

Paper 1445

A Neural Lip-Sync Framework for Synthesizing Photorealistic Virtual News Anchors

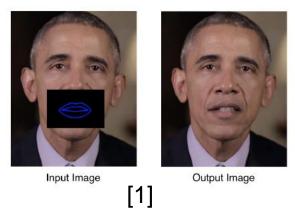
Ruobing Zheng, Zhou Zhu, Bo Song, Changjiang Ji

Moviebook Technology





Lip Sync "rewrite" the lip motions on a target video clip based on the given speech content.



nt Neural Networl

Related work:

[1] "Obamanet: Photo-realistic lip-sync from text"
[2] "Synthesizing obama: learning lip sync from audio"
S. Suwajanakorn



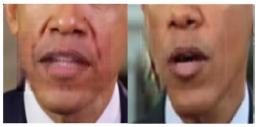


Two main problems

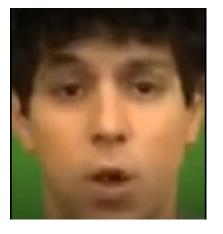
- Quality: Resolution, Visual consistency, Natural appearance
- Efficiency: Training, Inference







Obamanet 2017



Realistic Speech-Driven Facial Animation with GANs 2019





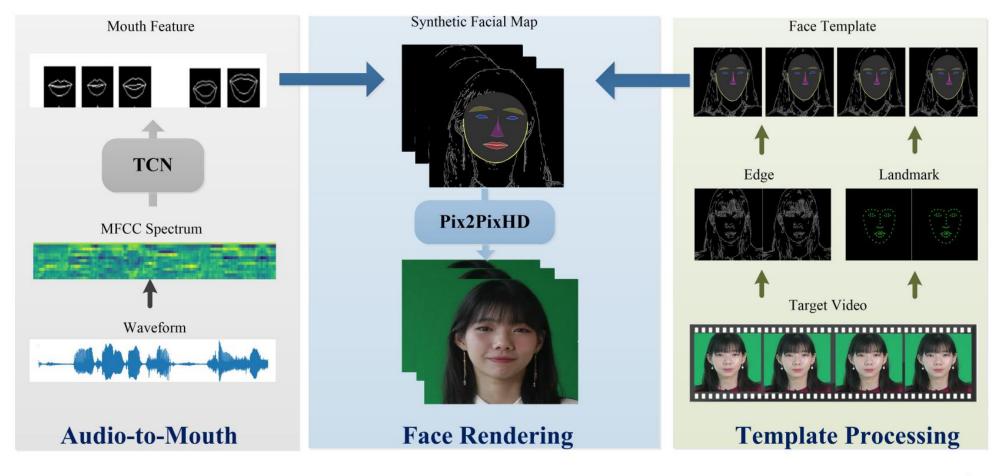
Our Solution

1. A pair of **Temporal Convolutional Networks(TCN)** learning the seq-to-seq mapping from audio signals to lip motion

2. An image-to-image translation-based **neural rendering model** converts synthetic face maps to high-resolution and photorealistic video frames



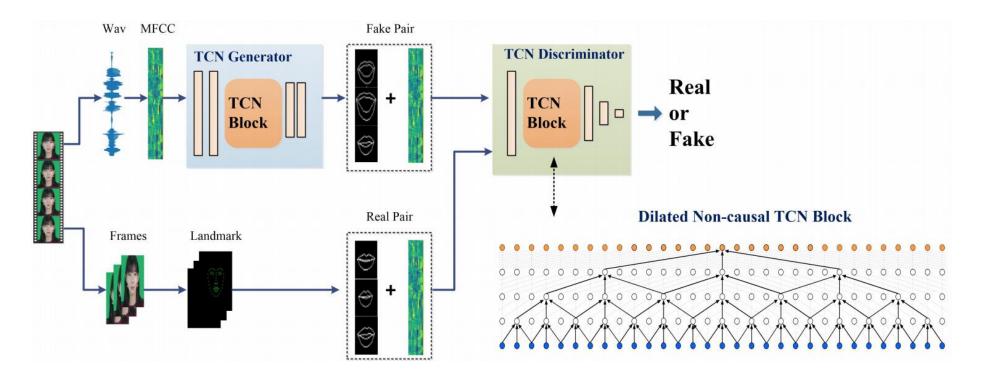








1. Learning Audio-to-Mouth Mapping

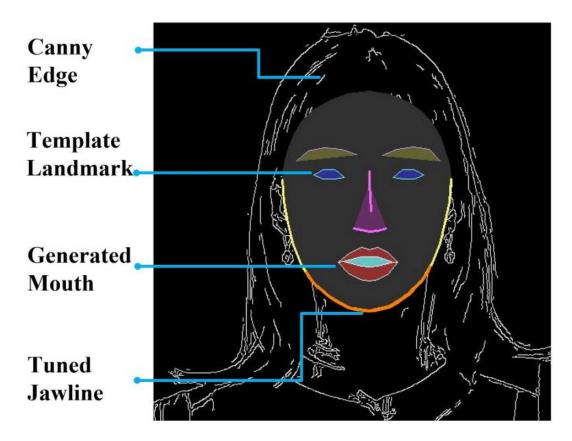


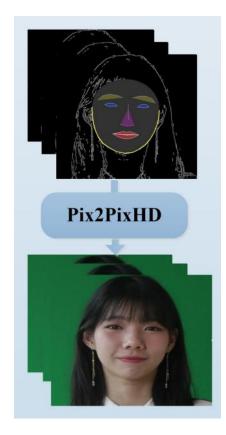
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2. Neural Rendering









Experiments: Audio-to-Mouth stage

TABLE I
COMPARING THE PERFORMANCE OF AUDIO-TO-MOUTH MAPPING
BETWEEN THE PROPOSED MODEL AND BASELINES.

Model	MSE	MAE	Int-MSE
Time-delayed LSTM	0.00366	0.0465	0.00735
Bi-LSTM	0.00357	0.0458	0.00712
Non-Causal TCN	0.00155	0.0278	0.00122
Adversarial TCN (our)	0.00141	0.0261	0.00132

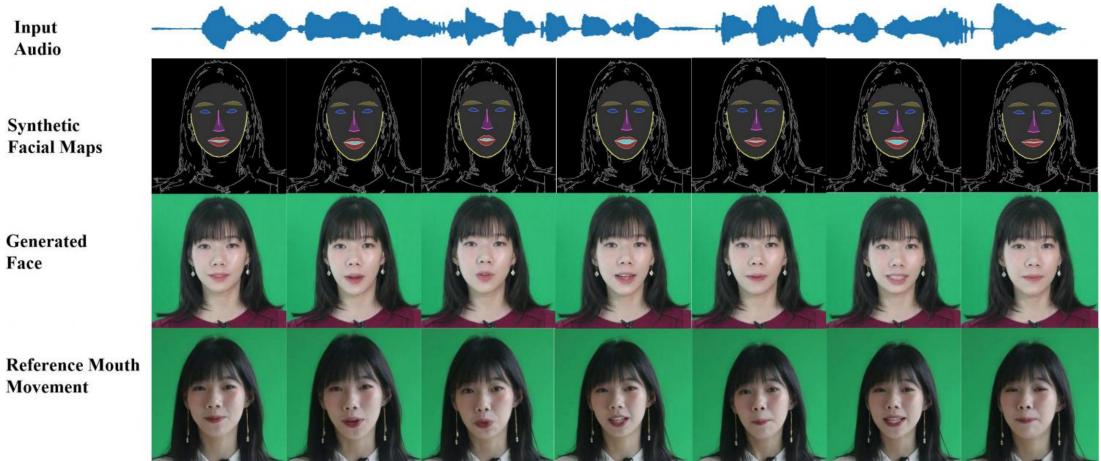
TABLE IICOMPARING THE TRAINING AND INFERENCE TIME (1-MIN AUDIO)BETWEEN LSTM, BIDIRECTIONAL LSTM, AND TCN.

Models	Batch training	Total training	Inference time
WIOUCIS	(s)	(min)	(s)
LSTM	0.069 ± 0.005	67.43 ± 5.62	2.272 ± 0.269
Bi-LSTM	0.124 ± 0.007	114.58 ± 3.76	3.376 ± 0.201
TCN	$\textbf{0.068} \pm \textbf{0.005}$	$\textbf{35.82} \pm \textbf{2.62}$	$\textbf{0.011} \pm \textbf{0.005}$





Experiments: Rendering stage





Thanks for watching our presentation!

If you are interested in our work, please contact

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