1. Introduction

Take a look at Figure 1 for two video sequences. The input is a YouTube clip of a Thai-Chi artist (the driving subject) performing a series of complex motions at the top row. Our algorithm’s output is shown at the bottom row. It refers to frames that appear to show a different person (the source subject) executing the same motions. The crux is that the source individual has never performed the same exact sequence of motions as the driver video - they were photographed doing another movement with no clear reference to the driving’s actions. By observing the figure, we can see that the source and the driving are of different appearances, have different backgrounds, and are dressed differently - a totally different style that we need to ignore when we extract the structure.

In this study, we propose a simple, however surprisingly efficient approach to the general motion transfer problem, which can be applied to any domain, similarly to (Siarohin et al., 2019), (Siarohin et al., 2020): Given a source image of a person with the wanted appearance, and a driving video with the wanted structure/geometry, we synthesize a video by applying a deep motion generator per-frame. We assist the generator by feeding it with compact structural representations of the source and each frame of the driving video. That way, we obtain the target of a video of the source appearance and the driving motion, given any domain. Keeping the generator as a frame processor enables it to be simple and fast to train and evaluate, but note that there are works which take into account temporal information, such as (Villegas et al., 2017) which make a use of LSTM.

Researchers of some notable works (Section 2) observe that keypoint-based pose preserves motion signatures over time, while abstracting subject identities. We therefore use the keypoint-based pattern without any other motion priors. We obtain the keypoints and use them to animate images in a way that doesn’t need any external information about the subject or any assumption or prior about the scene.

Our contribution is twofold: first, we demonstrate that removing the explicit motion prior from works such as FOMM is feasible to the task of image animation, and creates a compact, faster to train and evaluate model; And second, we make progress to achieve a better structure during animation, although further work (Section 5) is required to refine...
our model. We also split our approach by the proposal of two methods for absolute and relative motion transfer (Section 3.2), which covers both needs (when the source isn’t aligned well with the driving and needs to be matched to the current driving explicitly, and when it is aligned and it is wanted and more natural to only add the relative difference between the current driving and the driving during the first frame).

2. Related Work

Motion transfer has gained a lot of coverage over the last twenty years. Early approaches based on manipulating existing video footage to generate new content. These included searching for frames in which the body position corresponds to a desired motion and using them to generate a new content (Bregler et al., 1997). Our approach is equally designed for videos, but rather than manipulating existing images, we learn to synthesize new movements that were never seen before with the new identities.

A number of techniques are based on calibrated multi camera systems to scan a target player and use an adapted 3D model of the target to control their motion in a new frame (Cheung et al., 2004). Our solution instead examines the transition of movement between 2D video subjects and refrains from using data calibration, 3D space information or any other domain specific prior.

Latest approaches concentrate on the disentanglement of appearance and activity and synthesizing of new motion videos (Tulyakov et al., 2018). Similarly, we apply our representation of motion to different target subjects to generate new motions. However, In contrast to these works, we did not use GAN but an encoder-decoder approach.

Contrary to image animation approaches that were common up until recently, keypoint-based methods are now thought to have the ability to achieve high performance in the field of video reanimation. Some notable works in this area are (Siarohin et al., 2020), (Siarohin et al., 2019), (Kim et al., 2019), (Balakrishnan et al., 2018), (Ma et al., 2017) (Chan et al., 2019).

Our work does not depend on a strong motion prior directly, but rather on a structure mask derived from a keypoint detector of a motion-based model, such as (Siarohin et al., 2020). The idea of using drawn keypoints as a geometry representation (structural mask) was already used in image-to-image translation works such as TransGaGa (Wu et al., 2019), in addition to some of the video reanimation works mentioned earlier.

The concept of using a structural mask in the context of image animation is demonstrated in (Shalev & Wolf, 2020). However, the current work differs by basing the mask off a motion related keypoint module. By doing so, we create a bottleneck for the network which is dependent on the keypoint bottleneck used when training the keypoint module, in order to achieve generalization. In addition, it simplifies the network, makes it modular to the mask, and saves us the hassle of perturbing the input hoping to achieve an identity-less mask.

We purpose an heatmap mask (Section 3.1) for absolute animation, which differs from the drawn keypoint masks mentioned in previous works, in addition to a classical keypoint mask (Section 3.2) for relative animation w.r.t. difference between the current and first frames in the driving video.

3. Methodology

The network can be divided into two parts: obtaining the mask, and generating the synthesized frame. The generator architecture is constant amongst all of our variations, and can be described as low resolution generation from the source image, source mask and driving mask; Followed by up-scaling of the low scale synthesized prediction by passing it with the source frame to a high resolution generator. We created two different versions for the mask generator: the first, heatmap based mask, which is limited to absolute motion transfer; the second, keypoint based mask, which enables an optional relative motion transfer. The performance drop for our second version was expected because its mask contained less structural information. The first version is referred as a “keypoint heatmap mask” while the second is referred as a “circles mask” or “keypoints after softmax” mask.

3.1. First mask version for absolute motion transfer (with warping)

Our main mask for the project is obtained from carefully observing the keypoint module from (Siarohin et al., 2020). U-Net based keypoint modules of this form, work by extracting features, which pass through a conv layer to form a heatmap image \( K \) channels, where \( K \) is the number of keypoints. Then, a softmax is performed over the channels, and keypoints are extracted from the mean location of each heatmap channel. By carefully debugging the code, and the expectation for a segmentation map out of U-Net, we obtain Figure 1.

Summing over the channels, we get Figure 2.

which is our output mask, aka the heatmap, pre softmax mask.

3.2. Second mask version for relative motion transfer

We purposes an additional “circles” only mask which can be used in the context of relative motion transfer during
Figure 1. $K$ channels of the keypoint detector network used in (Siarohin et al., 2020), before the softmax activation. Our main motion prior in this project.

Figure 2. The sum of the $K$ channels which is fed as a structural mask into the generator.

Figure 3. $K$ channels of the keypoint detector network used in (Siarohin et al., 2020), after the softmax activation and Gaussian fit.

Figure 4. The sum of the $K$ channels which is fed as a structural mask into the generator, which is our output mask, aka the keypoints after softmax mask.

3.3. Architecture

Our architecture follows (Siarohin et al., 2020) without the dense motion module, after changing its keypoint generation module to return our mask. After the mask is obtained, we follow the encoder decoder approach as (Shalev & Wolf, 2020), which had success in similar tasks (Newell et al., 2016).

Namely, the encoder of the low resolution generator consists of $\text{conv}_{7 \times 7}$, $\text{batch\_norm}$, $\text{relu}$, followed by six residual blocks of $\text{batch\_norm}$, $\text{relu}$, $\text{conv}_{3 \times 3}$, $\text{batch\_norm}$, $\text{relu}$, $\text{conv}_{3 \times 3}$, (and a sum with the source). The residual blocks help to maintain the identity of the source image (He et al., 2015). The decoder consists of two blocks, each is a sequence of $\text{up\_sample}_{2 \times 2}$, $\text{batch\_norm}$, $\text{relu}$. The decoder is followed by a $\text{conv}_{7 \times 7}$ and a $\text{sigmoid}$ activation. For the high resolution generator, use an encoder (decoder) with five encoding (decoding) blocks, where each block is a sequence of $\text{conv}_{3 \times 3}$, $\text{batch\_norm}$, $\text{relu}$ $\text{avg\_pool}_{2 \times 2}$. 

By taking the softmax over the heatmap, we get Figure 3. Summing over the channels, we get Figure 4.
and each decoding block is a sequence of \textit{up\_sample}_{2\times2}, \textit{conv}_{3\times3}, \textit{batch\_norm}, \textit{relu}. We add skip connections from each of the encoding layers to its corresponding encoding layer, to form a U-Net architecture (Ronneberger et al., 2015).

3.4. Losses

We use the same perceptual loss as in (Siarohin et al., 2020) which is based on the implementation of (Wang et al., 2018). With the input driving frame $D$ and the corresponding reconstructed frame $\hat{D}$, the reconstruction loss is written as:

\[ L_{rec}(\hat{D}, D) = \sum_{i=1}^{I} |N_i(\hat{D}) - N_i(D)|, \]

where $N_i(\cdot)$ is the $i$th channel feature extracted from a specific VGG-19 layer (Simonyan & Zisserman, 2015) and $I$ is the number of feature channels in this layer. Additionally we use this loss on a number of resolutions, forming a pyramid obtained by down-sampling $\hat{D}$ and $D$, similarly to MS-SSIM (Wang et al., 2003), (Tang et al., 2019). The resolutions are $256 \times 256$, $128 \times 128$, $64 \times 64$ and $32 \times 32$.

4. Experiments

4.1. Datasets

The Tai-chi-HD dataset, which includes brief videos of people doing Tai-chi exercises, was used for training and evaluation. Following (Siarohin et al., 2020), 3,141 Tai-chi videos were downloaded from YouTube. The videos were cropped and resized to a resolution of $256^2$, while the aspect ratio was preserved. There are 3,016 training videos and 125 evaluation videos.

4.2. Comparison with Previous Works

In order to compare our work to previous works (Table 2) we used metrics previously used in similar papers. Average Key-points Distance (Cao et al., 2017) (AKD) measures the average key-points distance between the generated video and the source video. Average Euclidean Distance (Zheng et al., 2019) (AED) measures the average euclidean distance between the representations of the ground-truth and generated videos in some embedding space. In addition, we added the L1 distance as well. Our AED and AKD metrics were calculated using the following repository: https://github.com/AliaksandrSiarohin/pose-evaluation

Note that these metrics aren’t optimal as one can easily improve reconstruction by increasing the bottleneck, and we can see our artifacts in animation results (Table 3). However, our approach did follow the structure of driving video well and better than the others, and to improve the identity and background artifacts, we suggest some fixes in Section 5. Due to the smaller bottleneck of the second (softmax) mask, the pose worsened, but the generalization for the background improved (which also has to do with the low but non zero grayscale values given to the background in the heatmap mask representation, which can be solved with thresholding - see Section 5).

4.2.1. Qualitative Comparison

When comparing our work visually to (Siarohin et al., 2020), we can argue that we obtained a better pose which is almost the same with the original. We can observe a closer synthesized leg in the second frame (to the original driving), and a better pose (specifically the hands) on the third and forth frames. However, the background generated is damaged, due to the lack of thresholding in our mask which means we will always have noise to the background generation. See Section 5 for future suggestions. We can also see that the softmax (circular keypoint mask) version worked fine, preserved the background, but with a worse pose, due to less information in this type of mask.

5. Future work

We would like to test our module on more datasets, and compare them to the state of the art. In addition, summing the heatmap channels might not be optimal, and there is
certainly some space to try something deeper with the features extracted in the keypoint detector as an input, or feed all of the channels separately into the generator. We want to experiment with mask thresholds due to the distortions in the animation background, similarly to (Shalev & Wolf, 2020). We may also increase the number of keypoints, but that would probably be more beneficent to the second type of mask, and would increase the required GPU memory proportionally. We also suggest (in the second, circles only mask) coloring matching keypoints with the same color to help the module to learn a motion flow.

6. Conclusions

We constructed a novel method for image animation by moving the need for a strong motion prior (optical flow) to the assumption of a pre-trained keypoint detector/keypoint heatmaps prior to activation, which might be based on a motion prior. By doing so, we encapsulated motion to a motion mask, which has the keypoint bottleneck. The motion masks are then fed into a generator, which combines the appearance of the source image and the mask which represents the structure, decoupled from any appearance naturally by the assumption that during the training of the keypoint detector, the heatmap mask went into a keypoint bottleneck. After evaluation, we can conclude that our method is feasible and improves the pose although with some artifacts.

Software Data and more result videos

Detailed in our repository: https://github.com/or-toledano/animation-with-keypoint-mask

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