

Deep Feature Interpolation for Image Content Changes

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Why are image content transformations inspirational?

**“When the image is new, the world is new.”
Gaston Bachelard, The Poetics of Space**



Why are image content transformations inspirational?

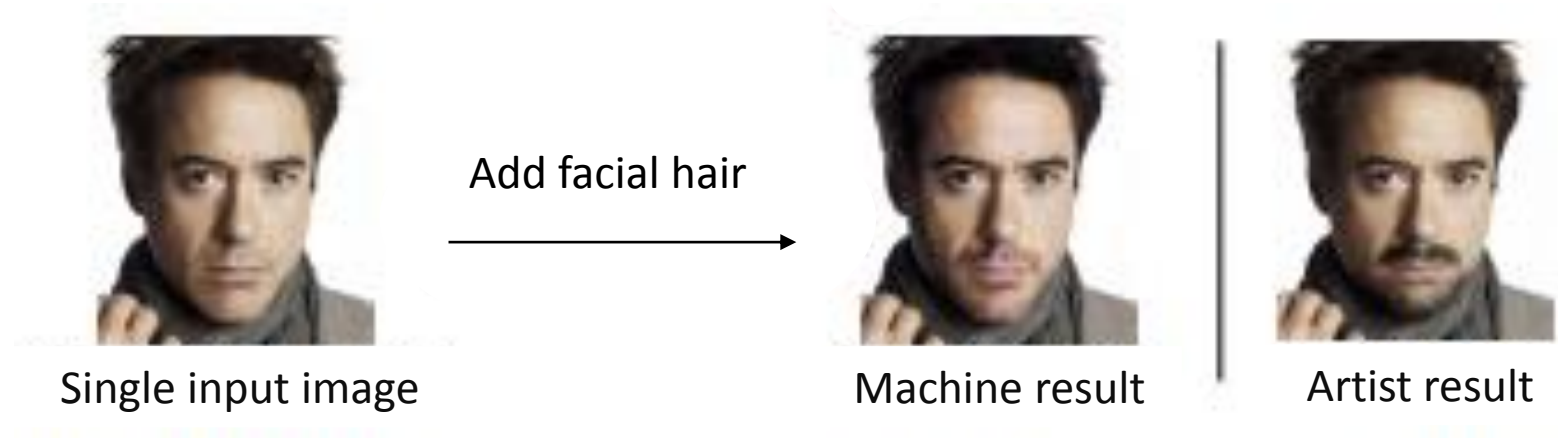


Fig.1 Editing image content [1]



Why are image content transformations inspirational?

- Active and challenging research area in computer vision and graphics
- Semantic transformation -> answers to questions: 'What if...?'
- Realistic results
- Applications
- Image inpainting



Related work

- Generative methods: Larsen et al. (2015) [2] and Radford et al. (2016) [3]
- Manipulation of latent space variables [4]
- Minimizing the witness function of MMD: Gardner et al. (2015) [5]
- Optimization of feature targets during reconstruction: Gatys et al. (2015) [6]
- Combination of several vision methods [7]



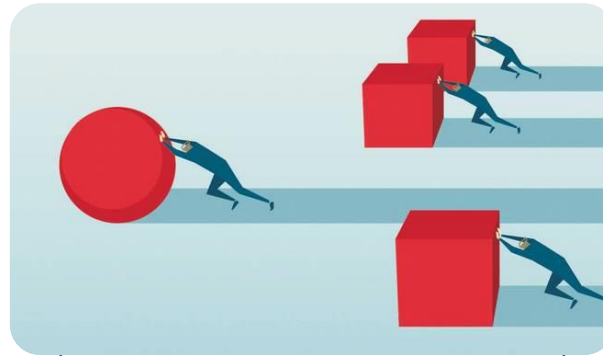
Motivation



Simple



Versatile



Fast



Deep Feature Interpolation

Notations:

x – test image

z – output image

$S^t = \{x_1^t, \dots, x_n^t\}$ – a set of target images with the desired attribute

$S^s = \{x_1^s, \dots, x_m^s\}$ – a set of source images without the attribute

$x \rightarrow \varphi(x)^*$ – obtaining a new representation of an image

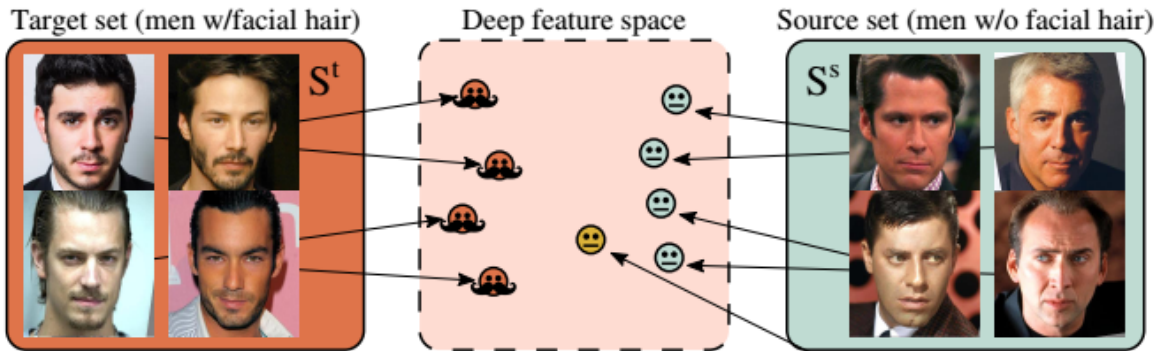
$\varphi(x)$ – a vector consisting of concatenated activations of the convnet* when applied to image x

*Provided with pre-trained VGG network

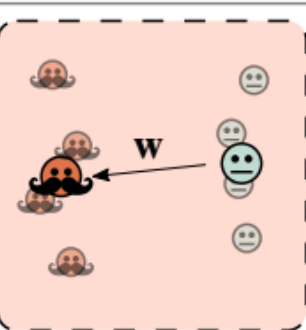
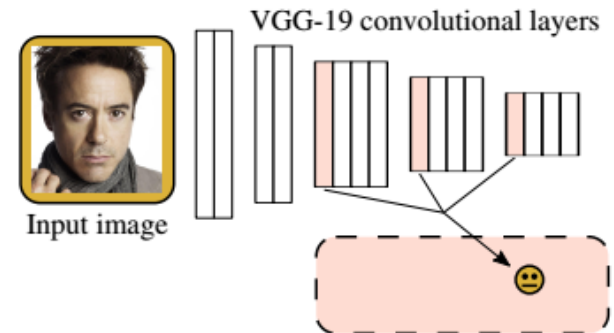


Algorithm:

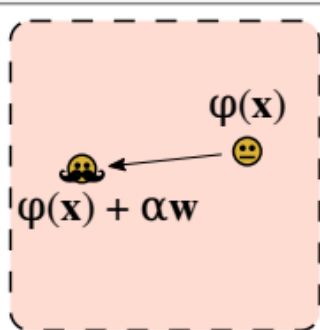
Step 1: Map images to deep feature space



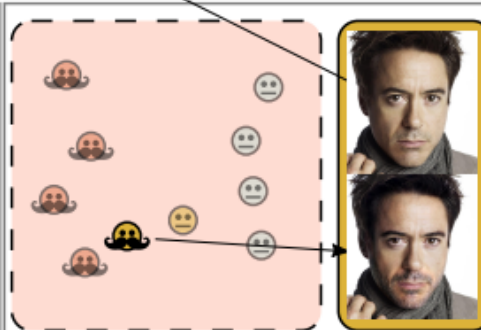
Step 1: Mapping details



Step 2: Compute attribute vector



Step 3: Interpolate in feature space



Step 4: Reverse mapping details

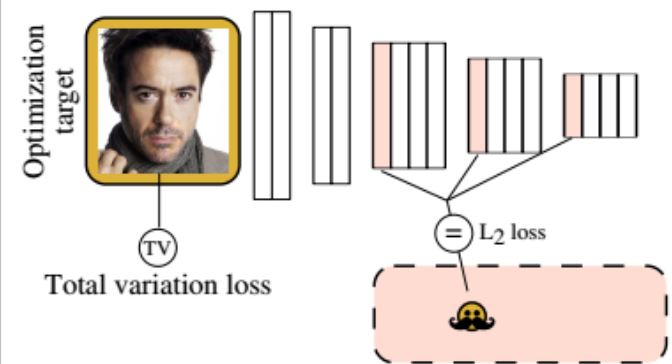


Fig.2 A schematic outline of DFI [1]

Details of the procedure:

- Selecting S^t and S^s
 - Assumption: the attribute vector w isolates the targeted information
 - $w = \varphi(z) - \varphi(x)$
 - Both sets should be as similar as possible
 - To ensure sufficient similarity, restrict to the K nearest neighbors of S^t to $\varphi(x)$
 - $\bar{\varphi}^t = \frac{1}{K} \sum_{x^t \in N_K^t} \varphi(x^t)$ and $\bar{\varphi}^s = \frac{1}{K} \sum_{x^s \in N_K^s} \varphi(x^s)$
- Deep feature mapping
 - The deep feature space should be suitable for:
 - linear interpolation
 - reverse mapping back into pixel space

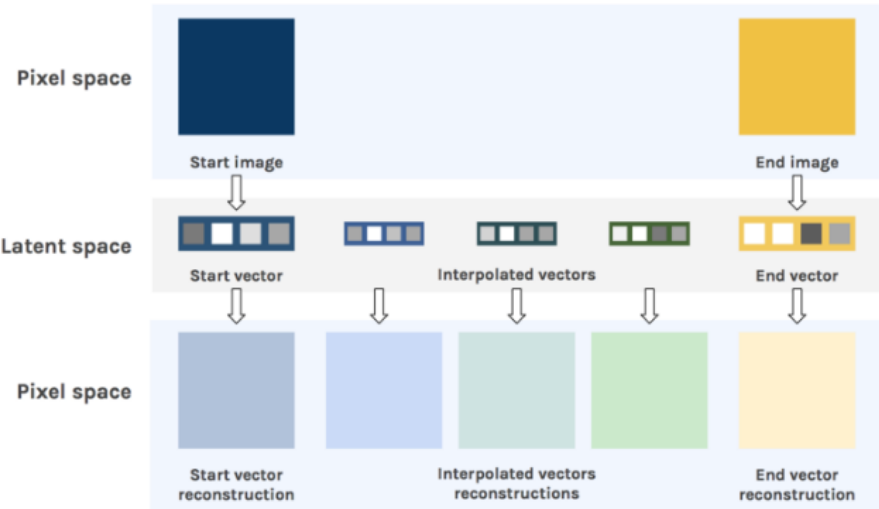


Details of the procedure:

- Image transformation
 - $\bar{\varphi}^t$ and $\bar{\varphi}^s$ will have very small components in most features
 - Features unrelated to the target attribute will be averaged to very small values and approximately subtracted away in the vector w
- Reverse mapping
 - $z = \operatorname{argmin}_z \frac{1}{2} \|(\varphi(x) + \alpha w) - \varphi(z)\|_2^2 + \lambda_{V\beta} R_{V\beta}(z)$
 - $R_{V\beta}$ - total variation regularizer
 - $R_{V\beta}(z) = \sum_{i,j} ((z_{i,j+1} - z_{i,j})^2 + (z_{i+1,j} - z_{i,j})^2)^{\frac{\beta}{2}}$
 - $\lambda_{V\beta} = 0.001$ and $\beta = 2$



Algorithm:



Interpolation in Latent Space



Fig.3 Interpolation in latent space [8]



Experimental results

Dataset

- Labeled Faces in the Wild (LFW)
 - 13, 143 images of faces
 - Predicted annotations for 73 different attributes
 - Six attributes for testing
 - senior, mouth open, eyes open, smiling, moustache, eyeglasses
- A high resolution dataset from CelebA, MegaFace and Helen + Google image search
- A shoes subset of UT Zappos50k





Original

Deep Feature Interpolation

AEGAN



Experimental results

older	mouth open	eyes open	smiling	moustache	glasses
4.57	7.09	17.6	20.6	24.5	38.3

Table.1 Perceptual study results [1]



Experimental results



Fig.4 Editing high resolution images [1]



Experimental results



Fig.5 Inpainting. LFW faces [1]



Experimental results



Fig.6 Inpainting. UT Zappos50k shoes [1]



Varying free parameters

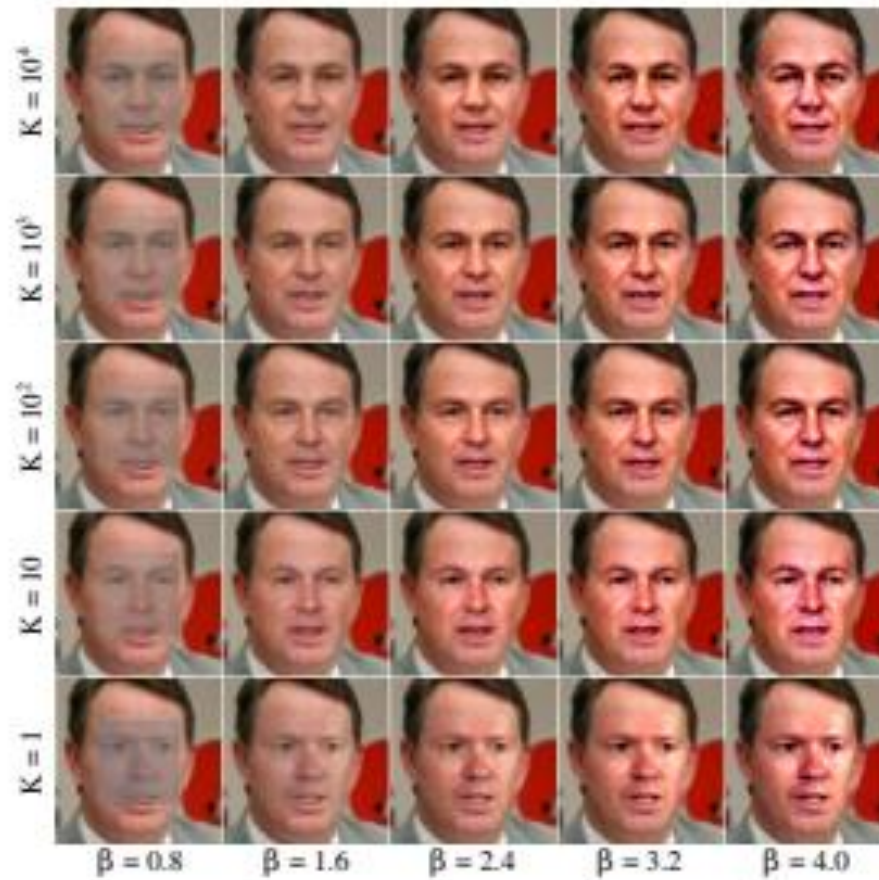


Fig.7 The effect of changing β and K [1]



Varying free parameters

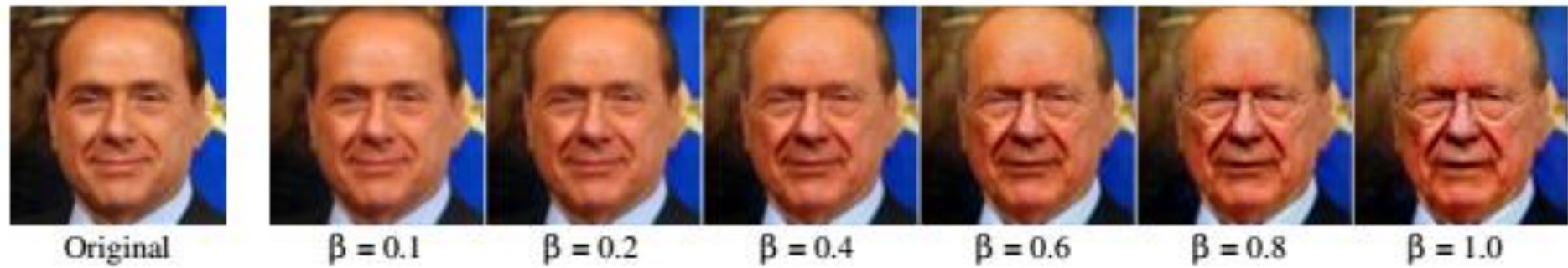


Fig.8 The effect of changing β [1]



Limitations

- Image alignment
- DFI is incapable of shape or rotation transformations
- Sample images have to be similar to target image
- DFI is unable to reconstruct the image properly when the masked region is a half of the image
- DFI is not powerful enough for complex tasks



Fig.9 DFI results of an image with the right half missing [1]



Summary

- Wide range image transformations
- Can be used as a baseline method
- According to the authors DFI is the first algorithm to enable automated high resolution content transformations

Future work

- Possibility to incorporate techniques from real-time style transfer to speed-up DFI



Thank you for your attention!
Questions?



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- [3] A. Radford, L. Metz, S.Chintala (2016) Unsupervised representation learning with deep convolutional generative adversarial networks.

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- [7] S. Suwajanakorn, S.M. Seitz, I. Kemelmacher-Shlizerman (2015) What makes Tom Hanks look like Tom Hanks.
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- [14] <https://www.iconspng.com/image/52040/tortoise-and-hare-fast-and-slow>