Mask inpainting with a GAN network

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Abstract

Our project aims to remove a face mask over a person's face, by reconstructing the covered part of the face. To have a more precise reconstruction of the missing parts (mouth and nose) behind the mask, we plan to use a second photo of the same person without the mask as a reference during the facial reconstruction process. There are no constraints on the quality of the reference photo, for instance the face can be taken from a different point of view than the first one. To sum up, given as input an image containing a person's face partially covered by a medical mask and another photo of the same person without any occlusions, the output will be the first image with the mask-covered parts, mouth and nose, reconstructed. Future development could lead to generalizing the occlusion caused by the mask to any type of occlusion possible.

1. Mask Segmentation

We made use of MediaPipe's FaceMesh [2] library to find facial landmarks over the face covered with the surgical mask and the reference photo. Facial landmarks are important to have an initial approximation of the region where to search the surgical mask and to warp the reference photo over the first one. To perform the segmentation of the mask we apply a k-means with k=3 over the polygon we created using face landmarks and pick the bigger region between the 3. The k has been choosen to be 3 as in the polygonal region we expect to find the mask, the background and the skin of the person's face. In the end, a binary image is created, with a 1 where the mask is present and 0 elsewhere, while in the original image, the mask area is filled with 0s.

2. Warping the reference photo

The objective of the reference photo is to guide the network to a more loyal reconstruction. As we allow the reference to have [avere un'angolazione diversa da quella frontale], we apply a thin-plate spline transformation to make it frontal [meh che traduzione brutta]. We use 30 specific landmarks as parameters as using more parameters lead to distortion given by the error in the landmarks detection and less lead to an imperfect warping. The same polygon region of Mask Segmentation is cut from the reference photo, the by applying the TPS is sticked to to main photo leading to a (partial) reconstruction.

3. Image inpainting

Image inpainting (a.k.a. image completion) is the task to fill a missing region in an image by predicting the value of the missing pixels in order to have a realistic image which is semantically close to the original one and visually correct. There are two different approches to achieve this task:

1. Low-level feature patch-matching which does not work pretty well with non-stationary use-cases (e.g. faces, objects or complicate scenes);

2. Feed-forward models with deep convolutional networks which overcome the problem of prevoious case exploiting semantics learned on large scale dataset.

We decided to follow the latter one designing a coarse-to-fine Generative Adversarial Network (GAN) characterized by:

- Generator:
  - Coarse network whose aim is the one to provide a rough estimation of missing pixels;
  - Refinement network which takes the output of the previous network as input and takes care of its detailed decoration.
- Discriminator which is responsible of distinguishing real samples from the one created by the generator.

3.1. Datasets

GAN networks are data-hungry and needs a lot of diverse training examples in order to generate quality images, for this reason we used the FFHQ 1024x1024 images [1], rescaled to 256x256, during training. In other GAN inpainting architectures, the mask region to reconstruct is usually calcuated during the training in a randomized way.

We do not have this randomization process, so for each image of FFHQ we precalculated the face region where the mask is weared using facial landmarks. For testing we used CelebA256.

3.2. Architecture

Our architecture is highly inspired by Free Form Image Inpainting with Gated Convolution [4] and DeepGIN [3].

3.2.1 Coarse Net

In this stage we decided to use the gated convolution so that the generator is able to learn a dynamic feature selection mechanism for each channel and for each spatial location. The feature selection mechanism takes into account not only the background and the mask given in input, but also the semantic segmentation in some channels.

3.2.2 Refine Net

References

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