RobustL2S: Speaker-Specific Lip-to-Speech Synthesis exploiting Self-Supervised Representations

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Abstract-Significant progress has been made in speakerdependent Lip-to-Speech synthesis, which aims to generate speech from silent videos of talking faces. Current state-of-the-art approaches primarily employ non-autoregressive sequence-tosequence architectures to directly predict mel-spectrograms or audio waveforms from lip representations. We hypothesize that the direct mel-prediction hampers training/model efficiency due to the entanglement of speech content with ambient information and speaker characteristics. To this end, we propose RobustL2S, a modularized framework for Lip-to-Speech synthesis. First, a nonautoregressive sequence-to-sequence model maps self-supervised visual features to a representation of disentangled speech content. A vocoder then converts the speech features into raw waveforms. Extensive evaluations confirm the effectiveness of our setup, achieving state-of-the-art performance on the unconstrained ➡ Lip2Way dataset and the constrained GRID and TCD-TIMIT condatasets. Speech samples from RobustL2S can be found at https://neha-sherin.github.io/RobustL2S/

I. INTRODUCTION Understanding lip movements offers a distinct advantage in situations where auditory cues are unavailable. It proves particularly valuable for individuals with hearing impairments, speech disorders and aids in speech rehabilitation by providing visual feedback [1]. The synthesis of accurate speech from lip movements can assist in tasks such as movie dubbing [2], lan-guage learning, forensic investigations [3], video conferencing in noisy conditions, voice inpainting [4] or giving artificial voice to people who cannot produce intelligible sound. The problem of Lip-to-Speech synthesis is inherently ill-posed because a sequence of lip movements can correspond to multiple possible speech utterances [5]. Additional challenges arise from factors such as head pose movements, non-verbal facial expressions, variations in capture quality, and ambient noise, which further complicate the problem. Reliance on contextual information, such as environment, place, topic, etc., can help alleviate the Lipreading challenges [6], [7]; however, such information may not always be available.

Most existing approaches constitute an encoder-decoder architecture; the encoder maps the lip sequence to intermediate representations, which are then directly decoded into melspectrograms. The major drawback of this approach is that apart from speech content, the decoder is also forced to predict the time-varying speaker and ambient noise characteristics present in the ground truth Mel. We hypothesize that this dependence hurts the model's performance in terms of speech intelligibility, reducing its usability for various downstream applications [8]. Our work addresses these limitations by



The proposed RobustL2S model utilizes lip encoder and speech Fig. 1. encoder to extract SSL representations from lip sequences and their corresponding speech. A Seq2Seq model maps the lip representations to speech representations, which are then decoded to synthesize speech.

taking a modularized approach, exploiting the advances in Self-Supervised Learning (SSL) in audio and audio-visual scenarios.

Fig. 1 illustrates the proposed RobustL2S framework. In contrast to direct mel prediction from lip features, we take a two-staged approach. The first step extracts SSL representations of lip sequences and maps them to corresponding speech SSL representations using a sequence-to-sequence (Seq2Seq) model. The key idea is to use speech embeddings that disentangle the content from the speaker and ambient information. The second stage maps the content-rich speech embeddings to raw speech using a speaker-conditioned vocoder. The proposed RobustL2S framework simplifies training and brings robustness to variations in head-pose, ambient noise, and time-varying speaker characteristics, leading to significant gains in speech intelligibility. To validate the efficacy of our approach, we perform comprehensive experiments on GRID [9], TCD-TIMIT [10] and Lip2Wav [5] datasets. The quantitative measures and MOS scores show that the synthesized speech generated by our method accurately represents the intended content and improves on the intelligibility/naturalness compared to current state-of-the-art methods [11], [12] on all three datasets.

More formally, our work makes the following contributions: (1) We propose a novel modularized framework for Lip-to-Speech synthesis exploiting self-supervised embeddings for both lip and speech sequences (2) A Seq2Seq network for cross-modal knowledge transfer to map lip SSL representations to speech SSL representations; and (3) Thorough experimental results demonstrating that RobustL2S is capable of synthesizing high-quality speech, achieving state-of-the-art results in objective and subjective evaluation without requiring additional data augmentation [11].

II. RELATED WORK

A. Lip-to-Speech synthesis

1) Constrained Lip-to-Speech synthesis: Constrained lip-tospeech synthesis tackles speech generation from videos with limited vocabulary and minimal head movement [9], [10]. Ephrat et al.[13] introduced a CNN-based approach to predict Linear Predictive Coding features from silent talking videos. They later enhanced their model to a two-tower CNN-based encoder-decoder architecture [14], encoding raw frames and optical flows separately. [15] propose a combination of an autoencoder for extracting bottleneck features from audio spectrograms and a lipreading network comprising CNN, LSTM, and fully connected layers, for visual feature extraction. On the other hand, [16] utilize a stochastic modeling approach employing a variational autoencoder. Other methods [17]-[20] employ GANs to synthesize speech from video frames. [21] train an attention-based encoder-decoder model to reconstruct speech from silent facial movement sequences without human annotations. [22] performs multi-modal supervision, using text and audio, to complement the insufficient word representations to reconstruct speech with correct contents from the input lip movements. [23] achieves zero-shot Lip-to-Speech synthesis using variational autoencoder to disentangle speaker and content information and a face identity encoder for unseen speakers.

2) Unconstrained Lip-to-Speech synthesis: Unconstrained lip-to-speech synthesis focuses on generating speech from realworld videos of individuals talking. This approach considers videos with an extensive vocabulary and significant head movements. Seminal work by Prajwal et al. [5] introduced a 3D-convolution plus autoregressive Seq2Seq model, adapted from Tacotron2 [24] for single speaker Lip-to-Speech synthesis. Their model generates mel-spectrograms based on the input video frames. In contrast, [25] employed a nonautoregressive architecture to expedite the inference process. It uses 3D-convolution blocks, a transformer condition module, and a Glow decoder module [26] for refining the melspectrograms. [27] expanded on [5] by training a transformer model to learn a joint latent distribution for speech generation. The VV-Memory architecture [28] combines audio and visual information using a key-value memory structure to enable video-to-speech reconstruction and speaker-independent speech retrieval. A recent work by [11] proposed an end-toend non-autoregressive transformer for synthesizing speech directly from unconstrained talking videos. Their approach involves a visual encoder, an acoustic decoder, a linear layer, and a GAN-based vocoder operating on Mel-spectrograms. LipSound2 [21] investigates cross-modal self-supervised pretraining of an encoder-decoder architecture with a locationaware attention mechanism to map face image sequences to mel-scale spectrograms. In contrast, our proposed RobustL2S differs by using content-rich SSL representations [29] and learning target speech representations from lip sequences.

B. Self-supervised representation for Lip-to-Speech synthesis

Traditional works on Lip-to-Speech synthesis encode lip or face sequences to hidden states, followed by a decoder to generate Mel-spectrograms. An independently trained vocoder transforms them into time-domain waves. However, these Mel frames are highly correlated along both time and frequency axes which may degrade the performance of entire Lip-to-Speech synthesis [30]. Moreover, these Mel-spectrograms have higher variance than that of quantized speech SSL representations increasing the complexity of training a Seq2Seq model. Due to its recent emergence, the utilization of SSL representation in Lip-to-Speech synthesis remains limited.

In VCVTS [12], vector quantized contrastive predictive coding (VQCPC) units are extracted from lip movements, and a speaker encoder, pitch predictor, and decoder are used to infer Mel frames. A separate voice conversion model and vocoder are employed for speaker representation learning and speech synthesis.

Revise [31] employs a combined audio-visual speech recognition module (P-AVSR - initialized with AV-HuBERT - an audio-visual SSL model) and a modified text-to-speech synthesis module (P-TTS) for generalized speech enhancement tasks. P-AVSR predicts discrete units derived from a self-supervised speech model, and P-TTS converts these units into speech using a modified HiFi-GAN[29] trained on the LJSpeech[32] dataset. Our work closely relates with [31] utilizing SSL representations for Lip-to-Speech synthesis. However, we utilize disentangled AV-HuBERT and HuBERT [33] features and a decoupled training procedure to train a Seq2Seq model. Additionally, the existing works have not yet fully capitalized on SSL representations for speaker-specific Lip-to-Speech generation, and our efforts aim to address this gap.

III. METHOD

A. Preliminaries

RobustL2S consists of three modules: an encoder that extracts lip and speech representation from their corresponding sequences, a Seq2Seq model that maps lip representations to speech representations, and a vocoder that synthesize speech using the speech representations. We introduce four functions as follows:

- $f_1: L^{T \times W \times H} \mapsto L_{ssl}$, which maps the input lip sequence to its corresponding SSL representation. Here, T represents the number of time-steps (frames), and H and W correspond to the spatial dimensions of the frames.
- $f_s: X \mapsto S_{ssl}$, which maps the ground-truth raw speech to its corresponding SSL representation.
- $f_{s2s}: L_{ssl} \mapsto S_{ssl}$, which maps the lip representation to its corresponding speech representation.

f_{voc}: S_{ssl} → X̂, which maps the speech representation to the synthesized speech X̂.

B. Encoder

Although our framework is compatible with various off-theshelf SSL models, we specifically utilize AV-HuBERT [34] for f_1 , our video encoder to extract lip representations. We use HuBERT [33] for f_s , to extract speech representation of target speech signal. The HuBERT and AV-HuBERT models, are trained using a masked-prediction loss to predict cluster IDs, which are learned using k-means clustering. They are initialized with MFCC features derived from acoustic frames, and subsequently more complex features derived from an audio or audio-visual encoder, depending on the specific model being used. AV-HuBERT incorporates a modified ResNet [35]. [36] as its frontend, coupled with a transformer encoder. We opted for AV-HuBERT instead of Visual-HuBERT for this task because AV-HuBERT exhibits superior performance in the lipreading task, as demonstrated by [34]. This improvement is observed when the target cluster IDs are derived from both audio and visual modalities, as opposed to a single modality, whether it be audio or visual. We also finetune the pretrained AV-HuBERT using an attention-based Seq2Seq cross-entropy loss as in [34].

C. Seq2Seq model

In recent years, Seq2Seq models have gained significant attention in the field of cross-domain generation. The core concept of our approach is to align representations from two different domains - visual and audio, that share a common generating process. By recovering correspondences between these domains, we facilitate the transfer of knowledge from one domain to the other.

Our Seq2Seq model, denoted as f_{s2s} , adopts a nonautoregressive-based encoder-decoder architecture to map lip representations to their corresponding speech representations. The encoder and decoder consist of feed-forward transformer blocks with self-attention [37], along with 1-dimensional convolutions inspired by Fastspeech2 [38]. A transposed convolution layer is used at the encoder to match the rate of video and audio representations. The encoder takes the lip representation L_{ssl} and encodes it into a sequence of fixeddimensional vectors. The decoder generates predictions for all representations of S_{ssl} simultaneously. We train three versions of the Seq2Seq model:

• $f_{s2s-units}$: This encoder-decoder architecture utilizes Cross-Entropy (CE) loss to train the model on the decoded speech units. The CE loss measures the difference between the decoded units and the ground-truth speech HuBERT units. The input to the architecture consists of cluster IDs from the video encoder, and the decoder predicts the corresponding HuBERT cluster IDs for the audio. The objective can be written as:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{N} S_{\text{ssl_units_i}} \log(\hat{S}_{\text{ssl_units_i}}), \qquad (1)$$

where S_{ssl_units} are the ground-truth speech units, \hat{S}_{ssl_units} are the decoded speech units, and N are the number of HuBERT units.

• $f_{s2s-features}$: Here the model learns mapping from audiovisual feature to corresponding speech feature vectors. This model utilizes L1 loss, quantifying the difference between the decoded features and ground-truth speech features. The objective can be written as:

$$\mathcal{L}_{L1} = \frac{1}{T} \sum_{i=1}^{T} |S_{ssl_features_i} - \hat{S}_{ssl_features_i}|, \qquad (2)$$

where $S_{\text{ssl}_{\text{features}}}$ are the ground-truth speech features, $\hat{S}_{\text{ssl}_{\text{features}}}$ are the decoded speech features, and T is the time-steps.

• $f_{s2s-features-ctc}$: This architecture follows the same structure as $f_{s2s-features}$, but also includes an additional fully connected linear head to predict CTC tokens after the encoder layer. For given input lip representation $L_{ssl} \in \mathbb{R}^{TxD}$ of length T and dimension D, let Enc_{ssl} be the output of encoder. The goal is to minimize the negative loglikelihood by using $P_{CTC}(S_{ssl}|Enc_{ssl})$ to train the model effectively using the CTC approach and is defined as:

$$\mathcal{L}_{CTC} := -\log P_{CTC}(S_{\rm ssl}|Enc_{\rm ssl}). \tag{3}$$

By weighted summing the L1 and CTC loss functions, the objective function can be formulated as:

$$\mathcal{L}_{\text{Tot}} = \alpha_{CTC} * \mathcal{L}_{\text{CTC}} + \alpha_{L1} * \mathcal{L}_{L1}, \qquad (4)$$

where $\alpha_{\text{CTC}} \in \mathbb{R}$ and $\alpha_{\text{L1}} \in \mathbb{R}$ are the hyperparameter that balances the influence between two loss.

D. Speech Vocoder

We use a modified version of HiFiGAN-v2 [39] to synthesize speech. It has a generator G and a discriminator D. Gruns S_{ssl} through transposed convolutions for upsampling to recover the original sampling rate followed by residual block with dilations to increase the receptive field to synthesize the signal, $\hat{X} := G(S_{ssl})$.

The discriminator in our model has the task of distinguishing the synthesized signal \hat{X} from the original signal X. It is evaluated using two sets of discriminator networks. The multiperiod discriminators operate on equally spaced samples of the signals, focusing on capturing temporal patterns and characteristics. On the other hand, the multi-scale discriminators analyze the input signal at different scales, enabling the model to capture both fine-grained details and global structure. The primary objective of the model is to minimize the discrepancy, measured by $D(X, \hat{X})$, between the original signal and the synthesized signal. This optimization process applies to all the parameters of the speech decoder, improving its overall performance and fidelity.

IV. EXPERIMENTS

A. Datasets

1) Lip2Wav: The Lip2Wav dataset [5] is a large, personspecific, unconstrained dataset, commonly used for learning Lip-to-Speech synthesis for individual speakers. It consists of real-world lecture videos featuring 5 different speakers. Each speaker has approximately 20 hours of video data, and the vocabulary size exceeds 5000 words for each speaker. We do experiments on all five speakers: Chess Analysis (chess), Chemistry Lectures (chem), Hardware Security (hs), Deep Learning (dl), and Ethical Hacking (eh).

2) *GRID-4S:* The GRID-4S is a subset of the GRID audiovisual dataset [9] specifically designed for constrained Lip-to-Speech synthesis. This subset includes two male speakers (s1, s2) and two female speakers (s4, s29), which are frequently used in the literature [5], [19]. The videos in the dataset were captured in an artificial environment. The vocabulary used in GRID-4S is limited to only 51 words. The sentences in the dataset follow a restricted grammar, with each sentence containing 6 to 10 words.

3) TCD-TIMIT-3S: The TCD-TIMIT-3S is a subset of the TCD-TIMIT dataset, which comprises recordings of 62 speakers captured under studio conditions. Among these speakers, three are trained lip-speakers. The primary objective of selecting this subset was to enable comparison with previous studies [5], [19]. Our focus was solely on the audio-visual data generated by these three lip-speakers. Each lip-speaker delivers 375 distinct sentences that exhibit phonetic diversity. Additionally, there are two sentences that are spoken by all three lip-speakers.

B. Implementation details

1) Data preparation: For the GRID-4S and TCD-TIMIT-3S datasets, we adhere to the convention of randomly selecting 90% data for training, 5% for validation, and 5% for testing, as established in previous works [5], [11], [17], [40]. For Lip2Way, we adopt the official data split [5]. For consistency, in line with previous works, we evaluated RobustL2S on the Lip2Wav dataset using a speaker-dependent setting [5], [14], [28]. This involved training the network separately with individual speakers. However, for the GRID-4S and TCD-TIMIT-3S datasets, we evaluated RobustL2S in a constrained (seen) speaker setting [5], [17], [40]. In this case, we trained a single speaker model for each dataset. The video sequences are resampled to a frame rate of 25 frames per second (fps), while the raw audio is sampled at 16kHz. We utilize the SFD [41] face detector to detect 68 keypoints, allowing us to crop a mouth-centered region-of-interest measuring 96×96 pixels. In order to solely assess the advantages of using SSL representation in our proposed setup, we opt not to employ any data augmentation techniques to enhance the quality of synthesized speech. The Lip2Wav dataset does not provide transcripts, so we rely on the Whisper small model [42] to extract transcripts. These transcripts are then used for finetuning the AV-HuBERT model.

2) SSL representation: We utilize the official fairseq repository implementation of the BASE models AV-HuBERT [34] and HuBERT [33] for our experiments. We fine-tune the AV-HuBERT pretrained model with an attention-based STS crossentropy loss for visual speech recognition [34]. To achieve this, a transformer decoder is added to the pretrained model, which autoregressively decodes the AV-HuBERT features to target character probabilities. The fine-tuned AV-HuBERT model extracts SSL representations for lip sequences, while HuBERT is employed to extract representations from speech signals. Both models provide 768-dimensional features. For $f_{s2s-units}$ model, following the approach in [33], [34], the lip features are clustered into 2000 AV-HuBERT units, while the speech features are clustered into 100 HuBERT units, using k-means clustering. For $f_{s2s-features}$ model, the output features from HuBERT and AV-HuBERT models are used directly.

3) Seq2Seq model: Our model comprises a 6-layer transformer encoder and decoder with a hidden dimension of 512 and 2 attention heads. we set the batch size to 32 and the maximum number of steps to 20,000. We employ the Adam optimizer with an initial learning rate of 4.4 x 10^{-2} , along with an annealing rate of 0.3 and annealing steps at [3000, 4000, 5000]. The HuBERT model encodes speech into features at a frame rate of 50Hz, while the SSL unit from AV-HuBERT is encoded at 25Hz. To match these rates, we incorporate a lightweight transposed convolution layer with a kernel size of [4,3] and a stride length of [2,1]. We set $\alpha_{\rm CTC}$ and $\alpha_{\rm L1}$ mentioned in (4) to 0.001 and 1, respectively.

4) Speech Vocoder: We use the official implementation of the adapted HiFiGAN-v2¹ to generate audio from speech SSL representations. This model employs encoding of raw audio into a sequence of discrete tokens from a set of 100 possible HuBERT tokens, with a code hop size of 160 raw audio samples. We set the batch size to 16, the learning rate to $2x10^{-4}$, the number of embeddings to 100, the embedding dimension to 128, and the model input dimension to 256. Following the approach in [43], F0 is not used as a feature in our training process. The aforementioned vocoder configuration is effective for speech units. However, for our investigated feature-based models, $f_{s2s-features}$ and $f_{s2s-features-ctc}$, we apply a pre-trained kmeans ² clustering model for speech HuBERT units. During the inference phase, the generated features undergo k-means clustering to obtain discrete speech units, which are then

passed through the speech vocoder. We train the vocoders for the three datasets separately. samples.

C. Evaluation metric

During our evaluation, we employ several metrics to assess the quality of the synthesized speech. These include: Word Error Rate (WER), Short-Time Objective Intelligibility (STOI) [44] and Extended Short-Time Objective Intelligibility (ES-TOI) [45]. Additionally, we conduct subjective evaluations using Mean Opinion Score (MOS), where human evaluators rate

¹https://github.com/facebookresearch/speech-resynthesis

²https://github.com/facebookresearch/fairseq/tree/main/examples/ textless_nlp/gslm/speech2unit

 TABLE I

 Performance comparison: Seq2Seq model vs. evaluated

 variations vs. no Seq2Seq model employed on chemistry

 speaker of Lip2Wav dataset.

Baseline (Ours)	STOI ↑	ESTOI ↑
f_l (pre-trained) + f_{voc}	0.447	0.22
f_l (finetuned) + f_{voc}	0.50	0.27
f_l (finetuned) + $f_{s2s-units}$ + f_{voc}	0.18	0.013
f_l (finetuned) + $f_{s2s-features}$ + f_{voc}	0.583	0.397
f_l (finetuned) + $f_{s2s-features-ctc}$ + f_{voc}	0.557	0.368

the quality, intelligibility and naturalness of the synthesized speech based on their subjective perception.

V. RESULTS

A. Need for Seq2Seq model

We tested our hypothesis of using a Seq2Seq model on the Lip2Wav dataset, specifically for a chemistry speaker and report our findings in Table I. Fine-tuning the AV-HuBERT model using transcripts consistently improved objective metrics by approximately 0.05 units on both the metrics compared to the pretrained version. Deploying the Seq2Seq model on the finetuned AV-HuBERT features $(f_l$ (finetuned) + $f_{s2s-features}$ + f_{voc}) resulted in an increase of approximately 0.08 and 0.12 units in STOI and ESTOI metrics, respectively, compared to not using the Seq2Seq model $(f_l(\text{finetuned}) + f_{voc})$. These results highlight the effectiveness of our Seq2Seq approach using SSL representations for Lip-to-Speech synthesis. The significant performance gap (approximately 0.39 units on both metrics) between the Seq2Seq model using SSL features and the model using SSL units on both evaluated metrics approximates the amount of information lost in speech reconstruction when audio-visual sequences are represented as SSL units instead of SSL features. From now on, we will refer to f_l (finetuned) + $f_{s2s-features}$ + f_{voc} as RobustL2S. The inclusion of CTC loss in our f_l (finetuned) + $f_{s2s-features-ctc}$ model resulted in a statistically insignificant decrease of approximately 0.02 units in STOI compared to the model without CTC loss, f_l (finetuned) + $f_{s2s-features}$. The decrease may be due to the lack of ground-truth transcripts in the Lip2Wav dataset. However, when evaluating our model using CTC loss on datasets (GRID-4S and TCD-TIMIT-3S) with ground-truth transcripts, we observed a slight increase of 0.02 units. Nevertheless, our focus is on working with datasets in the wild that generally lack ground-truth transcripts, so we proceed with experiments excluding the CTC loss.

B. RobustL2S in Constrained settings

Table II and III summarizes the performance of our RobustL2S in the context of Lip-to-Speech synthesis using constrained datasets: GRID-4S and TCD-TIMIT-3S. We compare our results with existing Lip-to-Speech synthesis works, including state-of-the-art approaches. We report the mean test scores on all four speakers of the GRID-4S dataset and all three speakers of the TCD-TIMIT-3S dataset, as documented in previous works. Remarkably, our RobustL2S approach demonstrates significant improvements in terms of STOI and WER

TABLE II PERFORMANCE COMPARISON IN CONSTRAINED-SPEAKER SETTING ON GRID-4S dataset

Method	STOI ↑	ESTOI ↑	WER \downarrow
Vid2speech [13]	0.491	0.335	44.92 %
Lip2AudSpec [15]	0.513	0.352	32.51 %
1D GAN-based [17]	0.564	0.361	26.64 %
Vocoder-based [40]	0.648	0.455	23.33 %
Ephrat et al. [14]	0.659	0.376	27.83 %
Lip2Wav [5]	0.731	0.535	14.08 %
VAE-based [16]	0.724	0.540	-
VCA-GAN [19]	0.724	0.609	12.25 %
kim et al. [28], [46]	0.738	0.579	-
RobustL2S	0.754	0.571	11.21 %

TABLE III Performance comparison in constrained-speaker setting on TCD-TIMIT-3S dataset

Method	STOI ↑	ESTOI ↑	WER \downarrow
Vid2speech [13]	0.451	0.298	75.52 %
Lip2AudSpec [15]	0.450	0.316	61.86 %
1D GAN-based [17]	0.511	0.321	49.13 %
Ephrat <i>et al</i> . [14]	0.487	0.310	53.52 %
Lip2Wav [5]	0.558	0.365	31.26 %
VCA-GAN [19]	0.584	0.401	-
RobustL2S	0.596	0.452	29.03 %

metrics when compared to other approaches. This improvement is particularly noticeable on the TCD-TIMIT-3S dataset, which contains a larger number of novel words that were unseen during training. This observation highlights the ability of our RobustL2S to accurately pronounce new words and effectively capture semantic information from lip movements, resulting in the generation of more intelligible speech.

TABLE IV Performance comparison in speaker-dependent setting on Lip2Wav dataset

Speaker	Method	STOI ↑	ESTOI ↑
Chemistry	Ephrat et al. [5]	0.165	0.087
	GAN-based [47]	0.192	0.132
Lectures	Lip2Wav [5]	0.416	0.284
(chem)	Hong et al. [28]	0.566	0.429
. /	RobustL2S	0.583	0.397
	Ephrat et al. [5]	0.184	0.098
Chess	GAN-based [47]	0.195	0.104
Analysis	Lip2Wav [5]	0.418	0.290
(chess)	Hong et al. [28]	0.506	0.334
	RobustL2S	0.517	0.340
	Ephrat et al. [5]	0.112	0.043
Deep	GAN-based [47]	0.144	0.070
Learning (dl)	Lip2Wav [5]	0.282	0.183
	Hong et al. [28]	0.576	0.402
	RobustL2S	0.627	0.419
	Ephrat et al. [5]	0.192	0.064
Hardware Security (hs)	GAN-based [47]	0.251	0.110
	Lip2Wav [5]	0.446	0.311
	Hong et al. [28]	0.504	0.337
	RobustL2S	0.511	0.337
Ethical	Ephrat et al. [5]	0.143	0.064
	GAN-based [47]	0.171	0.089
Hacking	Lip2Wav [5]	0.369	0.220
(eh)	Hong et al. [28]	0.463	0.304
	RobustL2S	0.493	0.277



Fig. 2. MOS scores on Intelligibility, Quality and Naturalness with their 95 % confidence interval computed from their t-distribution on GRID-4S dataset



Fig. 3. MOS scores on Intelligibility, Quality and Naturalness with their 95 % confidence interval computed from their t-distribution on Lip2Wav dataset

C. RobustL2S in Unconstrained settings

Table IV provides a synopsis of RobustL2S's performance on the Lip2Wav dataset. This dataset includes a significant amount of silences between words, and RobustL2S shows a notable improvement across all metrics. Despite Lip2Wav's data asynchrony issues, which may affect the quality of the generated speech, RobustL2S demonstrates substantial performance gains in objective metrics, highlighting its overall superiority in producing intelligible speech. However, it is worth noting that RobustL2S performs similarly or slightly worse than [28] on the *hs* and *eh* ESTOI metric. This could potentially be attributed to the poor resolution (480p and 360p) of the original videos, making it challenging to accurately recognize lip regions.

D. Subjective evaluation

Fig. 2 and Fig. 3 shows the MOS scores on intelligibility (MOS(I)), quality (MOS(Q)), and naturalness (MOS(N)) of synthesized speech from evaluated methods on Grid-4S and Lip2Wav datasets. We requested ten English proficient subjects to score five randomly selected samples from different methods on the Lip2Wav and GRID-4S datasets. It can be observed that our model outperforms the evaluated methods, exhibiting higher Mean Opinion Score (MOS) values. This demonstrates

that the proposed approach inherits the advantages of disentangled SSL features and the mapping of lip sequences to contentspecific information. As a result, our model not only inherently improves the intelligibility aspect of synthesized speech but also generates speech that is highly natural and of high quality.

VI. CONCLUSIONS

We propose a novel framework for Lip-to-Speech system, called RobustL2S, which accurately synthesizes spoken content from silent videos. This is accomplished by utilizing a non-autoregressive based sequence-to-sequence model to establish an inter-modality mapping, allowing us to learn a suitable decoding space from the lips' self-supervised (SSL) representations. We further demonstrate the effectiveness of mapping SSL features rather than SSL units for synthesizing intelligible speech. Both quantitative and qualitative results showcase state-of-the-art performance in constrained settings (such as GRID and TCD-TIMIT) and unconstrained settings (like Lip2Wav). In our future work, we aim to introduce emotive effects in the synthesized speech, considering that HuBERT embeddings are known to lack prosody information. Additionally, we plan to explore diffusion-based speech vocoders and their application in a multi-lingual setup. We commit to open-source our implementation on acceptance.

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