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 \( (W) \):

\[
y = W \cdot x
\]

Therefore, the direction \( (W) \) for a given attribute can be found by:

\[
W^* = \arg\min_W L(S) = \|W^T X - Y\|_2
\]

\[
Y = [y_1, y_2, \ldots, y_N]
\]

\[
X = [x_1, x_2, \ldots, x_N]
\]

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:

\[
y_2 = W^T \cdot (x + \alpha W)
\]

\[
= W^T \cdot x + \alpha W^T \cdot W = y_1 + \alpha
\]

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.