A Neural Virtual Anchor Synthesizer based on Seq2Seq and GAN Models

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ABSTRACT

This paper presents a novel framework to generate realistic face video of an anchor, who is reading certain news. This task is also known as Virtual Anchor. Given some paragraphs of words, we first utilize a pretrained Word2Vec model to embed each word into a vector; then we utilize a Seq2Seq-based model to translate these word embeddings into action units and head poses of the target anchor; these action units and head poses will be concatenated with facial landmarks as well as the former $n$ synthesized frames, and the concatenation serves as input of a Pix2PixHD-based model to synthesize realistic facial images for the virtual anchor. The experimental results demonstrate our framework is feasible for the synthesis of virtual anchor.

Index Terms: Computing methodologies—Computer graphics—Graphics systems and interfaces—Mixed/augmented reality; Computing methodologies—Computer graphics—Image manipulation—Image-based rendering

1 INTRODUCTION

Recently, the synthesis of images has received more and more attention [16][22][39][41], especially after the proposal of Generative Adversarial Network [11]. Among which, some methods explored the tasks of translating images of a domain to another [18][19][27][47], while some methods focused on the fidelity of synthesized images [8][21]. Meanwhile, many other RNN-based methods were also put forward to tackle problems of sequences [5][20][24][26][32][40]. However, the task of synthesizing photorealistic face images according to input words, simultaneously ensuring the mouth movements are consistent with the input words, is seldom explored [14][25].

Unlike previous similar tasks [14][15][30][31], we tackle this problem utilizing both GAN-based networks and RNN-based networks, avoiding complicated 3D face model computation. In order to translate input words into corresponding images, we firstly utilize a pretrained Word2Vec model [25] to embed each word into a vector. We then utilize a pretrained Seq2Seq-based model to translate these vectors into corresponding facial action units(AU) and poses(PS) of the target person. These AU and PS, concatenated with facial landmarks and former synthesized frames, are then translated into photorealistic images utilizing a pretrained pix2pixHD-based model [36]. Please note that our work only focuses on visual synthesis, audio synthesis is not considered here.

We take facial AU and PS as an important intermediate representation between input words and synthesized facial images. In training phase, we use a Seq2Seq-based model to train the word embeddings so as to output corresponding AU and PS. For simplicity we will abbreviate AU and PS as AU+PS, and abbreviate facial landmarks as FLM. The ground truth AU and PS are extracted from the person who is speaking those text. In this way, we train the Seq2Seq model to output appropriate AU+PS with words as input. Then for training the pix2pixHD-based model to synthesize the face image of virtual anchor, we concatenate the AU+PS and average FLM and also former $n$ synthesized frames. The average FLM are computed over all the extracted facial landmarks from the training examples. In this way, we utilize the AU+PS to preserve most important information of an individual, meanwhile sidestepping the difficulties of directly translating words into corresponding facial images. Our contributions can be summarized in two aspects:

1. We propose a novel framework for the synthesis of virtual anchor, whose mouth movements match the corresponding words.

2. We demonstrate the effectiveness of our proposed framework and the synthesized images’ fidelity.

2 RELATED WORKS

Face synthesis. Garrido et al. [9] proposed an image-based framework which is conceived as part image retrieval and part face transfer. Their system didn’t rely on a 3D face model to map source pose and texture to the target, which excels in simplicity when proposed. Thies et al. [33] proposed the first real-time facial reenactment system that requires monocular RGB input only, whose effectiveness was demonstrated in a live setup, where YouTube videos are reenacted in real time.

With the prevalence of Generative Adversarial Network (GAN) [11], many related methods are proposed to tackle the task of image synthesis, including the synthesis of facial images. Isola et al. proposed a GAN-based framework to tackle the task of image-to-image translation, which was demonstrated to be effective at synthesizing photos from label maps, reconstructing objects from edge maps, and colorizing images, among other tasks. Afterwards Wang et al. [37] proposed a framework for synthesizing high-resolution photo-realistic images from semantic label maps, which shows a promising prospective for the synthesis of face images from label maps. Zhu et al. [41] further proposed a framework for learning to translate an image from a source domain $X$ to a target domain $Y$ in the absence of paired examples, which is a significant advancement compared to the difficulty of obtaining paired training data. After the proposal of CycleGAN, many works based on CycleGAN have been proposed for the synthesis of videos of consecutive facial images [3][17][35][38][39]. Among which, Wang et al. [35] proposed a tracking method which combines a convolutional neural network with a kinematic 3D hand model, which can synthesize anatomically plausible and temporally smooth hand motions, while Wu et al. [38] present a ReenactGAN, capable of transferring facial movements and expressions from an arbitrary person’s monocular video input to a target person’s video utilizing a intermediate boundary latent space, which inspire our method greatly. Our method also utilize intermediate facial landmarks for a more photo-realistic and consecutive synthesis of facial images.

Sequence to Sequence. Since Sutskever et al. [32] proposed the Seq2Seq model, many relevant methods have been proposed to tackle the task of translating a sequence into another. The Seq2Seq model is an encoder-decoder architecture, with a multilayered LSTM [13] to embedding the words into vectors while another deep LSTM decodes the target words from these vectors. Gehring et al. [10] proposed an architecture entirely based on convolutional neural networks, which is equipped with gated linear
Figure 1: Flowchart of our whole framework. Firstly we utilize Word2Vec to embed words into vectors, then use Seq2Seq to translate vectors into AU+PS. Finally a Pix2PixHD-based generator G will use these generated AU+PS and average FLM as well as the former $n$ synthesized frames to synthesize face images.

Figure 2: Architecture of our Seq2Seq-based translator. The inputs are word embeddings while the outputs are AU+PS.

Figure 3: Architecture of our pix2pixHD-based generator. The generator takes AU+PS and average FLM as well as the former $n$ synthesized frames as input and outputs synthesized face image.

Vaswani et al. [34] proposed another network architecture Transformer, which is based solely on attention mechanisms without recurrence or convolutions. But for our specific task of translating word embeddings into AU+PS, little related work is proposed. In this work, we utilize the Seq2Seq architecture to conduct our translation from word vectors to corresponding AU+PS.

3 METHOD OVERVIEW

Our method goes like following steps (as shown in Figure 1): Firstly we embed some texts into vectors using Word2Vec [25], secondly we utilize a Seq2Seq-based model to translate these word embeddings into AU+PS, then we adopt another pix2pixHD-based network to synthesize face images according to those AU+PS and average FLM as well as the former $n$ synthesized frames. We hold the view that our method can sidestep the difficulty of directly translating words into corresponding facial images by introducing AU+PS and average FLM as intermediate representations. With both of which as a kind of spatial constraints for the training procedure, the GAN-based model can better synthesize more photorealistic and reasonable face images.

The Open-Face [2] provides a convenient way to consistently predict FLM, AU and PS for the face image. Thus, we use it to extract these information from images of target person. The AU+PS is a 20-D vector which comprises of a 17-D AU and a 3-D head pose. On the acquisition of text data, the sentence is obtained directly from the video with python library AutoSub and TTS.
4 Words to AU+PS

There exist some popular word embedding methods to represent the text into vectors, including Word2Vec [25], GloVe [28], ELMo [29] and BERT [7]. Here, for simplicity, we employ a pretrained Word2Vec model to embed each word into a 200-D vector. Then when training.

where the first term is the adversarial loss in Eq 3, the second term is

And the former AU+PS alone to generate the face sequence. Instead, we combine it as ground truth, while these word embeddings are taken as input.

Our encoder is defined as

where the LSTM computes the forward sentence encodings, and applies a linear layer on top.

And our decoder is defined as

where $h_{dec}$ is the hidden state of $l$-th decoder, and $y_{l-1}$ is the output AU+PS of the $(l-1)$-th decoder. The decoder outputs an AU+PS sequence , which will be used to synthesize the face sequence for the virtual anchor, this procedure will be detailed in Section 5.

5 Face Synthesis

Inspired by [4], we modify pix2pixHD [36] network to generate consecutive face images (as shown in Figure 3). We do not directly use AU+PS alone to generate the face sequence. Instead, we combine it with average FLM and the former $n$ synthesized frames to synthesize face sequence. Compared to AU+PS alone, combining AU+PS with average FLM allows our network to have spatial coordinate constraints during training, which can accelerate the convergence. And the former $n$ frames provide a kind of constraints of temporal correlation of the synthesized frames.

The objective of the generator $G$ is to translate AU+PS maps and average FLM as well as the former $n$ synthesized frames into realistic-looki.

The following combined loss is employed in our task:

$$L_{GAN}(G, D) = E_{(X, Y)}[\log D(X, Y)] + E_{X}[\log(1 - D(X, G(X))] (3)$$

Where $X$ means the former $n$ (AU+PS, average FLM) plus the current (AU+PS, average FLM), while $Y$ is the former $n$ ground truth images plus the current ground truth image. Finally, the following combined loss is employed in our task:

$$\min_{G} \max_{D} L_{GAN}(G, D) + \lambda_1 * L_{FM}(G, D) + \lambda_2 * L_{VGG}(G(x, y)) (4)$$

where, the first term is the adversarial loss in Eq 3, the second term is feature matching loss [36], the third term is perceptual reconstruction loss [56], and $\lambda_1$, $\lambda_2$ controls the importance of the three terms.

6 Experiments

To train our system, we collect more than 400 videos of ESPN shows (First Take and Undisputed) from youtube, these videos all have rich poses and facial expressions which serve as a good ground truth when training.

In our experiment, we set $n$ as 2. An example result is shown in Figure 4. We can see that the synthesized face images are realistic and the mouth movements are almost consistent with the corresponding words. This demonstrates our method’s effectiveness.

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