Where Visual Speech Meets Language: VSP-LLM Framework for Efficient and Context-Aware Visual Speech Processing

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Abstract

In visual speech processing, context modeling capability is one of the most important requirements due to the ambiguous nature of lip movements. For example, homophenes, words that share identical lip movements but produce different sounds, can be distinguished by considering the context. In this paper, we propose a novel framework, namely Visual Speech Processing incorporated with LLMs (VSP-LLM), to maximize the context modeling ability by bringing the overwhelming power of LLMs. Specifically, VSP-LLM is designed to perform multi-tasks of visual speech recognition and translation, where the given instructions control the type of task. The input video is mapped to the input latent space of a LLM by employing a self-supervised visual speech model. Focused on the fact that there is redundant information in input frames, we propose a novel deduplication method that reduces the embedded visual features by employing visual speech units. Through the proposed deduplication and Low Rank Adaptors (LoRA), VSP-LLM can be trained in a computationally efficient manner. In the translation dataset, the MuAViC benchmark, we demonstrate that VSP-LLM can more effectively recognize and translate lip movements with just 15 hours of labeled data, compared to the recent translation model (Anwar et al., 2023) trained with 433 hours of labeld data.

1 Introduction

Along with audio, visual speech (*e.g.*, lip movements) plays a critical role in human communication. With the increasing acknowledgment of the importance of visual speech, a diverse range of visual-based speech processing technologies (Assael et al., 2016; Petridis and Pantic, 2016; Chung and Zisserman, 2017a; Ma et al., 2021a, 2022b) is emerging. For instance, Visual Speech Recognition (VSR) (Kim et al., 2021; Ma et al., 2022a; Yeo et al., 2023a) allows for the identification of spoken words through the observation of lip movements alone, without the need for audio access. Most recently, the exploration has begun into Visual Speech Translation (VST) (Cheng et al., 2023), which directly generates translated text in the target language from the input lip movements of the source language.

One key challenge in visual speech processing is to distinguish homophenes (Kim et al., 2022). Homophenes refer to the words having different sounds but showing the same lip movements. Therefore, a crucial aspect of developing visual speech processing systems is in the modeling of context so that the same lip movements can be mapped into correct different pronunciations (that is distinguishing homophenes). Recently, Large Language Models (LLMs) (Zhang et al., 2022a; Brown et al., 2020; Workshop et al., 2022) are attracting significant attention across various fields (Han et al., 2023; Wu et al., 2023b; Fathullah et al., 2023), thanks to their versatility and strong ability to model context. Motivated by the recent success of LLMs, we try to investigate whether the rich context modeling ability of LLMs can be employed in visual speech processing and can mitigate the ambiguity of homophenes, especially focusing on two tasks, VSR and VST.

To this end, in this paper, we propose a new framework named Visual Speech Processing incorporated with LLM (VSP-LLM) that learns the seamless embedding of visual speech into the learned text space of LLMs. VSP-LLM employs a self-supervised visual speech model to embed the input visual speech into phoneme-level representations, where the derived phonetic information can be effectively associated with text (Zhang et al., 2022b). Moreover, to reduce the computational burden in training along with LLMs, we propose a novel deduplication method that reduces the input sequence lengths of LLMs. Concretely, we employ visual speech units, the discretized representations

of the features from a self-supervised model, as indicators for overlapped information between sequences. As the visual speech units can be regarded as pseudo-text (Lakhotia et al., 2021), the visual speech features assigned to the same visual speech units are averaged to reduce the processing of redundant information and improve computational efficiency. Through analysis, we show that we can reduce the sequence length by about 50% with the proposed deduplication without any performance degradation. Finally, the proposed VSP-LLM is jointly trained to perform VSR and VST with a single model which is the first explored in this paper. We show that by bringing the powerful context modeling ability into visual speech processing, we achieve state-of-the-art performances in both VSR and VST, and comparable performances with the previous methods even if we utilize just 15 hours of supervised data.

The key contributions of this paper can be summarized as follows: 1) To the best of our knowledge, this is the first work to incorporate visual speech modeling with LLMs and achieve state-of-the-art performances in VSR and VST. 2) This is the first to work to develop a unified visual speech processing model that can perform both VSR and VST with a single trained model. 3) We propose a novel visual speech deduplication that significantly improves computational efficiency. 4) We show that the proposed VSP-LLM can perform multi-tasks with superior performances even in limited training resource situations, just with 15 hours of labeled data by outperforming the recent translation model (Anwar et al., 2023).

2 Related Work

2.1 Visual Speech Processing

Visual speech processing technologies are mainly comprised of two parts, VSR and VST. VSR is a task to recognize the language content by watching lip movements, without any sound. The VSR technologies have greatly progressed with the development of deep learning. Early works (Chung and Zisserman, 2017b; Stafylakis and Tzimiropoulos, 2017; Petridis et al., 2017, 2018) utilize the CNN (He et al., 2016) and the RNN (Chung et al., 2014; Hochreiter and Schmidhuber, 1997) to devise a word-level VSR system. To expand the VSR systems into sentence-level, (Chung et al., 2017; Afouras et al., 2018) have utilized a multi-stage pipeline to automatically collect large-scale VSR data. Based on the large-scale VSR datasets, researchers (Serdyuk et al., 2022; Ma et al., 2021b) have developed the VSR systems from the perspective of architecture, especially the Transformer (Vaswani et al., 2017) have greatly improved the performance of VSR by enabling to capture of the context between any two positions of lip sequences. Moreover, the multimodal learning strategies (Zhao et al., 2020; Afouras et al., 2020; Ren et al., 2021; Ma et al., 2021a; Kim et al., 2021, 2022; Yeo et al., 2023b) have attempted to complement the insufficient visual speech representations by utilizing audio information. A recent self-supervised model known as AV-HuBERT (Shi et al., 2022), has significantly improved the visual speech representations by predicting the pseudo-label assigned from clustering audio-visual features, with a mask-prediction task like BERT (Devlin et al., 2019). According to the advancement of the VSR system, now we can recognize lip movements quite accurately through state-of-the-art VSR models such as AV-HuBERT. Building upon this, the exploration for VST has begun by introducing a Multilingual Audio-Visual Corpus (MuAViC) (Anwar et al., 2023) dataset and constructing a VST (Cheng et al., 2023).

Despite these research efforts, the development of visual speech processing systems enabling multi-task via a unified model, such as VSR and VST, has been never explored in the previous visual speech processing literature. Hence, the objective of this paper is to develop a unified model to perform multi-tasks, including VSR and VST, by utilizing a rich context modeling ability of LLMs.

2.2 Integration of speech models and LLMs

LLMs have shown remarkable success in various tasks due to their extensive linguistic knowledge and contextual understanding. While leveraging such inherent advantages of LLMs, several studies have tried to seamlessly integrate text-based knowledge with other modalities, particularly in the audio speech domain. For example, AudioPaLM (Rubenstein et al., 2023) has been proposed to build a unified model interacting between text language and audio speech. To naturally bridge the gap between the two modalities, AudioPaLM has developed a multimodal vocabulary composed of discrete tokens representing both text and speech. Fathullah *et al.* (Fathullah et al., 2023) have employed LLaMA as a speech recognition decoder, so that the speech sequence features obtained from a conformer en-

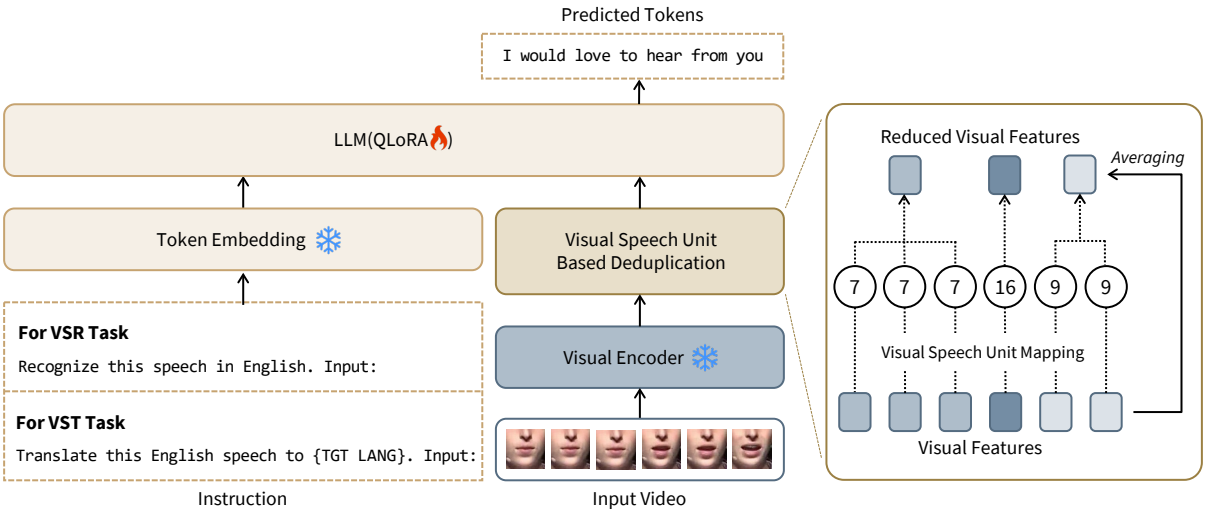

Figure 1: Illustration of our VSP-LLM framework. Visual speech representations encoded from the visual encoder are mapped to visual speech units. Then the visual speech representations are reduced through averaging based on the mapped visual speech units. These reduced representations are fed into the Large Language Model (LLM) along with text instructions. Throughout this process, the LLM is kept frozen, with only a small number of QLoRA parameters being fine-tuned.

coder were designed to be directly mapped into text tokens, the domain of LLaMA. Moreover, Wu *et al.* (Wu et al., 2023a) have tried to address the inherent problem of mismatched sequence lengths between speech signals and text, while taking LLaMA as a speech translation decoder. So, they have compressed the speech sequence feature and matched its sequence length with that of the text.

However, while the existing studies have primarily focused on incorporating LLMs with the audio speech modality, the exploration of such integration for visual speech processing remains unexplored. In this paper, we propose a novel framework that integrates visual speech processing with LLMs. Specifically, we attempt to mitigate the homophenes problem, one of the key challenges in the field of visual speech processing, by leveraging the rich context modeling capabilities of LLMs. Additionally, to address the training load issues arising from the integration of the visual speech model and the Language Model (LLM), we introduce the concept of a visual speech unit. Through the implementation of visual speech units, we propose a novel visual speech deduplication method that compresses redundant representations while preserving contextual information.

3 Method

Figure 1 shows the overall framework of the proposed Visual Speech Processing incorporated with LLM (VSP-LLM). It includes a visual encoder that embeds the input video into the input space of a pre-trained LLM, a visual speech unit based deduplication module that discards redundant information in contiguous frames, and an instruction embedding component that serves as a task specifier. In the following, we describe each component in detail.

3.1 Visual-to-Text Space Mapping

Our primary objective is to employ the rich context modeling capability of LLM in our visual speech modeling. To accomplish this, we need to represent the input video in a manner that aligns closely with linguistic information, thereby facilitating the association between visual inputs and the text space of the pre-trained LLM. Motivated by the recent success of the self-supervised speech models (Hsu et al., 2021; Shi et al., 2022) that showed the learned representations are highly correlated with phonetic information (*e.g.*, phoneme) (Pasad et al., 2023), we employ AV-HuBERT (Shi et al., 2022) for our base visual encoder. Then, a learnable visual-to-text embedding layer is introduced to map the visual representations into the input space of LLM. We name this process as visual-to-text space mapping.

To investigate how well the visual representation aligns with the text embedding space of the LLM, we compute the cosine similarity between the visual speech representation and the token embeddings of the LLM, mapping it to the text token with the highest similarity. Figure 2a shows an example of a textualized visual speech representation. An intriguing observation is that, with

well-structured visual-text space mapping, textualized visual speech representations can exhibit pronunciation resembling real words. However, we observe redundant information when mapping entire video frames to text due to the similarity of adjacent frames. For instance, words like 'is' and 'a' are repeated multiple times, and the word 'social' is mapped as a long stretch. This redundancy increases computational load when visual speech representations are fed into LLM. To address this, we propose a novel method called "Visual Speech Unit-based Deduplication" to remove redundancy while retaining semantic content.

3.2 Visual Speech Unit based Deduplication

Compared to the length of the input video, the length of the text is much shorter. This is similar to the relationships between speech and text in Automatic Speech Recognition (ASR) (Graves and Graves, 2012), where the input speech is almost always longer than the output text. Therefore, when we map visual speech representations into text space through visual-to-text space mapping, the resulting embedded output matches the length of the input video frames. If we directly provide it to the LLM, a large computational burden is inevitable. Here, we note that the video is smooth in temporal and the contiguous frames contain overlapped information, and propose to reduce the length of the embedded representation before feeding it to the LLM.

To this end, we first extract the pronunciation cue from the visual representations through discretization. Recent literature (Lakhotia et al., 2021) shows that discretized self-supervised speech features, termed speech units, contain phonetic information while suppressing non-linguistic variations. Motivated by this, we propose to extract a visual version of speech units, namely visual speech units, which can be obtained by performing K-means clustering on the self-supervised visual speech representations. By doing this, we can access the pronunciation information for each video frame without requiring any text input (Lee et al., 2022). Then, by employing the visual speech units as pseudo text, we investigate the overlapped contiguous frames. Finally, the corresponding visual features are averaged out. For instance, if the obtained visual speech units are $\{7, 7, 7, 16, 9, 9\}$ as illustrated in Figure 1, then the visual features at positions 1, 2, and 3 are averaged together, and those at positions 5 and

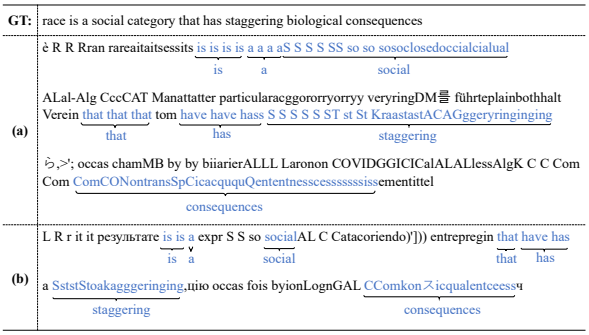

Figure 2: Textulaization results of the visual speech representations. GT, (a), and (b) indicate the ground truth, textualization without deduplication, and textualization with deduplication, respectively.

6 are averaged, resulting in 3 frames. We find that the proposed visual speech unit based deduplication reduces the sequence lengths by about 46.62% compared to the input video lengths. Most importantly, we observed that the deduplication process does not result in any drop in performance. The reduced visual features, when converted into text (Figure 2b), maintain the meaning of each word while the duplication of each word has been removed. For instance, the recurrence of 'is' and 'a', which appeared multiple times in the original feature, is reduced, and the length of 'social', which has a long stretch, is also drastically reduced.

3.3 Multi-task Learning with Instruction

One advantage of bridging LLMs into visual speech processing is that we can leverage the versatility of LLMs as well. To investigate this, we train the proposed VSP-LLM with two tasks, VSR and VST. VSR aims to recognize the input silent speech while VST aims not only to predict the recognized speech but also to translate it into the target language. We design the system so that tasks can be controlled by inputting instructions directly into the LLM. When performing the VSR task the instruction is set to as below,

```
Recognize this speech in English.
Input: ${Dedupped_Visual_Feature}
```

where the deduplicated visual features are inserted after the instruction. Otherwise, to perform VST, the following instruction is employed.

```
Translate this English speech to ${TGT LANG}.
Input: ${Dedupped_Visual_Feature}
```

where the target language is used for the position of `TGT LANG`. The objective function for each task

can be written as follows,

$$\mathcal{L} = -\sum_{l=1}^{L} \log p(y^l | X, I, y^{<l}), \quad (1)$$

where X is input video, I is instruction used, $y^{<l}$ is the previous predictions, and L is the length of ground truth. Please note that this is the first work exploring a unified framework of VSR and VST. For training, we employ the recently proposed QLoRA (Dettmers et al., 2023) to further relieve the computational load in training LLM.

4 Experiment

4.1 Dataset

Lip Reading Sentences 3 (LRS3) (Afouras et al., 2018) is the most widely-used dataset for VSR, which comprises 433 hours of English audio-visual speech corpus with transcription data. These corpora are collected from the TED and TEDx talks. We utilize the LRS3 dataset to and measure the VSR performance of the proposed unified model.
Multilingual Audio-Visual Corpus (MuAViC) (Anwar et al., 2023) is a multilingual audio-visual dataset designed for speech recognition and speech-to-text translation. It includes 1200 hours of audio-visual corpus in 9 languages, providing full transcriptions and covering 6 English-to-X translations, as well as 6 X-to-English translation directions. To evaluate the VST performance of our model, we utilize English-to-X translation data from MuAViC dataset, where X can be among four languages, Spanish (Es), French (Fr), Portuguese (Pt), and Italian (It). For training our model, we combine LRS3 (Afouras et al., 2018) and English-to-X translation data of MuAViC (Anwar et al., 2023).

4.2 Implementation Details

Preprocessing. The video is resampled at 25 fps, and facial landmarks are detected using RetinaFace (Deng et al., 2020). Mouth regions are cropped using bounding boxes of size 96×96 and converted to grayscale. During training, we apply data augmentation by randomly cropping the video to 88×88 and horizontally flipping it.
Architecture. We use the AV-HuBERT *large* (Shi et al., 2022) pre-trained on LRS3 (Afouras et al., 2018) and VoxCeleb2 English (Chung et al., 2018) as our visual encoder. In all experiments, except the ablation part, we utilize 200 clustered visual speech units. For the LLM, we adopt LLaMA2-7B (Touvron et al., 2023) and fine-tune it using QLoRA (Dettmers et al., 2023) with the rank value of 16 and a dropout rate of 5%. To align the dimensions of the visual representation from the visual encoder to the LLaMA input embedding, we use a single linear layer as our visual-to-text embedding layer.
Training and evaluation. We follow AV-HuBERT (Ren et al., 2021) except for the number of updates and learning rate. We conduct training with 15K updates and a learning rate of $1e^{-3}$ for LRS3 1h, 5h, 10h, and 30K updates with a learning rate of $5e^{-4}$ for LRS3 30h and 433h. Adam optimizer is employed for training with $\beta_1 = 0.9$ and $\beta_2 = 0.98$, utilizing a tri-stage learning rate scheduler. The training process is executed on 8 3090 RTX GPUs. For decoding, we use a beam search with a beam width of 20 and a length penalty of 0. We assess the performance of our model using Word Error Rate (WER) for the VSR task and BLEU score (Papineni et al., 2002) for the VST task. We use total FLOPs per epoch as a metric to measure the model operation count during training.

4.3 Experimental Results

4.3.1 Comparison with State-of-the-arts

In this subsection, we compare the proposed unified model with state-of-the-art VSR methods and VST methods. Please note that the proposed model can perform multi-tasks VSR and VST with a single trained model while the other models need a single model per specific task.

Table 1 presents the performance comparisons of the proposed method with state-of-the-art VSR methods on the LRS3 dataset. The top section of Table 1 outlines the performance of current supervised approaches that depend on extensive labeled training data, while the lower section presents a comparison with other self-supervised methods. Table 1 demonstrates that our approach achieves performance on par with others by employing just 30 hours of labeled data, despite the proposed unified model's ability to handle multiple tasks—VSR and VST—simultaneously. Additionally, with the use of 433 hours of data, our method reaches state-of-the-art performance, achieving a Word Error Rate (WER) of 26.9%, surpassing other self-supervised approaches. Moreover, Table 1's upper part shows that the existing supervised methods record exceptional performance using (tens of) thousands of labeled data. However, it is important to highlight that the proposed unified model can obtain compa-

	Method	Pre-training Data (hrs)	Labeled Training Data (hrs)	Recognition Task	Translation Task	WER(%)
Supervised	Afouras et al. (2018)	-	1,519	✓		58.9
	Shillingford et al. (2019)	-	3,886	✓		55.1
	Makino et al. (2019)	-	31,000	✓		33.6
	Prajwal et al. (2022)	-	2,676	✓		30.7
	Ma et al. (2021b)	-	595	✓		30.4
	Ma et al. (2023)	-	3,448	✓		19.1
	Serdyuk et al. (2022)	-	90,000	✓		17.0
	Chang et al. (2023)	-	100,000	✓		12.8
Self-supervised	AV-HuBERT (Shi et al., 2022)	1,759	30	✓		32.5
	VATLM (Zhu et al., 2023)	1,759	30	✓		31.6
	RAVen (Haliassos et al., 2022)	1,759	30	✓		32.5
	AKVSR (Yeo et al., 2023a)	1,759	30	✓		29.1
	Proposed Method	1,759	30	✓	✓	29.6
	AV-HuBERT (Shi et al., 2022)	1,759	433	✓		28.6
	VATLM (Zhu et al., 2023)	1,759	433	✓		28.4
	RAVen (Haliassos et al., 2022)	1,759	433	✓		27.8
	AKVSR (Yeo et al., 2023a)	1,759	433	✓		27.6
	Proposed Method	1,759	433	✓		27.5
		1,759	433	✓	✓	26.9

Table 1: The performance comparisons with state-of-the-art supervised and self-supvervised VSR methods. Compared to the self-supervised methods, the proposed unified model, which can perform both VSR and VST, achieves state-of-the-art recognition performances. Furthermore, our method obtains comparable performances even with much less amount of training data. Please note that the only method which can perform recogntion and translation at once is the proposed model.

Method	Modality	Labeled data(hrs)	BLEU ↑				
			En-It	En-Fr	En-Pt	En-Es	Avg
Anwar et al. (2023)	AV	433	20.7	25.3	20.5	26.6	23.3
AV-HuBERT	V	433	21.5	26.5	26.7	24.5	24.8
Cascaded (AV-HuBERT + MT)	V	433	22.2	23.9	24.4	23.5	23.5
Proposed Method	V	15	**20.3**	**24.4**	**24.7**	**24.7**	**23.5**
Proposed Method	V	433	**29.4**	**33.0**	**33.7**	**33.8**	**32.5**

Table 2: The experimental results showing the effectiveness on VST, English to target language (En-X) speech translation tasks, on MuAViC.

rable performances to several supervised methods.

Table 2 presents the comparison results of VST performance. We construct two baseline models for comparison. The first, AV-HuBERT, is trained similarly to our approach, utilizing both VSR and VST datasets. The second model is a cascaded system that incorporates a pre-trained AV-HuBERT for VSR with a neural machine translation model (Fan et al., 2021). Through this comparison, our proposed unified model demonstrates superior VST performance across four English-to-X translation tasks, achieving BLEU scores of 29.4, 33.0, 33.7, and 33.8 for English to Italian, French, Portuguese, and Spanish, respectively. Moreover, it is worth noting that the proposed method achieves a 23.5 BLEU score on average with only 15 hours of labeled data, outperforming the audio-visual speech translation model (Anwar et al., 2023) trained with 433 hours of labeled data.

4.3.2 Effectiveness of Rich Context Modeling

We have developed a unified model incorporating Large Language Models (LLMs) to leverage their advanced context modeling capabilities. Therefore, in this section, we conduct a qualitative experiment to demonstrate the effectiveness of the proposed VSP-LLM in handling homophenes, a challenging problem that requires substantial context understanding to accurately identify homophenes. Figure 3 shows several transcription examples obtained from AV-HuBERT and our model, illustrating how our proposed method accurately generates words by considering the entire context of a sentence. For instance, in a homophene case, AV-HuBERT incorrectly transcribes "barrow", a word that looks similar on the lips visually but differs in meaning from “marrow”. On the other hand, our method correctly generates "marrow", leading to complete

Homophemes Cases		Other Cases	
Ground Truth:	you destroy all the bone marrow in the cancer patient with massive doses of chemotherapy	**Ground Truth:**	but before that cooperation could be realized kennedy was assassinated and that part of the
AV-HuBERT :	you destroy all the bone barrow in the cancer patient with massive doces of chemotherapy	**AV-HuBERT :**	but before that cooperation could be realized the energy was assassinated and that part of the
Proposed Method :	you destroy all the bone marrow in the cancer patient with massive doses of chemotherapy	**Proposed Method :**	but before that cooperation could be realized kennedy was assassinated and that part of the
Ground Truth:	so the very first thing we wanted to do in this building was look at the air system	**Ground Truth:**	what is the exact relationship between levels of greenhouse gases and planetary
AV-HuBERT :	so the very first thing we wanted to do in this building was look at the hair system	**AV-HuBERT :**	what if the exact relationship between governments greenhouse houses and plant on it
Proposed Method :	so the very first thing we wanted to do in this building was look at the air system	**Proposed Method :**	what if the exact relationship between government greenhouse gases and planetary
Ground Truth:	you don't have to bring any quarters because the washer and dryer are free	**Ground Truth:**	and when i talk to judges around the united states which i do all the time now they all say the same
AV-HuBERT :	you don't have to predict any words because the washers trial are free	**AV-HuBERT :**	and when i talk to just around the united states which i do all the time now they all say the same
Proposed Method :	you don't have to put in any words because the washers and dryers are free	**Proposed Method :**	and when i talk to judges around the united states which i do all the time now they all say the same
Ground Truth:	i looked at my friend who drilled seven dry wells writing off more than a billion dollars for the	**Ground Truth:**	and when i look at the criminal justice system in the united states today i feel the exact same way that i did about the state of
AV-HuBERT :	i looked at my friends who trilled at safeest trials running of more than a billion dollars for the	**AV-HuBERT :**	and when i look at the criminal justice system in the united states today i felt the exact same way that i did about the state of
Proposed Method :	i looked at my friends who drilled the deepest wells running off more than a billion dollars for the	**Proposed Method :**	and when i look at the criminal justice system in the united states today i feel the exact same way that i did about the state of

Figure 3: The qualitative results showing that the contextual modeling ability of LLM, which is adopted in our method, can improve the homophene problem and other confusing cases. The red and blue words indicate the wrong predictions from AV-HuBERT. However, as shown in the examples, the proposed method can generate correct words by considering the entire context (*e.g.,* '*barrow*' to '*marrow*').

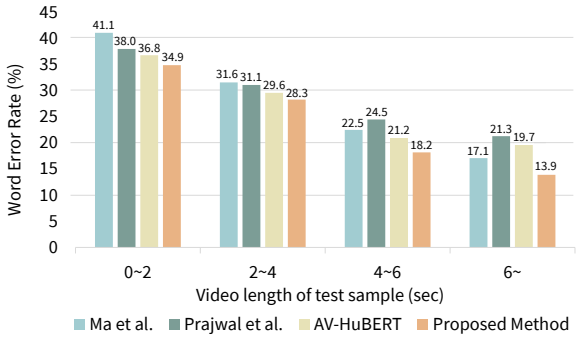

Figure 4: VSR performance analysis on LRS3 with varying video length of test samples. Due to the strength of contextual understanding ability of LLM, the proposed method shows superior performance with longer videos.

the accurate phrase "bone marrow" in the context of describing a cancer treatment process. Similarly, AV-HuBERT's transcription of "hair" is contextually inappropriate for a sentence discussing considerations regarding building systems. Our method, however, accurately outputs "air," resulting in the correct phrase "air system". Also, we can observe similar results in the other cases, not the homophene problem only. For example, the proposed method can generate the word "planetary" in the context of asking about the relationship between greenhouse gases and "planetary". These results corroborate that our approach can more effectively comprehend contextual clues and generate more precise and natural answers, due to the integration of LLM.

Number of Clusters	BLEU ↑					Length of sequence	FLOPs (P)
	En-It	En-Fr	En-Pt	En-Es	Avg		
-	18.4	23.7	22.4	23.6	22.0	1.00	27.2
2000	18.1	22.9	22.3	21.4	21.2	0.70	21.3 (21.7%)
200	20.3	22.8	23.3	22.0	22.1	0.53	17.9 (34.2%)
50	18.5	22.2	22.9	21.5	21.3	0.45	16.1 (40.8%)

Table 3: Analysis on computational efficiency with varying number of visual speech unit clusters. When the deduplication strategy is adopted, the proposed method obtains comparable performances with greatly reduced sequence length and training FLOPs.

Additionally, we evaluate the VSR performance across various video length segments to explore the effectiveness of LLM in handling long speech. Figure 4 shows that WER decreases as video length increases. Notably, our proposed method exhibits outstanding recognition performance, with a WER of 13.9% on videos longer than 6 seconds. Furthermore, our method demonstrates consistent performance improvements as the length of the video increases, compared to other methods. It indicates the effectiveness of LLM's context modeling in longer video utterances, which demand a more comprehensive understanding of context.

4.3.3 Effectiveness of Deduplication

We conduct experiments to assess the effectiveness of our deduplication strategy. For the deduplication process, the number of clusters for visual speech units is required to be determined, and we show

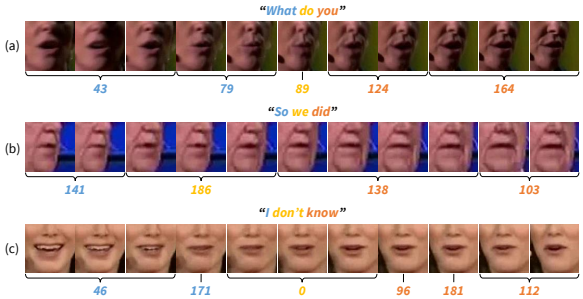

Figure 5: Visualization results showing how video frame features are deduplicated and mapped into visual speech units. By doing so, the redundant frame features can be reduced efficiently.

Method	Labeled Data(hrs)	BLEU ↑					WER(%) ↓
		En-It	En-Fr	En-Pt	En-Es	Avg	
AV-HuBERT	1	0.1	0.1	0.1	0.1	0.1	97.1
Proposed Method	1	4.5	7.8	8.0	7.1	6.9	62.0
AV-HuBERT	5	3.2	6.2	4.2	4.4	4.5	71.7
Proposed Method	5	15.4	19.4	18.6	18.6	18.0	36.6
AV-HuBERT	10	5.1	8.3	8.0	6.1	6.9	59.7
Proposed Method	10	20.3	22.8	23.3	21.9	22.1	34.4
AV-HuBERT	15	5.5	9.2	8.2	6.7	7.4	57.3
Proposed Method	15	20.3	24.4	24.7	24.7	23.5	33.3

Table 4: Impact of the amount of labeled data. It shows that a small amount of labeled data is sufficient to construct a unified VSR and VST model by leveraging contextual understanding capabilities of LLM.

the effectiveness according to the number of clusters. Table 3 presents these results, and the first row shows the performance of the baseline which does not utilize the deduplication. The baseline obtains an average BLEU score of 22.0 with 27.2 peta FLOPs per training epoch. In contrast, our method acquires comparable performance, while significantly reducing the sequence length and computational resources (FLOPs). Specifically, with 200 clusters for visual speech units, our method not only maintains a similar performance level with a 22.1 average BLEU score but also cuts the sequence length by 53%. Consequently, the FLOPs are greatly reduced to 17.9, marking a 34.2% decrease. These experiments confirm that deduplication, applied to visual speech units, effectively eliminates redundant information.

Moreover, we delve into the deduplication process by examining it at the video frame level to check whether consecutive visual features, characterized by similar lip movements, are grouped into the same visual speech unit. Figure 5 provides several visual examples alongside their corresponding phrases and video frames. In Figure 5 (a), as a speaker articulates "*What do you*", it's noted that 11 video frames can be expressed by 5 visual speech units. For instance, the visual sequences for the sound "wha" belong to the same 43rd unit. Similarly, Figure 5 (c) illustrates that the four frames corresponding to "I" can be efficiently represented by the 46th and 171st visual speech units. Through this analysis, we confirm that visual features with similar lip shapes can be effectively deduplicated, significantly reducing the visual sequence's length.

4.3.4 VSP-LLM in Data-limited Situation

Leveraging the contextual understanding capabilities of LLM, which are pre-trained on vast text corpora, we suppose that a small amount of labeled data is sufficient for constructing a unified VSR and VST model. This is because the proposed VSP-LLM endeavors to establish the visual-to-text mapping while entrusting the task of language modeling to the LLM. To validate it, we train VSP-LLM with different amounts of labeled data; **1 hour**, **5 hours**, **10 hours**, and **15 hours**. For comparison, we also develop AV-HuBERT (Shi et al., 2022) on the same data. Table 4 displays the VSR and VST performances. In all experimental conditions, regardless of the amount of data used, our proposed method significantly outperforms AV-HuBERT. Moreover, when using only 15 hours of labeled data, our unified method achieves a WER of 33.3%. This is a noteworthy achievement, particularly when compared to the previous VSR (Makino et al., 2019) model achieving a WER of 33.6%, by using 31k hours of labeled data for training.

5 Conclusion

In this paper, we proposed a novel framework, Visual Speech Processing with LLMs (VSP-LLM), designed to leverage the context modeling ability of LLMs. Through this framework, we built a unified model that can perform multi-tasks, VSR and VST, with a single model. Moreover, the proposed deduplication strategy reduces the redundant information of visual speech representations based on pronunciation information modeled from visual speech units. Through extensive experiments, we verified that the proposed deduplication method can reduce the visual sequence length by about 50% without dropping the performance. In addition, we validated the effectiveness of the VSP-LLM by achieving a superior performance in the MuAViC benchmark with only 15 hours of labeled data.

6 Limitations

We have proposed a powerful visual speech processing method that incorporates LLMs to recognize and translate lip movements into other languages, leveraging the rich context modeling ability of LLMs. Despite the impressive improvement in the performance of this proposed method, the utilization of LLMs has been limited to VSR and VST tasks. While the LLMs have the capability to enable diverse tasks such as dialog generation, we could not utilize various capabilities of LLMs due to the lack of labeled data for the aforementioned tasks in visual speech processing. However, given that the integration of visual speech with LLMs is still in its early stages, we anticipate continued advancements in this field.

7 Broader impact and ethics

As the use of Large Language Models (LLMs) is expanding into other modalities such as visual and audio to leverage the rich context modeling ability, building effectively integrated frameworks with LLMs becomes a key problem. In this paper, we have attempted for the first time to integrate visual speech processing with LLMs and effectively reduce the computational cost through a proposed deduplication strategy based on visual speech units. We believe the proposed method can contribute to visual speech processing. We comply with the ACL Ethics Policy and all experiments are conducted with the dataset publicly available.

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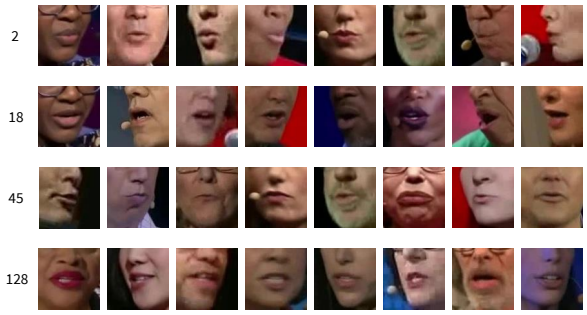

Figure 6: Visualization of video frames corresponding to visual speech units. Each number indicates an index of visual speech unit.

A Visualization of Visual Speech Units

The visualization results of the visual speech units are shown in Figure 6. In this paper, we use 200 clusters in order to generate visual speech units. Through analyzing the results, we verify that the video frames assigned the same visual speech unit have similar lip movement.

B Examples of Predicted Sentences

The examples of recognized and translated transcription by the proposed unified model are shown in Figure 7. For generating transcription, we use a single-trained model that performs both VSR and VST tasks.

VSR		
English (En)	Ground Truth:	it was faulty and most of the time I had to restart it over and over before it worked
	Prediction:	it was failing most of the time I had to restart it over and over before it worked
	Ground Truth:	like we evolved on this planet in the context of all the other animals with which we share
	Prediction:	can we evolve on this planet in the context of all the other animals with which we share
VST		
Spanish (En-Es)	Ground Truth:	tenemos las herramientas pero perdemos la voluntad y el momento colectivo
	Prediction:	tenemos las herramientas pero falta la voluntad colectiva y el momento
	Ground Truth:	hay amor y hay amistad y hay protección
	Prediction:	hay amor y amistad y protección
Italian (En-It)	Ground Truth:	utilizza esperienza basata su situazioni simili per imparare a gestire
	Prediction:	utilizza l'esperienza passata basata su situazioni simili per imparare a fare
	Ground Truth:	il testo si è sviluppato da questo slash
	Prediction:	testando si è sviluppato uno da questo slush
French (En-Fr)	Ground Truth:	comment estce que tu es juste maintenant
	Prediction:	comment tu es juste maintenant
	Ground Truth:	ce changement devient plus rapide
	Prediction:	ce changement se fait plus rapidement
Portuguese (En-Pt)	Ground Truth:	e eu quero fazer o ponto que como membros da sociedade que precisamos
	Prediction:	e eu quero fazer o ponto de que como membros da sociedade podemos fazer
	Ground Truth:	mas a magnitude do problema é quando precisamos aceitar
	Prediction:	mas a magnitude do problema é uma vez que precisamos aceitar

Figure 7: Examples of VSR predictions produced by our proposed model on LRS3 test set. Deletions from the ground-truth text are highlighted in Red, while substitutions are shown in Blue.