

# SegTalker: Segmentation-based Talking Face Generation with Mask-guided Local Editing

## Supplementary Material

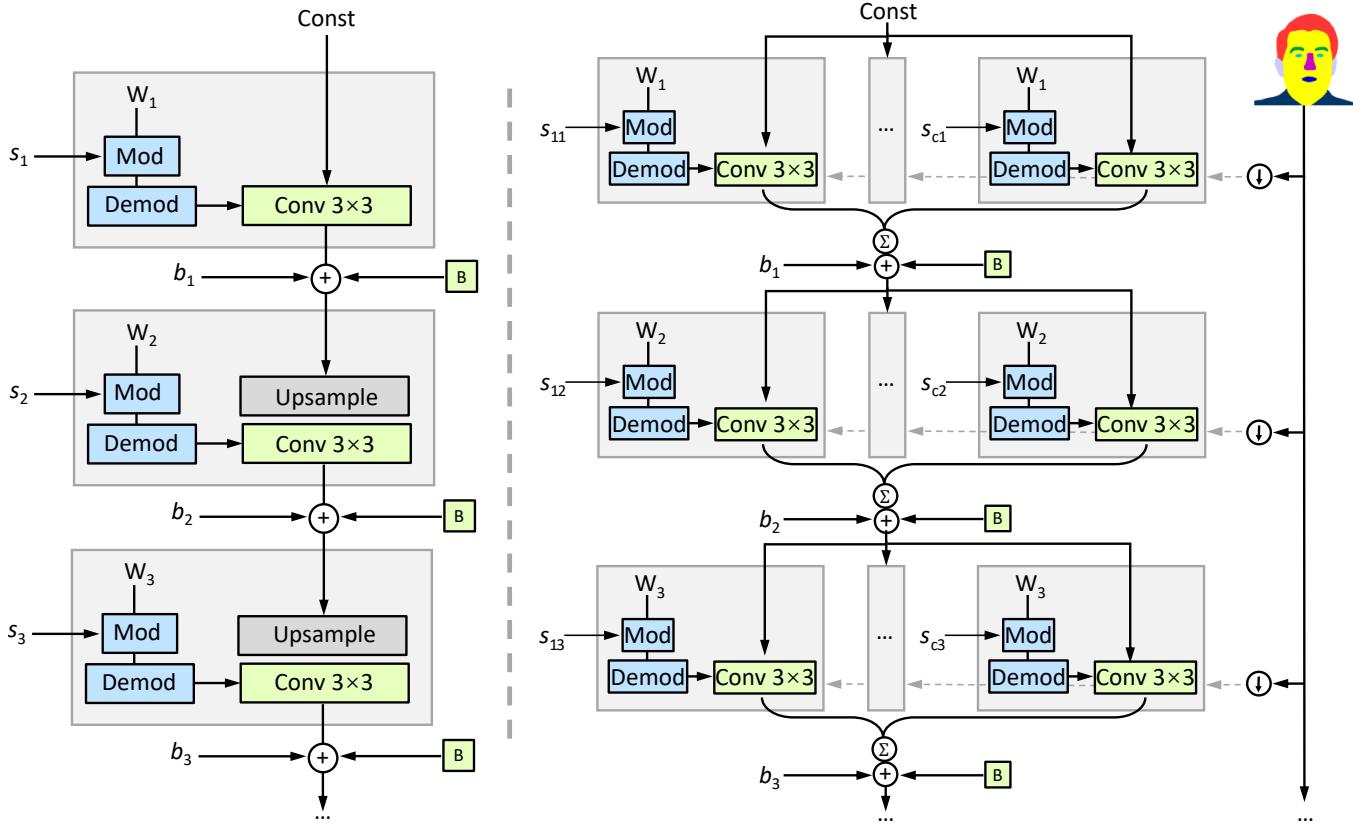


Figure 1: Comparison of the original StyleGAN and the employed mask-guided StyleGAN. Left: Original StyleGAN; Right: Mask-guided StyleGAN.

### A MASK-GUIDED GENERATOR DETAILS

We utilize a mask-guided generator to integrate style codes with segmentation for synthesizing video frames, which are illustrated in fig. 1. The original StyleGAN start from a constant feature with a spatial size of  $4 \times 4$  and consist of a series of style blocks. Each block contains a modulation, a demodulation and a  $3 \times 3$  convolution layer. a noise broadcast operation  $[B]$  is introduced to improve the diversity of generative images.  $W$  and  $b$  in each block are denoted as learnable weights. A additional upsampling layer with a factor of 2 is employed between two blocks to increase the resolution of feature maps.

Unlike the global semantic control through style codes in the original StyleGAN, we extract localized style codes corresponding to different semantic sub-regions via masks, thereby enabling localized control. We extend the style block of original styleGAN into a mask-guided style block according to a mask. In particular, we aggregate the intermediate feature maps along with per-region

mask, which are formulated as:

$$F_l = \sum_{j=1}^C (F_{l-1} * W'_{jl}) \circ (\text{Down}(M)_i == j), \{l = 1, 2, \dots, C\} \quad (1)$$

$$W'_{jl} = \text{Demod}(\text{Mod}(W_l, s_{jl})) \quad (2)$$

where  $F_l$  and  $F_{l-1}$  denote the feature map of layer  $l$  and layer  $l - 1$ , respectively.  $W'_{jl}$  represent the scaled kernel weight for the  $j$ -th semantic region in the  $l$ -th layers.  $\text{Down}(\dots)$  function down-samples the mask to align with the input feature map. We follow the same modulation and demodulation as described in the original StyleGAN. In eq. (2),  $W_l$  denotes the original kernel weight for  $l$ -th layer and  $s_{jl}$  denotes the style codes of  $j$ -th semantic regions for  $l$ -th layer.

## 117 B MORE RESULTS

### 118 B.1 Talking Segmentation

119 We present more qualitative audio-driven talking segmentation  
 120 results, which are shown in fig. 2. Examination results show the  
 121 generated segmentations effectively delineate distinct facial regions,  
 122 even elaborating details such as earrings. Furthermore, the gener-  
 123 ated lip motions exhibit robust synchronization with the reference  
 124 video.

### 126 B.2 Talking Face

128 We present more qualitative results with state-of-the-art talking  
 129 face methods: SadTalker, Wav2lip and VideoReTalking, where the  
 130 results are illustrated in fig. 3. The generated frames of SadTalker  
 131 exhibit poor visual quality and can not handle the scenarios of heav-  
 132 ily variant pose move. The synthesized faces of Wav2lip exhibit  
 133 worse detail in the lip and teeth regions. Although VideoReTalk-  
 134 ing can yield visually gratifying results, it exists identity drift and  
 135 contains artifacts in local regions. Qualitative results demonstrates  
 136 that our method produces more realistic and high-fidelity results  
 137 while maintaining rich facial textures and identity details.

### 138 B.3 Additional Facial Editing

140 More facial editing cases can be found in fig. 4. In fig. 4, by simply  
 141 editing the eye regions of mask, we can manipulate blinking in a  
 142 controllable manner to synthesize realistic talking face videos.

## 175 B.4 Additional Swapping Background

176 Additional swapping background results are shown in fig. 5. Our  
 177 model intrinsically disentangles the foreground and background,  
 178 allowing for seamless background swapping and augmenting the  
 179 application scenarios of talking faces.

## 181 C LIMITATIONS AND DISCUSSIONS

182 Although our method generates realistic and high-fidelity video  
 183 which enable facial editing from a audio and a video, there still have  
 184 some limitations in our framework. Since our approach employ  
 185 facial editing by simply manipulate mask, currently only some  
 186 simple attribute such as blinking, eyebrows can be achieved. Future  
 187 research will concentrate efforts on exploring textual guidance  
 188 methods to enable global and local attribute editing capabilities for  
 189 talking face videos.

190 However, synthesized videos have the potential to be exploited  
 191 for spreading misinformation, defrauding the public, and infringing  
 192 on personal privacy. To mitigate this threat, researchers have pro-  
 193 posed various techniques such as digital watermarking technology  
 194 for detecting synthetic media. Future research needs to continue  
 195 strengthening ethical and legal norms to ensure the healthy devel-  
 196 opment and application of talking face technologies.

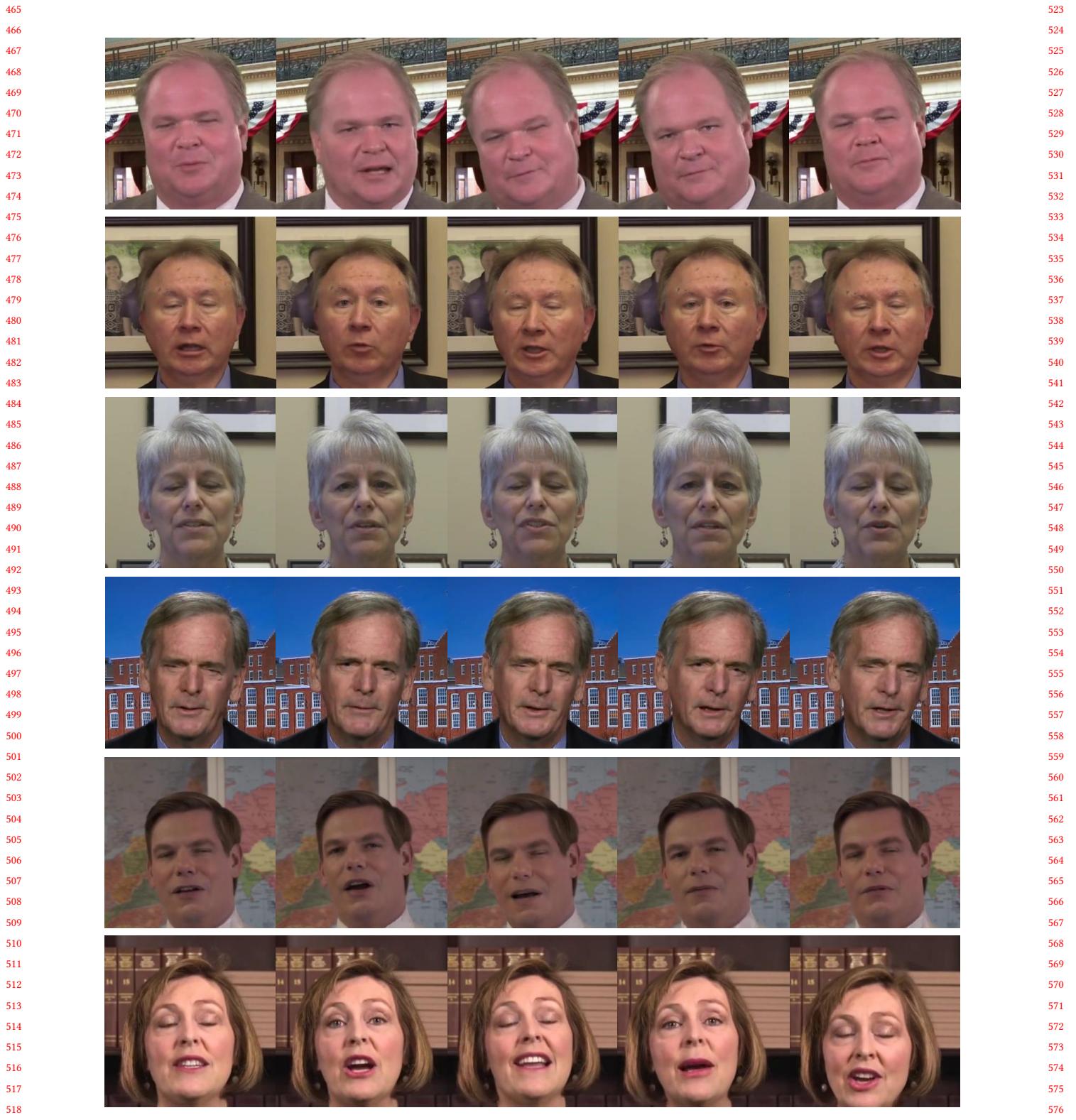
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**Figure 2: Visualization of synthesized segmentation(row 1, row 3, row5, row7) and real images(row 2, row 4, row6, row8). It can be seen that TSG can produce lip synchronized segmentation.**



**Figure 3: Additional qualitative comparisons of our results with several state of the art methods for talking face synthesis. In each block, our method is illustrated in the first row and synthesized images of different method (SadTalker, Wav2lip, VideoReTalking) follow the next.**



**Figure 4: Additional qualitative results of facial editing. Our method produces more high-fidelity results in editing regions while maintaining the details and identity information of other regions.**

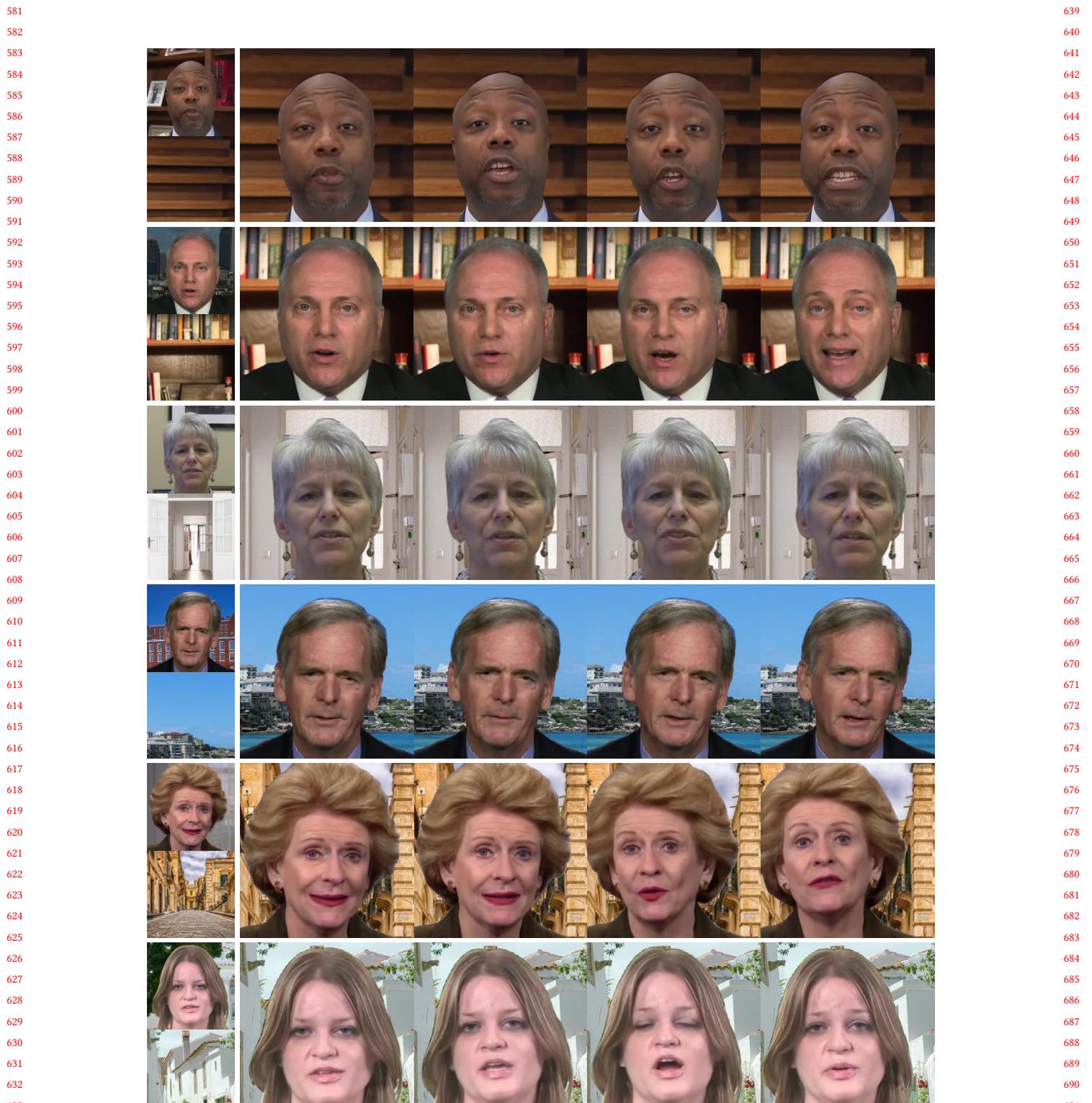


Figure 5: Additional example of Swapping background. Given a video and a background image, our method can produce natural and photo-realistic swapping videos.