# Style Transfer for Headshot Portraits

**Team Name: A3D** 

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Repo URL: <u>a3d-link</u>

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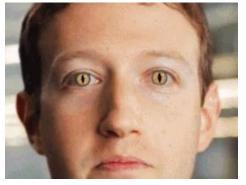
## **Objective**

The main objective of our project is to transfer the visual style of the example portrait made by an artist onto another image, which basically means to match the appearance of the input subject to the

example.



# **Motivation**



The editing process to create different renditions of headshot photos to achieve a compelling style requires advanced skills because features such as the eyes, the eyebrows, the skin, the mouth and the hair, all require specific treatments.



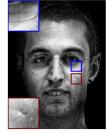
The tolerance for errors is low, and one bad adjustment can quickly turn a great headshot into an uncanny image. Many compelling looks require maintaining a visually pleasing appearance while applying extreme adjustments.

# **Understanding of the Paper**









(c) Without robust transfer



(d) Our robust transfer

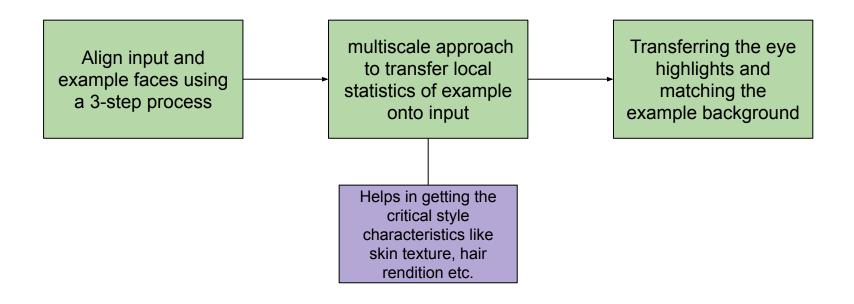
The paper uses a multiscale technique to robustly transfer the local statistics of an example portrait onto a new one. This technique matches properties such as the local contrast and the overall lighting direction while being tolerant to the unavoidable differences between the faces of two different people.

All the facial features are treated differently on the basis of characteristics like lighting etc., this challenge is overcome by an approach specific to faces.

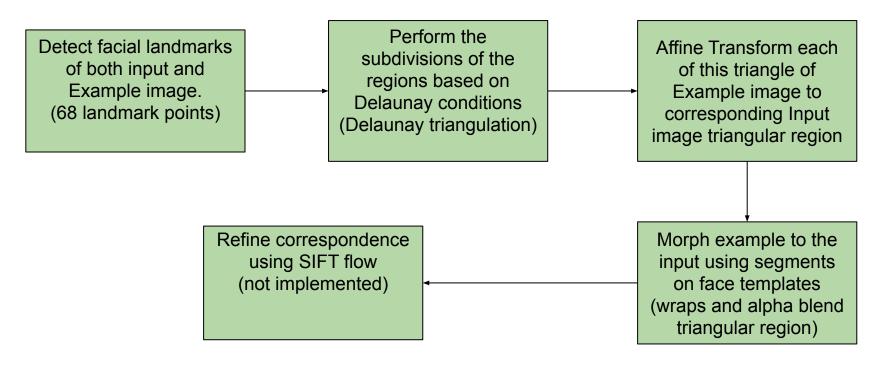
#### Our Notes

:https://github.com/Digital-Image-Processing-IIITH/dip-m22-project-a3d/ blob/main/docs/Paper Notes.pdf

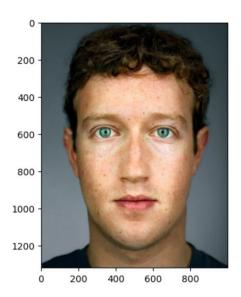
## Approach



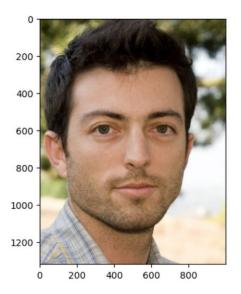
## Dense Correspondence Approach

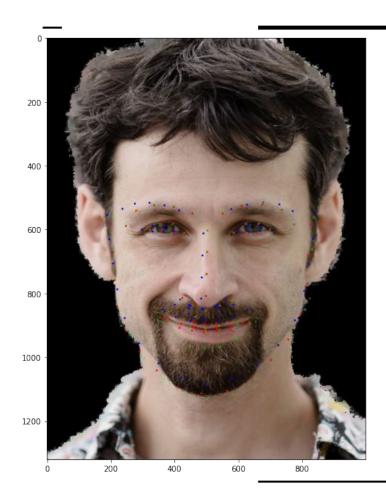


# **Example Image**



# Input Image



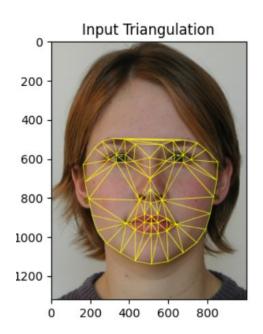


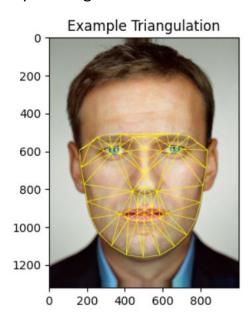
Comparison of 3 different techniques of landmark detection

Blue landmarks -> dataset landmarks Green landmarks -> OpenCV Red landmarks -> Dilib

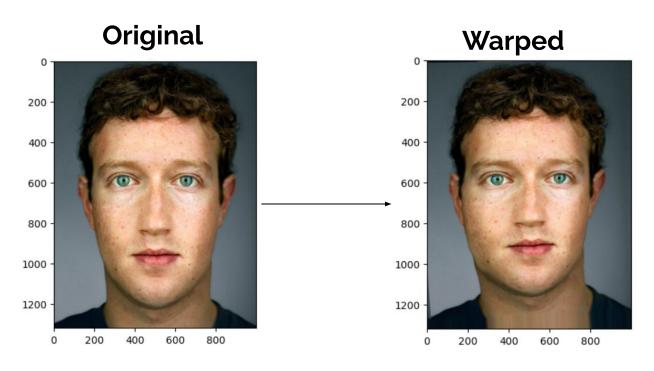
# **Triangulation Outputs**

Below are the Delaunay triangulation outputs we got

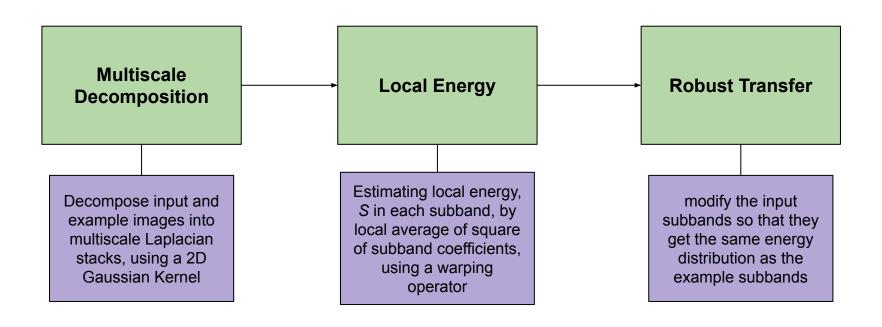




# **Warped Outputs**

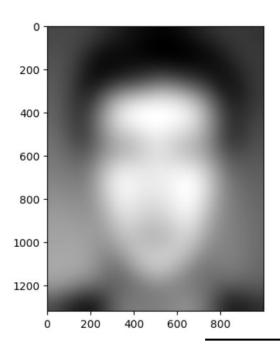


## Multiscale Approach

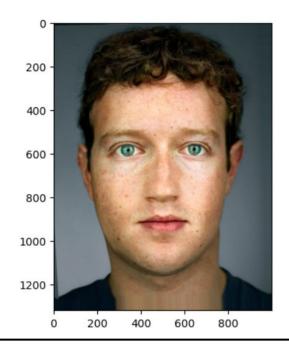


#### **Residual Image Output**

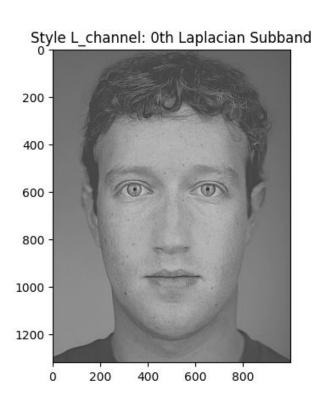
$$R[I] = I \otimes G(2^n)$$
 with n levels

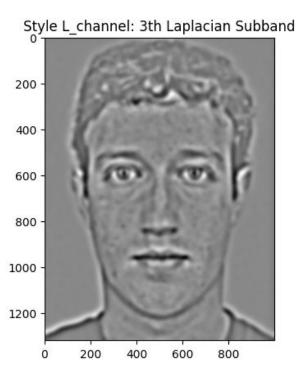


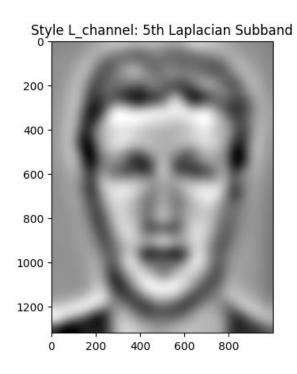
#### **Warped Image Output**



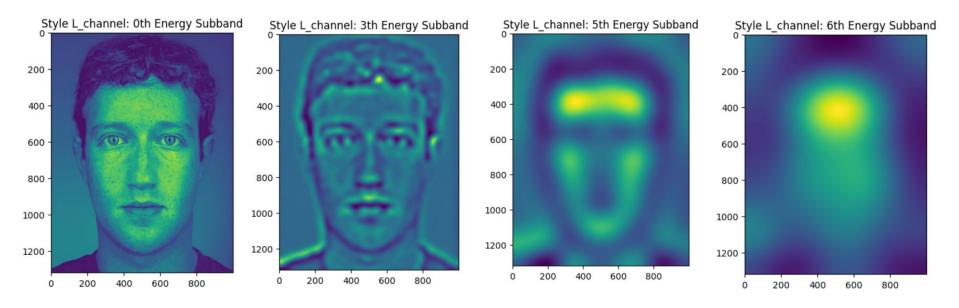
# **Multiscale Laplacian Stacks**







#### —Local Energy Subbands



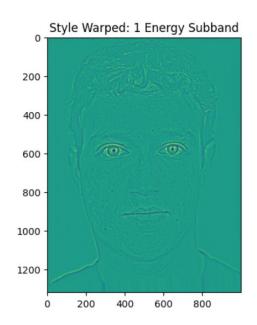
#### **Energy Maps**

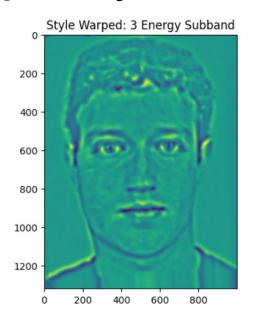
$$S_{\ell}[I] = L_{\ell}^{2}[I] \otimes G(2^{\ell+1})$$

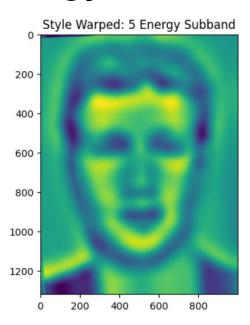
$$\tilde{S}_{\ell}[E] = W(S_{\ell}[E])$$

Computing local energy for both images using the given equation, which allows to capture the frequency profiles in the images. These energy maps get the strengths in lighting and color

# Warped Style Local Energy Subband



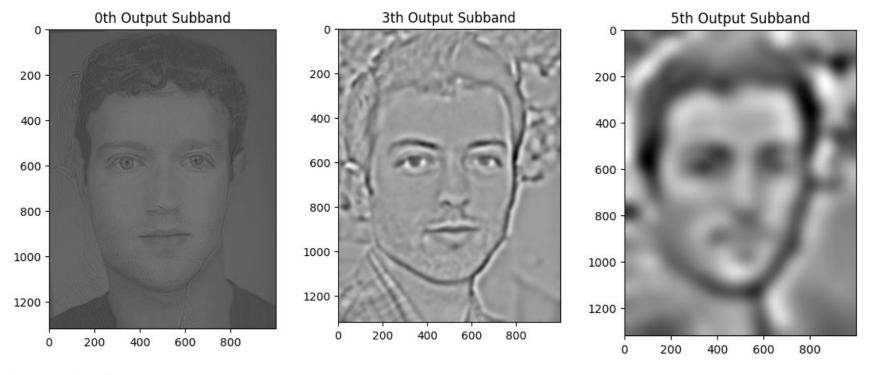




$$\tilde{S}_{\ell}[E] = W(S_{\ell}[E]) \longrightarrow$$
 Warping operator

$$R[O] = W(R[E])$$
 It gives Warped example residual

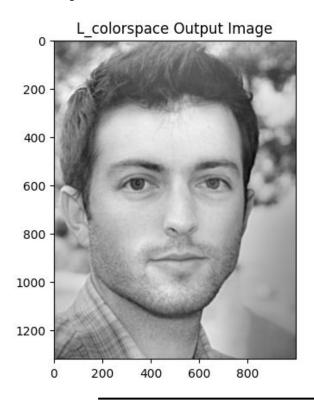
#### Robust Transfer -

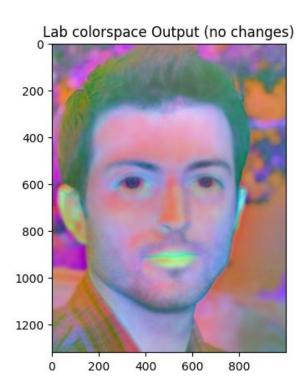


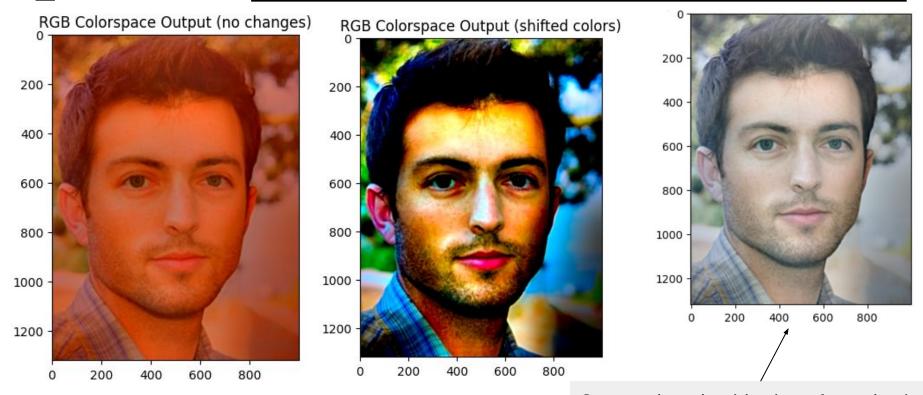
 $L_\ell[O] = L_\ell[I] imes \mathrm{Gain}$  with  $\mathrm{Gain} = \sqrt{rac{ ilde{S}_\ell[E]}{S_\ell[I] + \epsilon}}$ 

we modify the input subbands so that they get the same energy distribution as the example subband

#### **Aggregate Outputs**



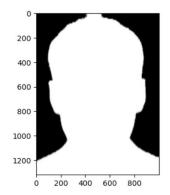




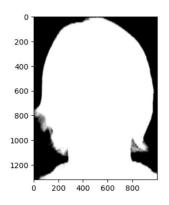
Output when algorithm is performed strictly on just RGB colorspace instead of LAB

#### Post Processing

#### **Example Image**

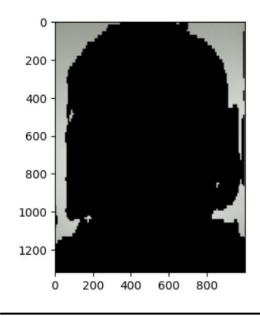


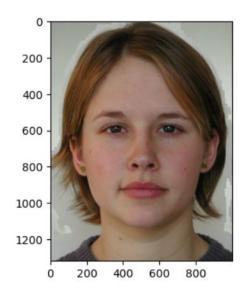
#### Input Image



#### Background - Replacing input background with example background

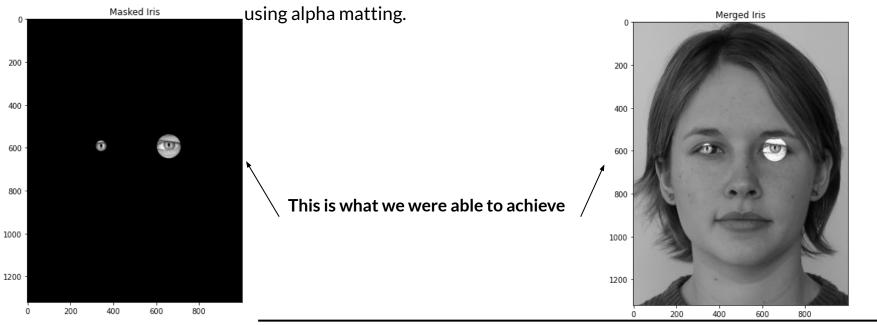
Get masks — → get background → replace background → get imperfection mask — → image implanting





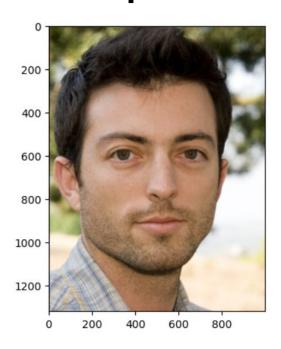
#### Post Processing

**Eye Highlights** (couldn't implement it fully) - Separating the specular reflection from the example eyeball and copy that onto input's eyes. This involved: -

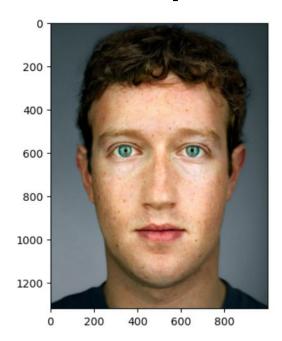


### **Final**

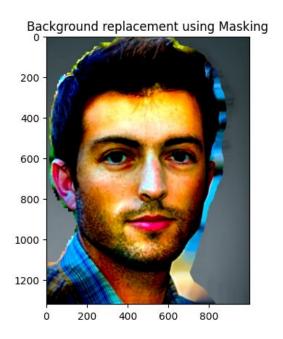
# Input



# Example



# Output











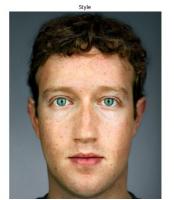
Adding Background Mask







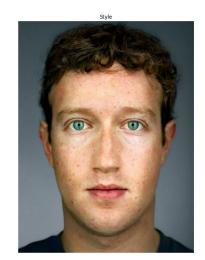








Adding Background Mask















Adding Background Mask













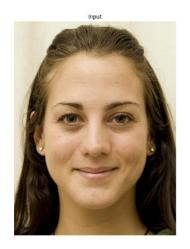


Adding Background Mask















Adding Background Mask





















#### Limitations

- Results of style transfer are affected since conversion from LAB to RGB colorspace is not done properly, but using the algorithm in RGB colorspace strictly gives us surprisingly good results
- Not able to get the complete background transfer from example to input when there is low contrast.
- Not able to eliminate hair features from style images properly
- Doesn't work properly when huge difference in skin colors
- Low lighting doesn't low style features to get eliminated easily

#### **Contributions**

Adhiraj Deshmukh - Paper readings, dense correspondence, energy maps (multiscale transfer), combining all outputs

Aparna Agarwal - Paper readings, laplacian stacks; energy maps (multiscale transfer), background (post processing)

Anjali Singh - Paper Readings, multiscale decomposition (multiscale transfer), background; Eye highlights (Post processing), ppt work

Deepthi Chandak - Paper readings, eye highlights, ppt work

#### **Dataset**

Link to the dataset: <u>click here to download</u>

# Thank You:)