Beyond Colour Matching for Makeup Transfer

Team 13:

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Introduction

- Among the many face beautification techniques, makeup application is the most popular one.
- Makeup transfer is the process of transferring makeup features from one reference face to another.
- There are challenges involved like: accurately extracting features from the face, retaining the shape and appearance of the makeup and accommodating extreme makeup styles.
- Our model aims to build a makeup transfer method that works for both light and extreme makeup styles; deal with complicated makeup patterns, be robust to head pose, and produce high-quality outputs.

Problem Statement

Makeup transfer is that the task of applying on a supply face the makeup vogue from a reference image. With makeup recognition, the makeup test can be a very important application in all commercial and recreational activities, however it is still difficult due to the variety of makeup combinations. The generated models based on deep learning do not give satisfactory results.

So, we target to remodel the colour distribution whereas conjointly protective the form and look of the makeup pattern.

Objectives

- To transfer makeup style while retaining the natural face features.
- To account for different scenarios of makeup transfer
- To develop a comprehensive makeup transfer method that works for both light and extreme styles.
- To retain the original shape and quality of the facial image
- To introduce new makeup transfer datasets
- To successfully transfer the face blushes to capture the glowing skin foundation.
- To obtain state-of-the-art quantitative and qualitative performance.

Literature Survey

Photo-Realistic Facial Details Synthesis From Single Image (2019)

- Anpei Chen, Zhang Chen, Guli Zhang, Kenny Mitchell, Jingyi Yu

- Provides high-fidelity proxy geometry and fine geometric details based on emotional cues, expressions, appearance, and lighting.
- Their technique can produce, from a single image, ultra high quality 3D faces with fine geometric details under various expressions and lighting conditions.
- Their model generates realistic facial features like wrinkles.

Issues:

- There was no consideration of occlusions, hard shadows, which could lead to incorrect displacement estimations.
- Because it's reliant on accurate pixel appearance distributions, geometric detail prediction can't handle low resolution images.

Literature Survey

PSGAN: Pose and Expression Robust Spatial-Aware GAN for Customizable Makeup Transfer (2019)

- Wentao Jiang, Si Liu, Chen Gao, Jie Cao, Ran He, Jiashi Feng, Shuicheng Yan

- Additionally, PSGAN can modify the shade of makeup transfer by virtue of its spatial-aware makeup matrices, substantially extending the application range of makeup transfer.
- Capable of handling various expressions and poses of the head.

Issues:

- Does not provide satisfactory results on retaining facial features following makeup transfer
- Their methods fail to perform transfer on faces with different sizes.

Literature Survey

Local adversarial disentangling network for facial makeup and de-makeup (2020)

- Qiao Gu et al.

- Transfers and removes dramatic makeup styles seamlessly.
- It is possible to generate photorealistic results that preserve facial identity.
- Struggles to remove extreme makeup styles where colors are highly consistent in local regions but vary sharply across local patches.

Issues:

- Extreme makeup styles fail to produce satisfactory results.
- Suffers when the head pose of the source and the reference faces are different, producing noticeable artifacts.

Literature Survey

Beautyglow: On demand makeup transfer framework with reversible generative network (2021)

- Hung-Jen Chen et al.

- It can be easily extended to other applications in which two latent vectors need to be decomposed.
- It is possible to manipulate latent vectors to produce realistic images, even when the makeup is light.

Issues:

- Focuses only on the conventional regions of the face i.e. lips and eyes
- A naive approach to transform from light to heavy makeup.

Outcomes of Literature Survey

Photo-Realistic Facial Details Synthesis From Single Image(2019):

Works on various expressions and lighting conditions and also generates realistic facial features like wrinkles. Uses Conditional Generative Adversarial Net based model.

PSGAN: Pose and Expression Robust Spatial-Aware GAN for Customizable Makeup Transfer (2019):

Handles different expressions as well as poses of the face.
Fails on faces with different sizes.

Local adversarial disentangling network for facial makeup and de-makeup (2020):

Uses multiple overlapping local discriminators to realistically transfer makeup styles.
Suffers when the head pose of the source and the reference faces are different

BeautyGlow: decompose makeup and non-makeup components in the latent space(2021):

It decomposes makeup and non-makeup components in the latent space.
It does not work well on extreme makeup styles.

Dataset

Stickers:

1. Consists of 577 high quality images.
2. Contains various types of patterns of flowers, crystals, gems, henna, daisy, leaf, tattoo.

CPM-Synt-1

1. Contains real faces with synthetically added makeup patterns.
2. Consists of a total of 5555 after-makeup images

CPM-Synt-2

1. This dataset contains image triplets: (source image, reference image, ground-truth)

CPM-Real

1. Contains 3895 RGB images
2. Contains real faces with real in-the-wild makeups.
3. Contains varying makeup styles from light to heavy.

Methodology

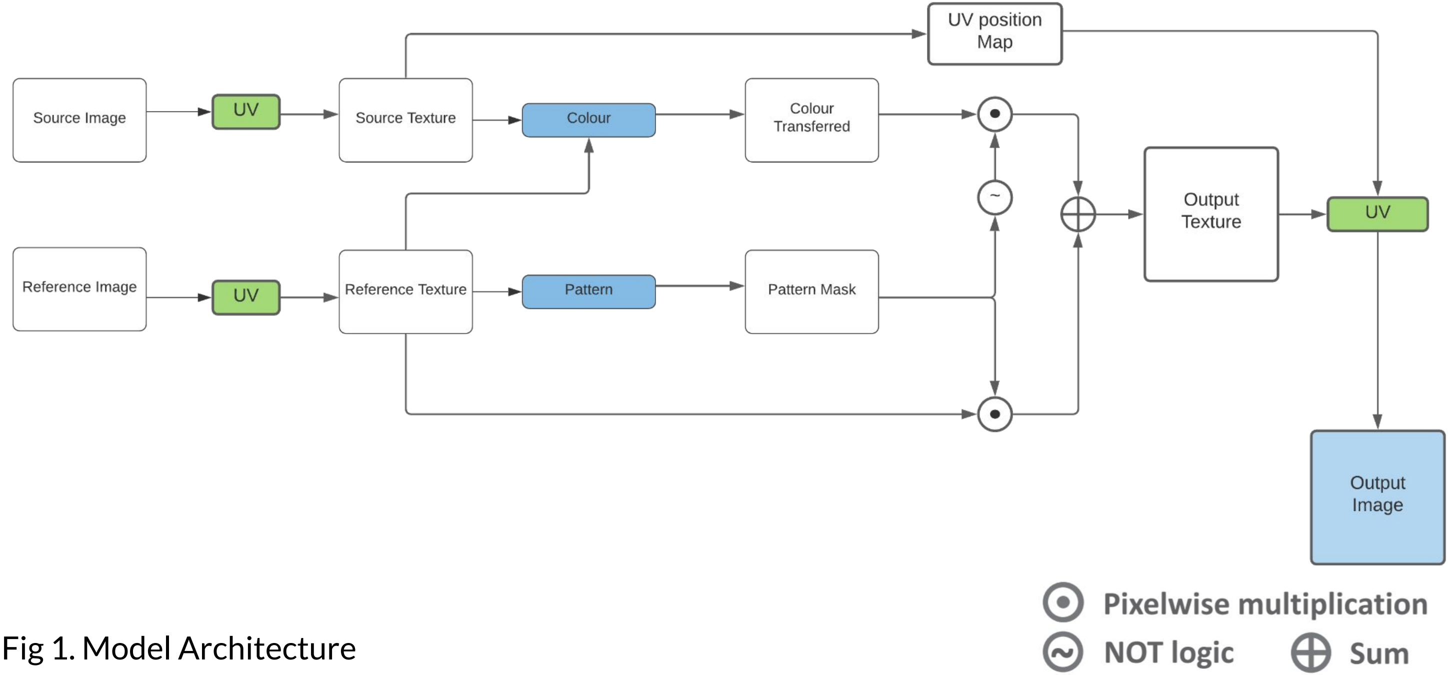


Fig 1. Model Architecture

Methodology

Step 1: The input images I^n_s , I^m_r are converted to UV texture maps T^n_s , T^m_r .

- This is done to remove misalignment i.e. head poses, 3D shape etc, between input and targeted image.
- We use PRNet, which has extended this idea and introduced a UV position map representation to encode any 3D face shape.
- PRNet is a network that process 2D image with three channels encoding the XYZ coordinates of the 3D face with respect to the camera coordinates.
- Alongside the UV position map, we do texture mapping to get the paired texture map.

PRNet

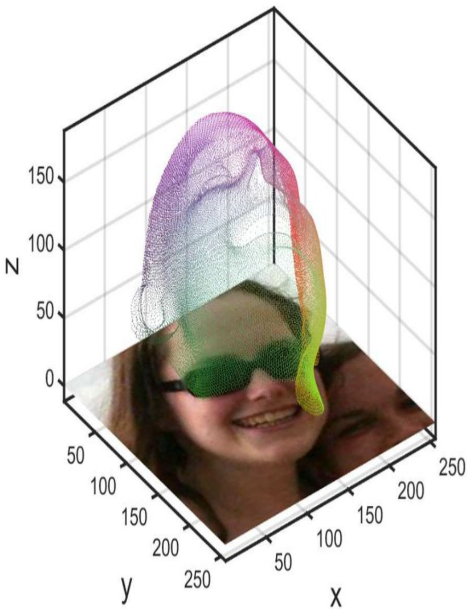
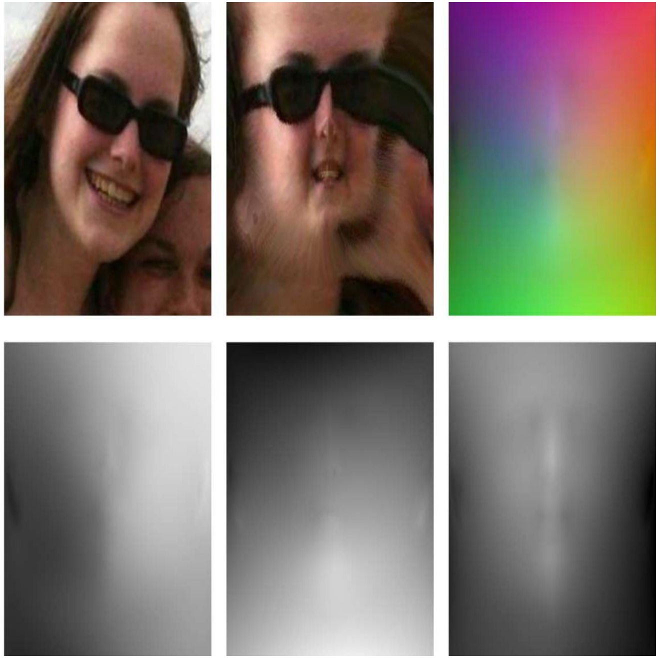


Fig 2. UV position map



The illustration of UV position map.

Left: 3D plot of input image and its corresponding aligned 3D point cloud(as ground truth).

Right: The first row is the input 2D image, extracted UV texture map and corresponding UV position map. The second row is the x, y, z channel of the UV position map.

Methodology

Step 2: The texture maps are passed to two parallel branches for makeup transfer.

- Train a color-based makeup swapping network C that swaps makeup color on cosmetic regions between the source and the reference image with a loss function
- The loss function is a weighted sum of adversarial loss (L_{adv}), cycle consistency loss (L_{cyc}), perceptual loss (L_{per}) and histogram matching loss (L_{his}).

  $L = L_{adv} + L_{cyc} + L_{per} + L_{his}$

Step 3: The makeup-transferred texture T^m_s is formed by combining the outputs of those branches, and this UV texture map is converted to the image space to obtain the final output I^m_s.

BeautyGAN

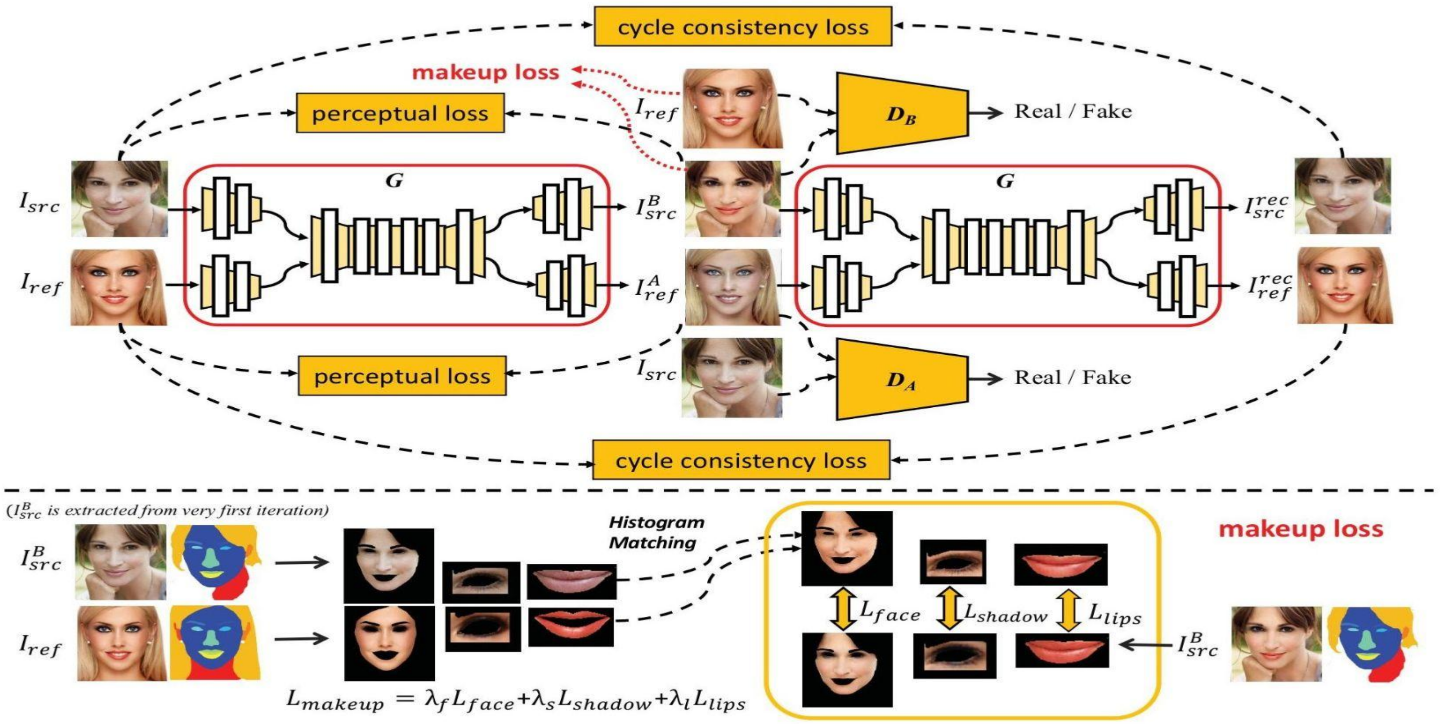


Fig 3. BeautyGAN Model Architecture

Work Done

- Dataset collection: Stickers, CPM-Synt-1, CPM-Synt-2, CPM-Real
- Working on training networks Individually: PRNet
- Implemented the Makeup Colour Transfer Branch
- Implemented the Pattern Transfer Branch
- Combined the two branches
- Evaluated the result on a metric: beauty Score

Evaluation Metrics

Beauty Score:

- Beauty Score uses quality detection and control.
- It analyzes the fuzzy degree, angle, light intensity and other features of the face in the picture to judge the image quality.
- It gives a score between 0-100, 100 being the best score.
- The score displays additional information of the face:
    - Angle
    - Light intensity
    - Face Shape
    - Face Type

Results (Colour)

Fig 4. Makeup Colour Transfer Result

Results (Pattern)

Fig 5. Makeup Pattern Transfer

Results (Colour and Pattern)

Fig 6. Colour + Pattern Transfer

Results (Colour and Pattern)

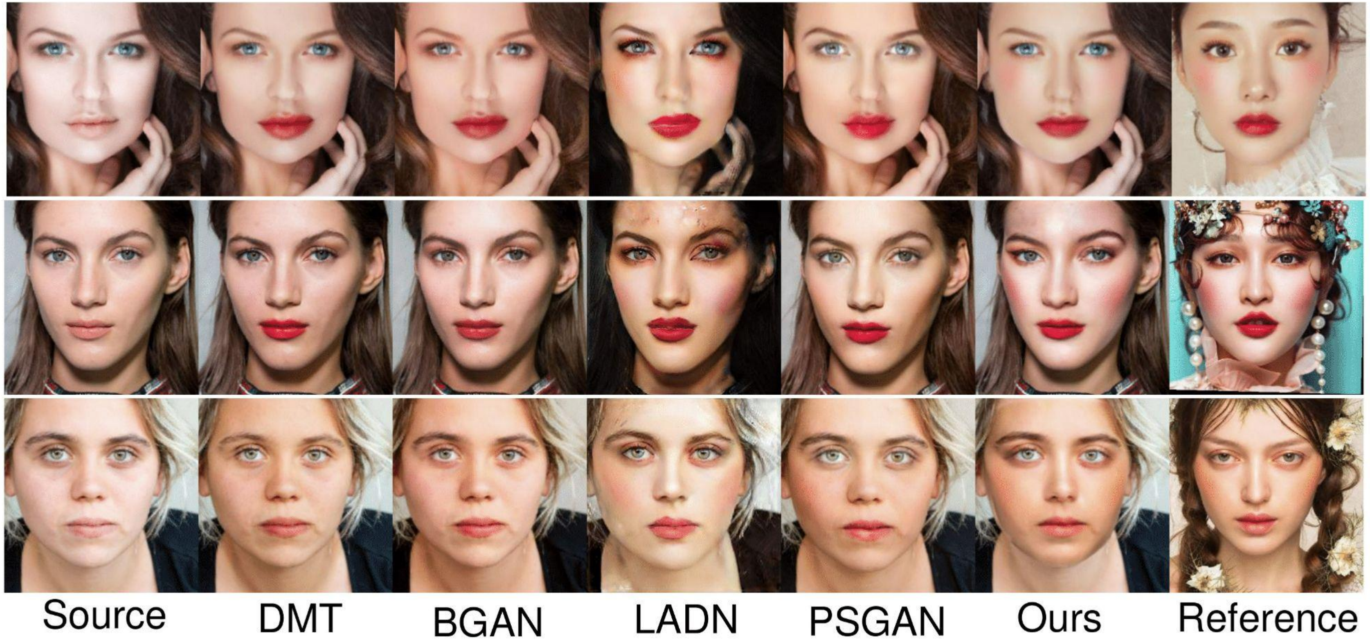


Fig 8. Images Comparison of different models

Results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    "left": 48.53,
    "top": 10.25,
    "width": 320,
    "height": 315,
    "rotation": 0
  },
  "face-probability": 1,
  "angle": {
    "yaw": -3.15,
    "pitch": 9.46,
    "roll": -1.07
  },
  "age": 22,
  "beauty": 0.8754,
  "expression": {
    "type": "none",
    "probability": 1
  },
  "face-shape": {
    "type": "heart",
    "probability": 0.3
  },
  "face-type": {
    "type": "human",
    "probability": 0.71
  }
}
```


Fig 7. Beauty Score Output

Results

Dataset	DMT	BGAN	LADN	PSGAN	Ours
CPM Real	0.853	0.847	0.837	0.859	0.861
CPM Synt 1	0.874	0.876	0.871	0.88	0.878
CPM Synt 2	0.836	0.838	0.834	0.839	0.841

Table 1: Beauty Score for different model

Results (Colour and Pattern)

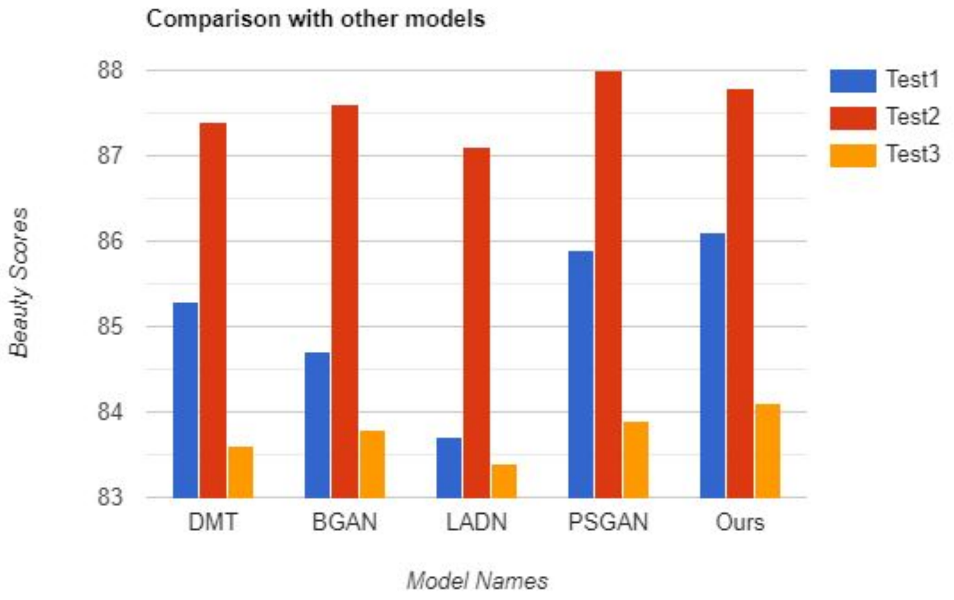

Fig 7. Comparison of different models

THANK YOU