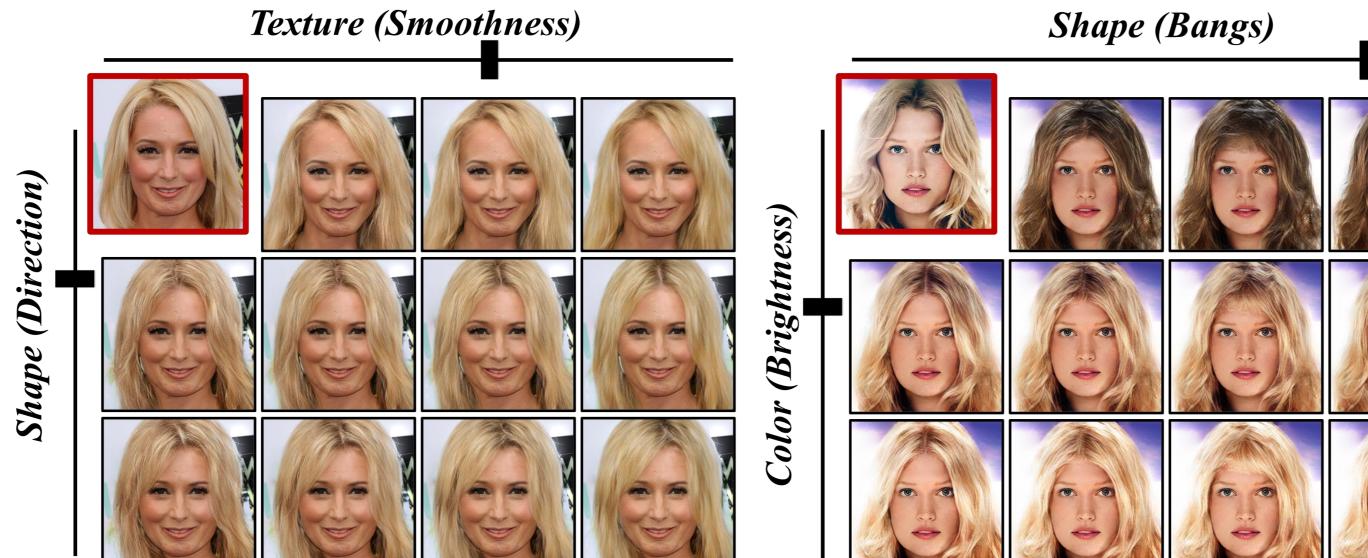


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## 3. Training Objectives

Reconstruction Loss: constrain the Realism correctness of the attribute editing (GAN) Loss

Distribution Loss: model each representation as a Gaussian

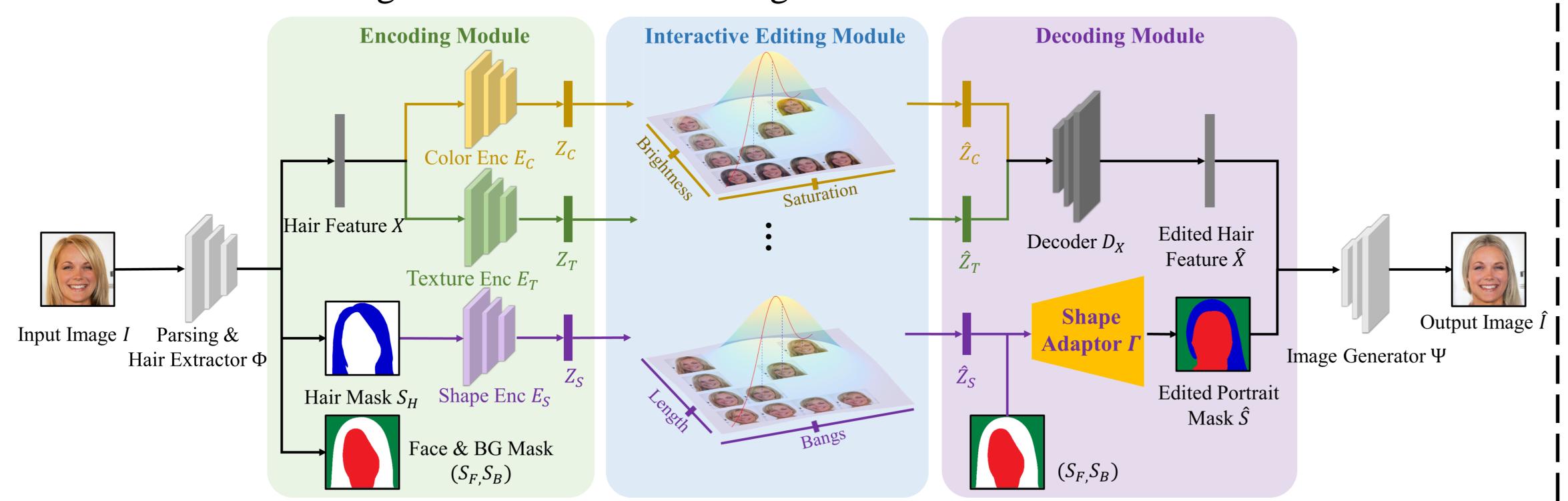
$$\mathcal{L} = \lambda^{real} \mathcal{L}^{real} + \sum_{k \in \{C, T, S\}} (\lambda_k^{rec} \mathcal{L}_k^{rec} + \lambda_k^{dist} \mathcal{L}_k^{dist})$$

Different forms respecting to the natures of each attribute

• Color: supervised • Texture: unsupervised • Shape: supervised with shape adaptor

#### 2. Method

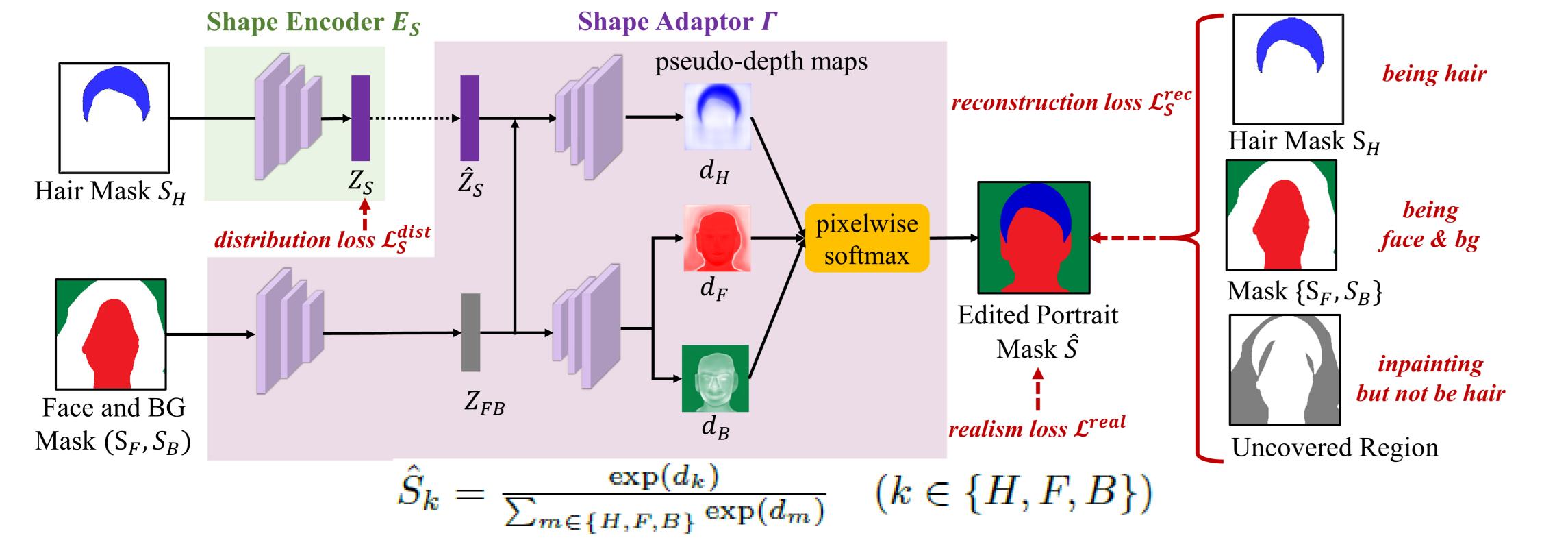
• Disentangle hair into three attribute representations: color  $Z_C$ , texture  $Z_T$  and shape  $Z_S$ . Model each representation as a standard multivariate Gaussian distribution for continuous editing within a reasonable range of values



Interactive editing

$$(Z_C, Z_T, Z_S) \xrightarrow{f_{\text{sliding bars}}; f_{\text{references}}; f_{\text{painted mask}}} (\hat{Z}_C, \hat{Z}_T, \hat{Z}_S)$$

• A learning-based shape adaptor for hair alignment and face inpainting

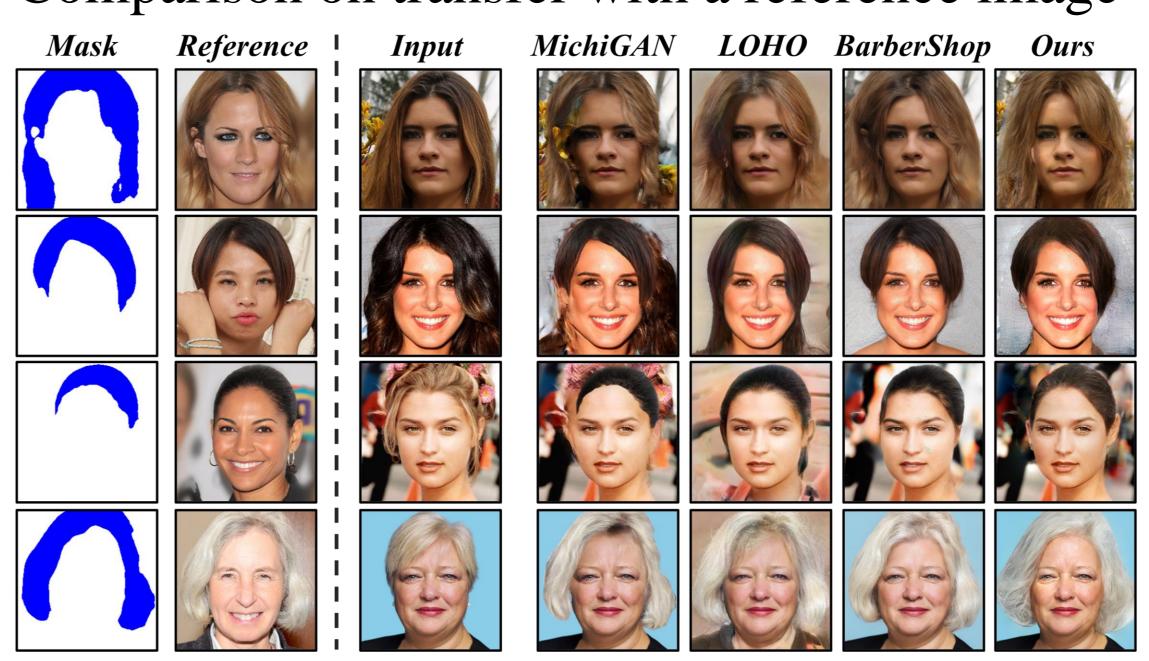


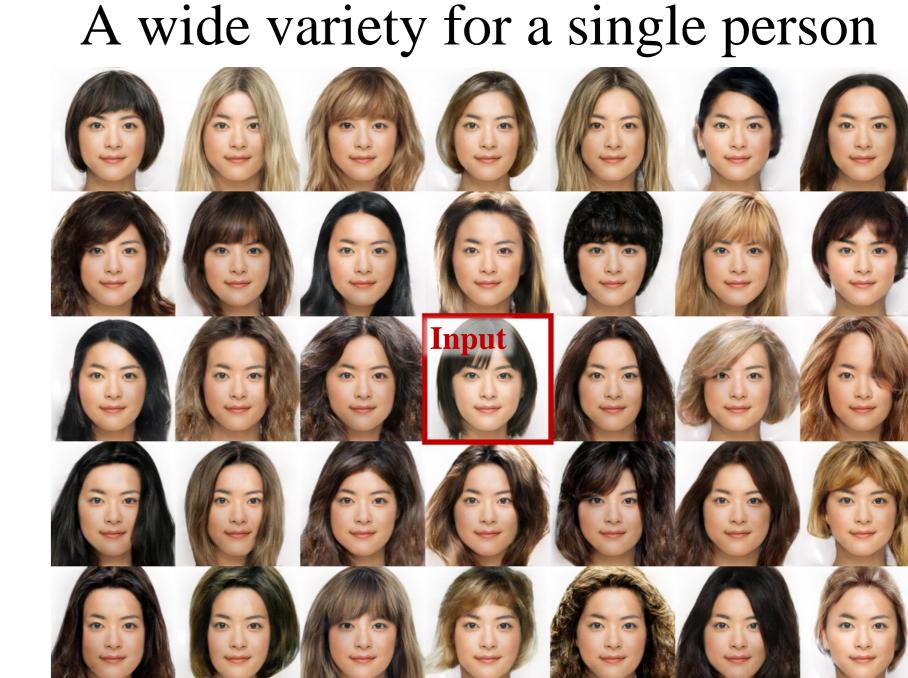
## 4. Experiments

## Comparison of Functionality of different methods

Functionality	MichiGAN [24]	LOHO [21]	BarberShop [28]	CtrlHair (ours)
Interaction Mode	references	references	references	$\operatorname{references}$
	painted mask		painted mask	painted mask
	$\operatorname{sketch}$			sliding bars
Editing Flexiblity	coarse, discrete			fine-grained, continuous
Shape Editing	replace directly			shape adaptor

#### Comparison on transfer with a reference image





#### Continuous and fine-grained editing

