Face editing using a regression-based approach in the StyleGAN latent space

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Goal

Changing a face attribute without changing any of the other attributes and identity.

How

- Encoding the face into a latent space of StyleGAN.
- Finding an appropriate editing direction in a latent space of StyleGAN.
- Applying the editing direction to the face latent code.
- Generating the edited image using the modified latent code.

Our Novelty

Finding an appropriate editing direction in a latent space of StyleGAN.

Approach

- A recent research has shown that the StyleGAN latent space contains smooth linear directions that allow the creation of a regression model for attributes.
- It means that it is possible to produce real-world predictions (y), e.g. age in years or head pose in degrees given a face latent code (x) using a linear regression (W):

$$y = W.x$$

- Therefor, the direction (W) for a given attribute can be found by:

$$W^* = \underset{W}{\operatorname{argmin}} L(S) = \|W^T X - Y\|_2 \quad (1)$$

$$Y = [y_1, y_2, \ldots, y_N] \quad X = [x_1, x_2, \ldots, x_N]$$

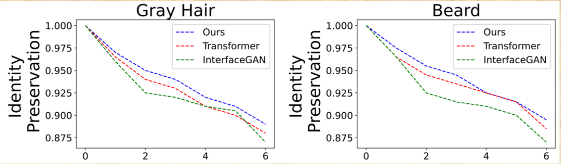
- Where x_i is the latent vector of the i-th image in the dataset, y_i is the value for the target attribute, and N is the number of images in training.
- This suggests that if we move in the attribute's linear latent direction, the amount of the corresponding attribute of a given image would change.

$$\begin{aligned} y_2 &= W^T \cdot (x + \alpha W) \\ &= W^T \cdot x + \alpha W^T \cdot W = y_1 + \alpha \end{aligned}$$

Approach

- However, it does not mean that other attributes do not change. Equation (1) has many solutions, but we are only interested in those that do not change other attributes.
- We can restrict the system to solutions that retain the identity of the person and minimize the changes to other attributes by adding regularizers to the optimization criteria:
- **Weight magnitude** regularizers based on the L_1 and L_2 metrics.
- **Orthogonality regularization** between attribute directions to encourage disentanglement.

Results



A quantitative comparison of identity preservation. Our methods shows less identity change compared to the state of the art.

Results