CBG Cyber@ Ben-Gurion University of the Negev

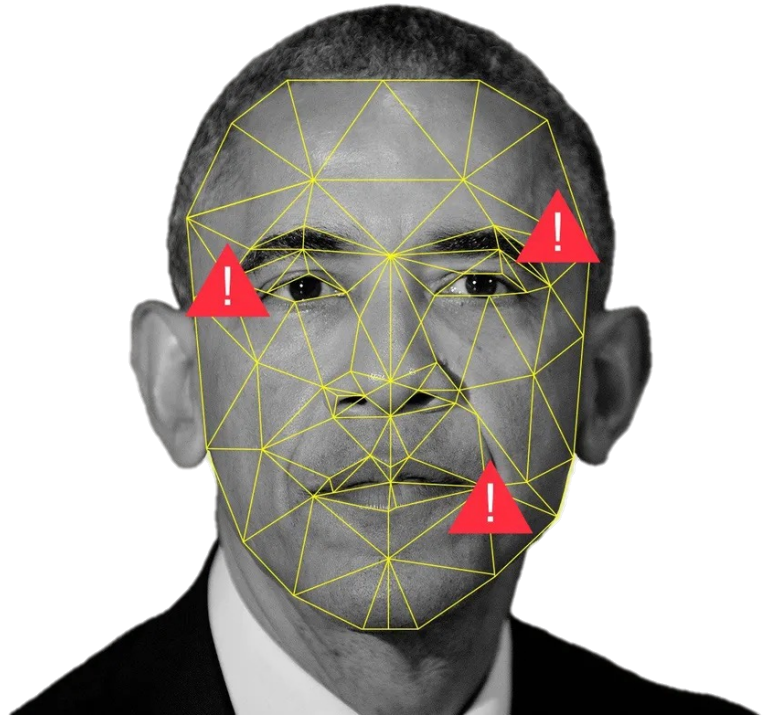
Robustness of Real Time deepfakes

Evaluating the robustness of real time deepfakes by implementing avatarify and examining edge cases on it

INTRODUCTION

Deepfakes

- ✓ Deepfake is a general term that encompasses the use of deep learning algorithms in order to create synthetic media, in which one subject in an existing visual and/or audio content is usually replaced with another's likeness.
- ✓ In recent years, deepfakes have garnered widespread attention for their uses in spreading fake news, committing financial fraud, creating pornographic materials, and many other disturbing uses. This has led to a significant need to identify and restrict their use.



Motivation

- ✓ Real time avatars are far from perfect, as they are not robust when it comes to edge cases. This includes facial gestures in the driving video, objects in the source or target media that make it difficult to identify facial boundaries, etc.
- ✓ These limitations can create visual glitches and distortions that can be detected and therefore can be utilized for failures detection. This observation drives a growing amount of research dealing with those inaccuracies for dual use – correcting them in order to improve the deepfakes' credibility or exploiting them to distinguish deepfakes from real content.
- ✓ In this work, we evaluate the robustness of real time deepfakes by implementing first order motion model-based avatarify and examining various edge cases on it. After demonstrating failures in the implementation, we also provide a method to utilize them for failures detection.

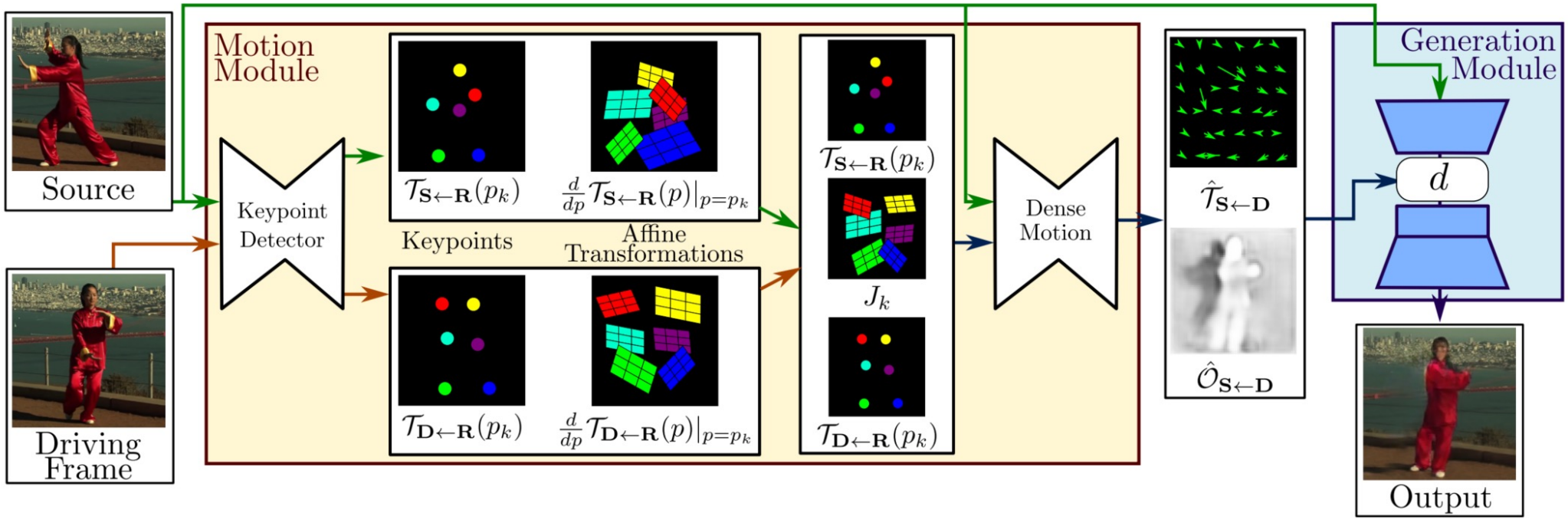
METHODS

First Order Motion Model

- ✓ Siarohin et al. propose the First Order Motion Model for Image Animation, which addresses the task of generating a video sequence so that an object in a source image is animated according to the motion of a driving video.
- ✓ Once their proposed method is trained on a set of videos depicting objects in the same category, it can be applied to any object in this category, without using annotations or prior knowledge about the object to be animate. This is done using a self-supervised formulation, for detaching appearance information and motion information from each other.
- ✓ The motion is represented as a set of keypoints displacements and local affine transformations. Finally, a generator network combines the appearance extracted from the source image with the motion representation of the driving video.
- ✓ First Order Motion Model outperforms state of the art on all the benchmarks on a variety of object categories.

METHODS

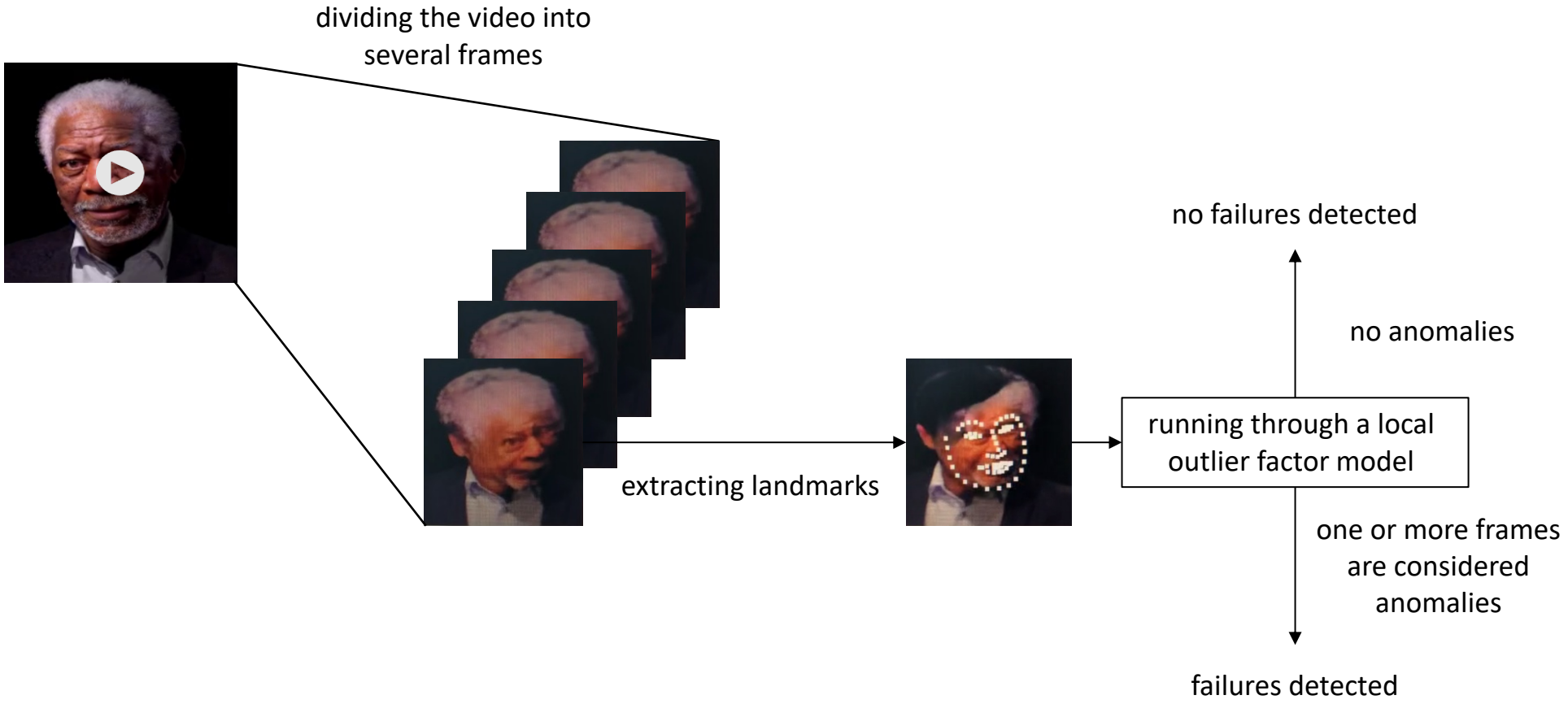
First Order Motion Model



Failures Detection Method

- ✓ To address the task of detecting avatarify failures in an output video, we simplified it to the problem of detecting avatarify failures in a target image which contains face warping artifacts and general distortions. The main idea behind our method is that on average the face proportions of different individuals are similar. This way, when the face in the video is distorted, its facial proportions are anomalous, and we can preform anomaly detection to identify such distortions.
- ✓ To do so, the method starts with dividing the video into frames. For each frame we extract the facial landmarks, calculate Euclidean distance between all the points.
- ✓ We then normalize and run the results through the local outlier factor model with 20 neighbors. The test was done using the Yale Face Database, which contains 165 grayscale images in GIF format of 15 individuals, when for each subject, there are 11 images, one for each different facial expression or configuration. This is in practice using novelty local outlier factor, since the dataset contains only ordinary faces.
- ✓ The test includes making prediction on each frame of the video. If one or more frames are considered anomalies, we declare that the video contains failures.

Failures Detection Method

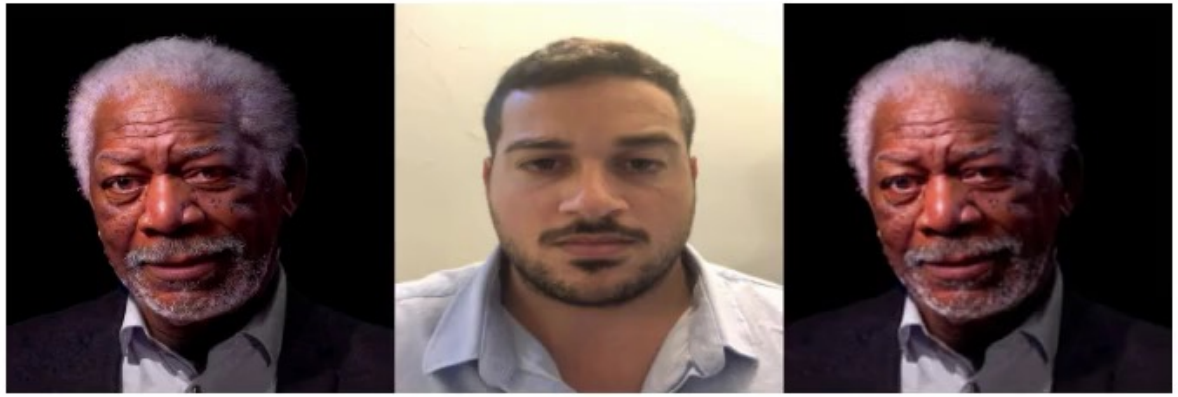


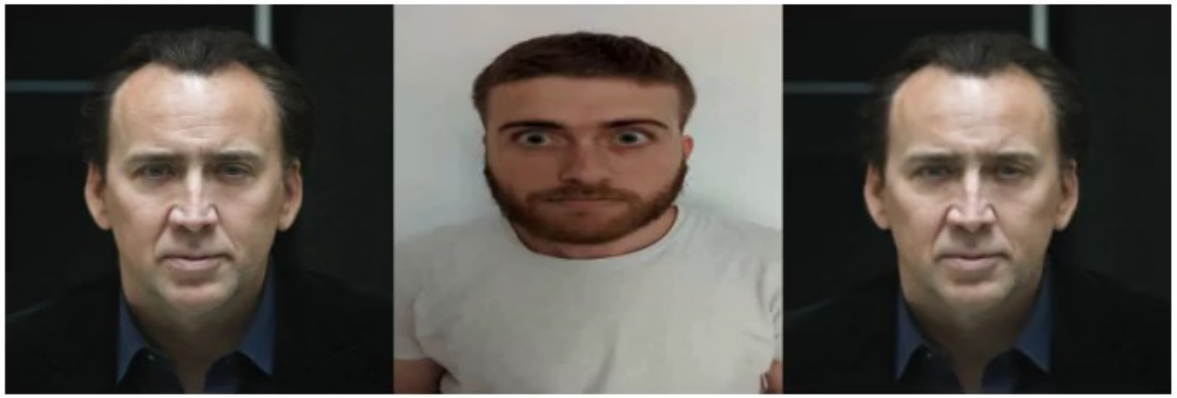
First Order Model Robustness

- ✓ Since we focused on the implementation which work in a way that a face in a source image is animated according to the motion of a driving video, we tried to test its limitations by passing driving videos with various facial gestures and head tilt as input. This includes winks, tongue out, smiles, eyebrow raise, different head tilts, etc.
- ✓ From the output videos, it was clear that the avatarify does not work on certain artifacts. For example, avatarify is not able to create videos with a tongue out at all, as well as creating a proper dental structure.
- ✓ The most significant limitation we identified in the implementation, is the creation of a video that includes head tilts.

EXPERIMENTS & RESULTS

First Order Model Robustness





Failures Detection

- ✓ In order to test our proposed method, we fed it with two videos – authentic video and a deepfake of Morgan Freeman, derived from the authentic video as a driving video using the First Order Motion model. When we ran the method on each of the two videos, we found that indeed no failures were detected in the original video, while in the deepfake they were.
- ✓ Note that in some cases the face in the target image is distorted enough that it is not possible to identify the face, and therefore to determine the landmarks. This fact can be exploited for further improvements in the failure detection task.

Conclusions

- ✓ As the impact of social media on our world grows moment by moment, along with the negligible cost and lack of need for experience enabling almost anyone to create high quality deepfakes, this emerging technology poses a serious threat to society.
- ✓ In this work we experimented with an implementation of real time deepfakes, the first order motion model-based avatarify, proposed by Siarohin et al., and evaluated its robustness by examining various end cases on it.
- ✓ We have learned that avatarify implementations are not robust, and that various facial gestures and artifacts can cause significant failures in the target videos. It seems that most failures caused by head tilt and rotations in the driving video, as well as gestures which include objects that the model does not recognize in the source image, such as tongue or teeth.
- ✓ After demonstrating failures in the implementation, we also provided a method to utilize them for failures detection. We were able to successfully demonstrate our method on two videos – authentic video and a deepfake. No failures were detected in the original video, while in the deepfake they were.

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Thank You