



Cross-Modal Mutual Learning for Audio-Visual Speech Recognition and Manipulation

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Introduction

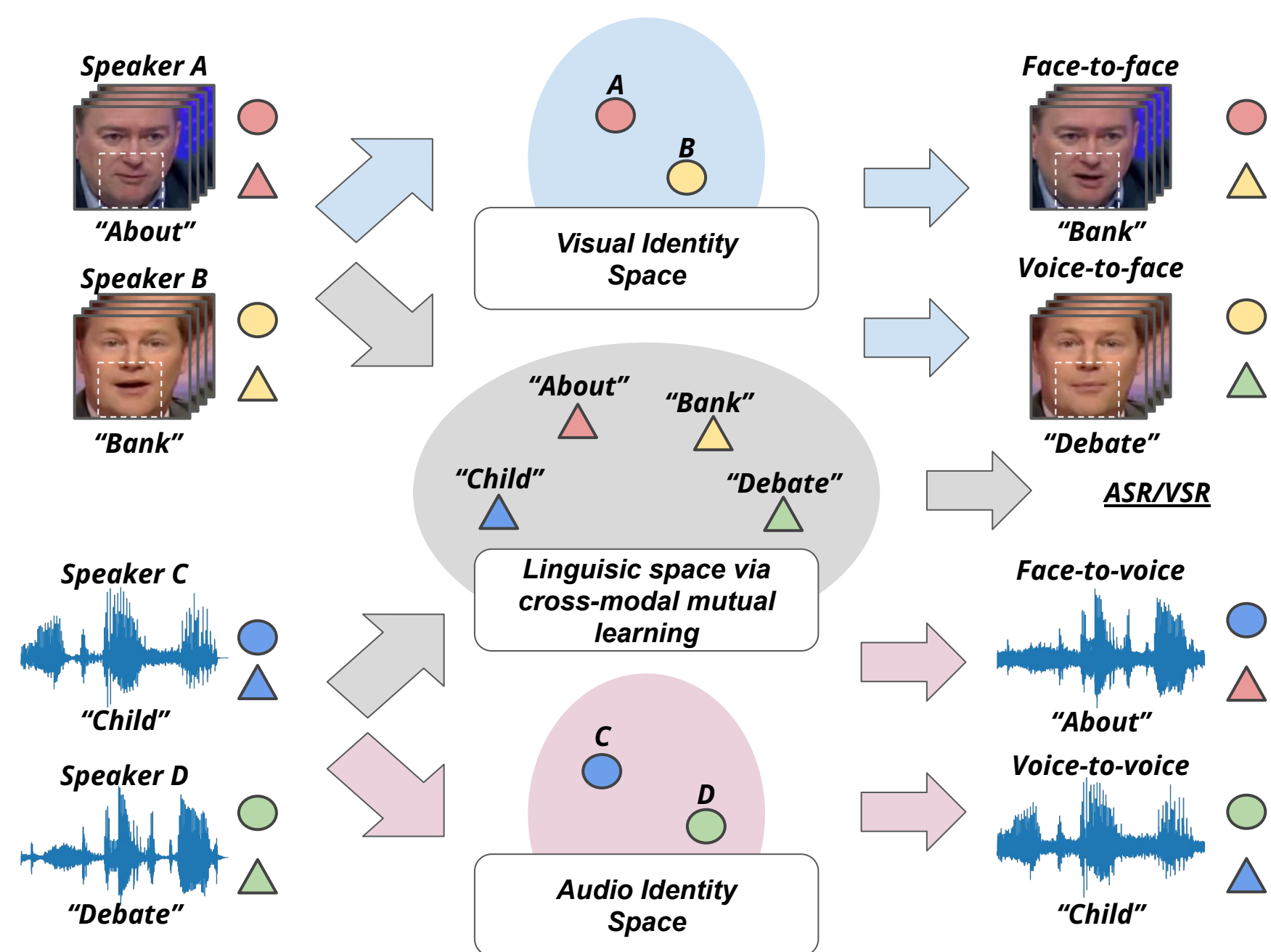


Figure 1: Illustration of joint audio-visual speech recognition and manipulation.

- Audio-visual speech synthesis is an extension of audio-visual speech recognition, aiming at generating realistic talking face video or audio outputs based on the desirable identity and linguistic information.
- We present a **unified framework** for jointly addressing the above six different intra/cross-modality **synthesis** and **recognition** tasks.

Contribution

- We present a **unified framework** for joint audio-visual speech recognition and synthesis.
- To transfer linguistic knowledge across modalities, we advance **cross-modal mutual learning** which **aligns** cross-modality data, producing **modality-agnostic linguistic representation** for AVSR.
- Our framework allows manipulation of visual and/or audio speech data, conditioned on the desirable **linguistic** or **subject identity** information of the inputs from the **same** or **distinct modalities**.

Approach

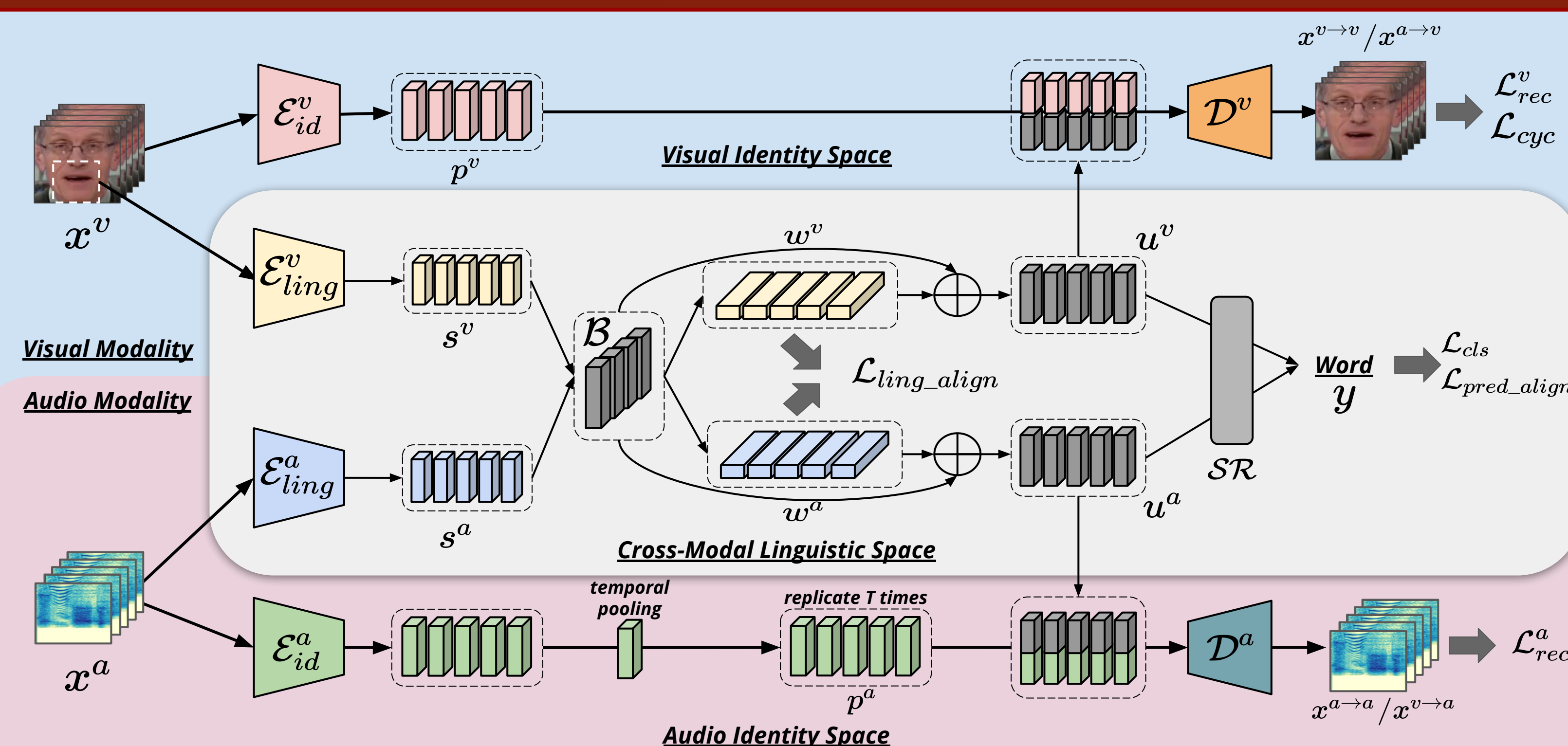


Figure 2: Our proposed framework for audio-visual speech recognition and manipulation

Cross-Modal Mutual Learning

$$\mathcal{L}_{ling_align} = \mathcal{KL}(w^a || w^v) + \mathcal{KL}(w^v || w^a)$$

$$\mathcal{L}_{pred_align} = \mathcal{KL}(d^a || d^v) + \mathcal{KL}(d^v || d^a)$$

$$\mathcal{L}_{mml} = \mathcal{L}_{cls} + \lambda_l \mathcal{L}_{ling_align} + \lambda_p \mathcal{L}_{pred_align}$$

- To **suppress** the modality information, we have s^v and s^a described as a linear combination of each modality-invariant codeword/basis in \mathcal{B} .
- To **relate** visual and audio data, we **mutually align** the basis weight and the word prediction distribution across visual and audio modalities.

Analysis on the Modality-Invariant Codebook

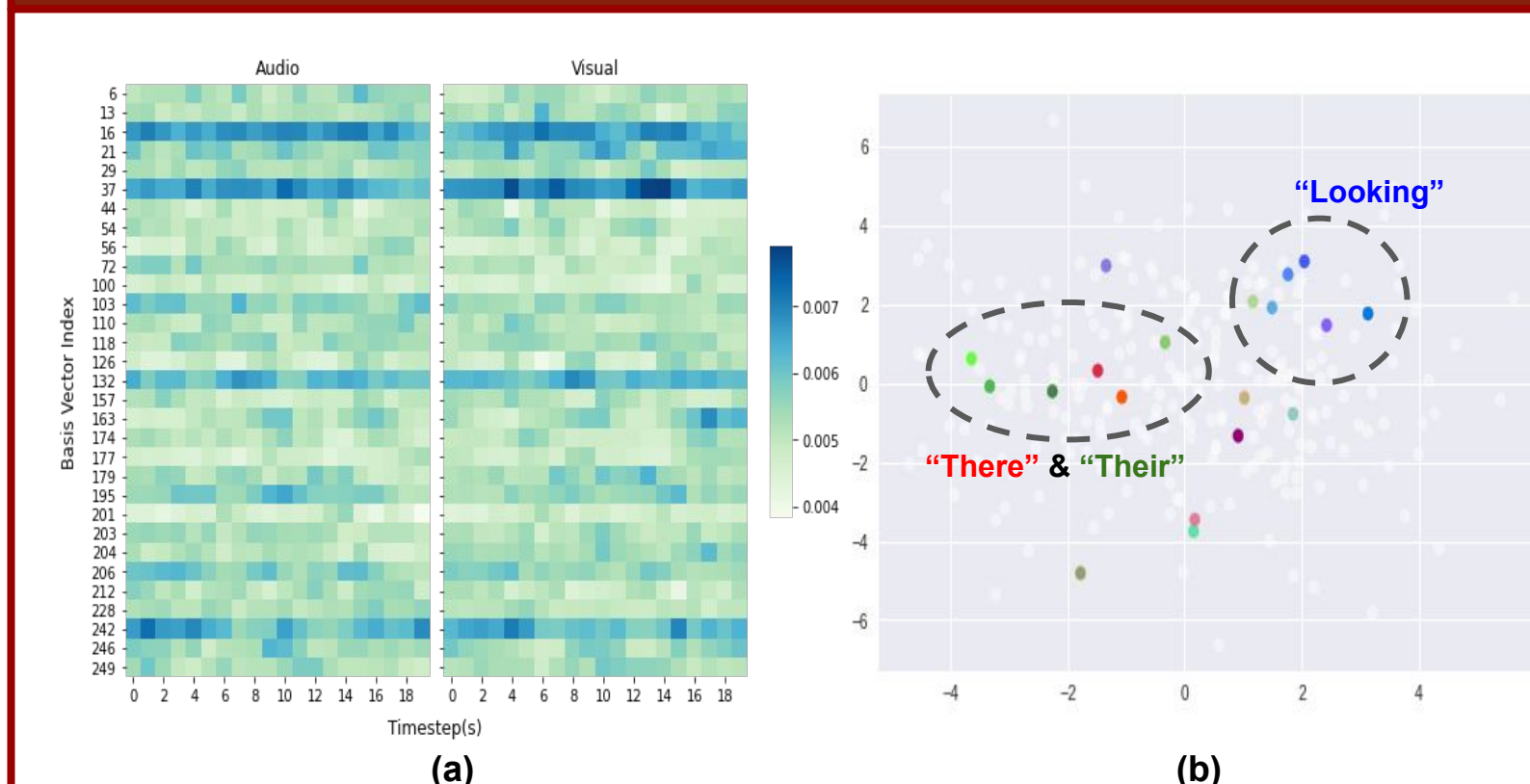


Figure 3: (a) Distributions of top-30 basis weights from audio and visual modalities of word "about". (b) 2D visualization via PCA of basis vectors for words with similar/dissimilar pronunciations.

- In Figure 3 (a), we see that the derived basis weights of audio/visual modality **share similar distributions**.
- In Figure 3 (b), we see that words with **similar pronunciation** tend to select **similar basis vectors**.

Experiments & Results

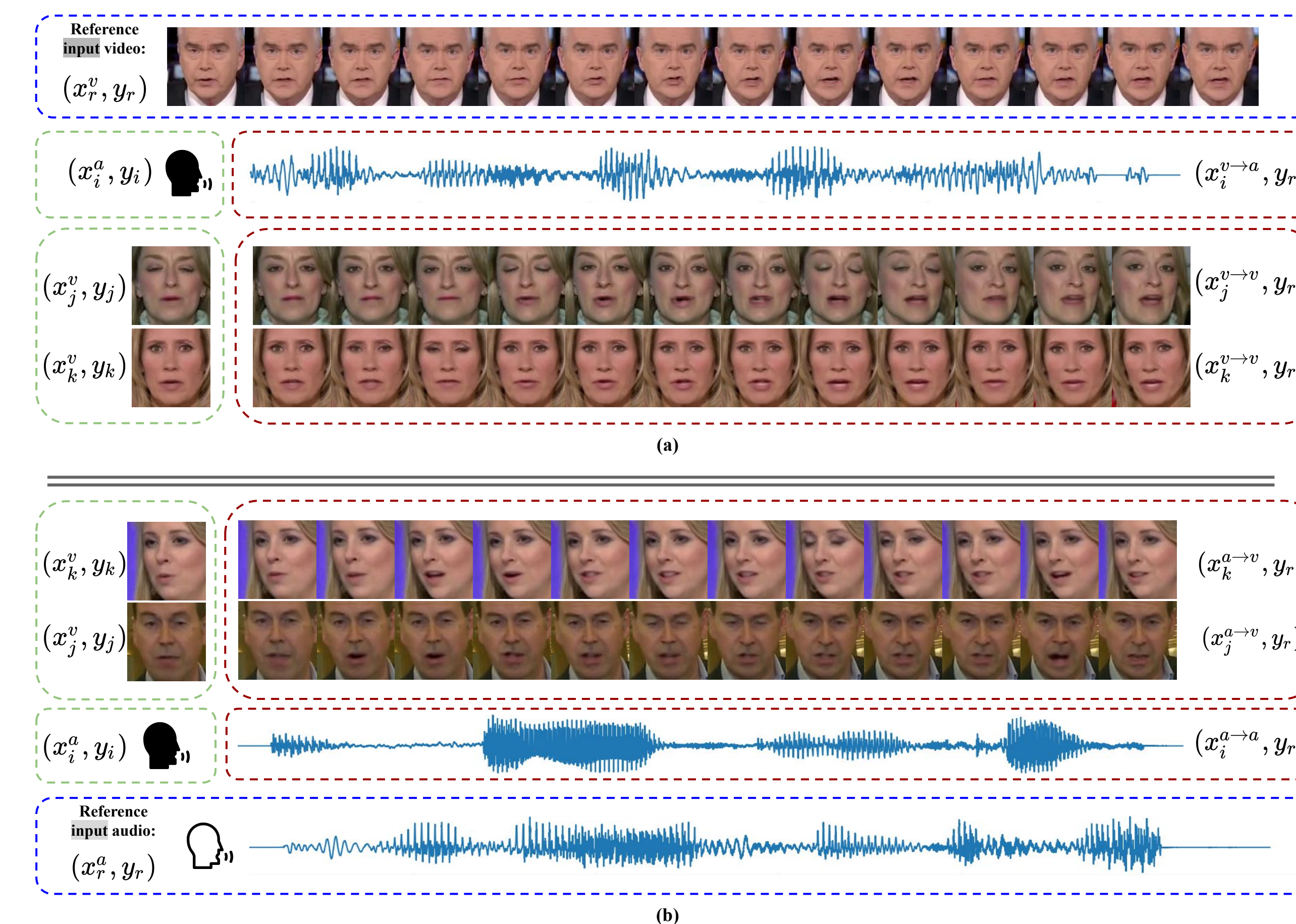


Figure 4: Example of intra/cross-modality synthesis: (a) face-to-voice & face-to-face synthesis, and (b) voice-to-face and voice-to-voice synthesis.

Method	Task	PSNR	SSIM	LSA.
DAVS	Intra	26.8	0.88	12.2
Ours	Intra	33.4	0.96	22.1
DAVS	Cross	26.7	0.88	10.7
ATVNet	Cross	30.9	0.81	12.3
LipGAN	Cross	33.4	0.96	11.3
Wav2Lip	Cross	31.2	0.93	<u>23.2</u>
Ours	Cross	<u>32.46</u>	<u>0.95</u>	27.7

Table 1: Quantitative evaluation of **talking face generation**.

Methods	Rec. Backbone	LRW Visual	LRW Audio	LRW-1000 Visual
DAVS	None	67.5	91.8	-
Bi-LSTM	LSTM	84.3	-	-
MSTCN	ResNet	85.3	98.5	41.4
DSTCN	SEDenseNet	88.4	-	43.7
Bi-GRU	GRU	85.0	-	48.0
(Ren et al. 2021)	Transformer	85.7	-	-
Ours w/o syn.	ResNet	88.4	98.5	50.5
Ours	ResNet	88.5	98.4	50.3

Table 3: Quantitative evaluation of **speech recognition**.

- Talking face video of satisfactory quality and **much higher lip sync accuracy (LSA.)**

Method	Task	STOI	ESTOI	PESQ
VQ-VAE	Intra	0.852	0.720	1.943
Ours	Intra	0.866	0.746	2.248
Lip2Wav	Cross	0.543	0.344	1.197
Ours	Cross	0.571	0.363	1.540

Table 2: Quantitative evaluation of **voice generation**.

- Accurately recognize** audio/visual speech content

Experiment Setting	LRW Visual	LRW Audio	LRW-1000 Visual
Baseline	87.85	98.45	49.24
Ours (+ B)	88.14	98.46	49.51
Ours (+ B + L _{align})	88.45	98.48	50.46
Ours (+ B + L _{align} + L _{rec})	88.47	98.40	50.32

Table 4: **Ablation studies** of our model design on speech recognition.

- Human voice of **better quality**
- Each module in cross-modal mutual learning **benefits ASR and VSR**