Multi-modal Speech Transformer Decoders: When Do Multiple Modalities Improve Accuracy?

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ABSTRACT

We investigate how different input modalities (audio, image, lip movements, etc.) impact speech recognition performance in decoder-only discrete-token language models:

- Does adding more context and more modalities increase accuracy?
- Does the accuracy benefit depends on the audio noise?
- Do *synchronized* vs. *unsynchronized* modalities behave differently?

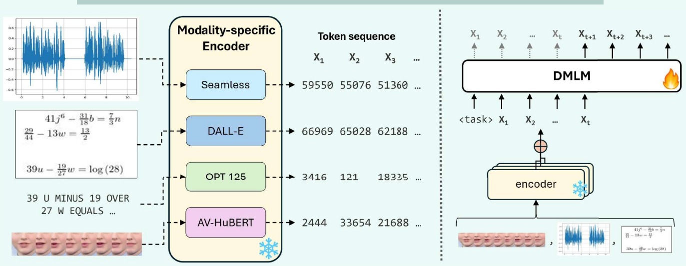
Key results:

✓ **Integrating more modalities can increase accuracy** but the benefit depends on the amount of audio noise.

✓ **Image context provides its greatest benefit at *moderate* audio noise levels**; moreover, it exhibits a different trend compared to inherently synchronized modalities like lip movements.

✓ **Filtering the most relevant visual information improves accuracy** on both synthetic (3-Equations) and real-world datasets (SlideAVSR).

ARCHITECTURE: Discrete Multi-modal Language Model (DMLM)



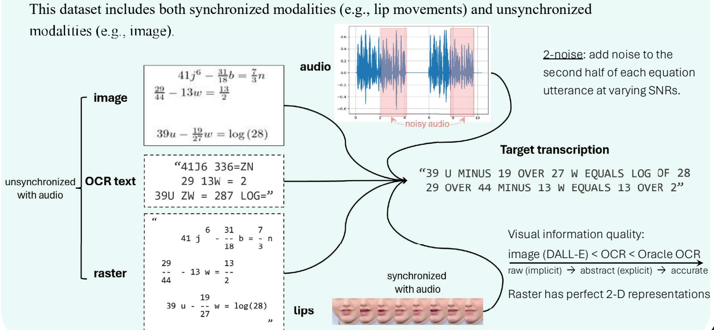
Pipeline:

1. Tokenize input data with frozen modality specific encoders into discrete token sequence.
2. Concatenate the sequence to a task description (e.g., "[ASR]")
3. Pass the entire sequence to the DMLM.

3-EQUATIONS DATASET

We create a dataset (3-Equations) on which we can control its characteristics precisely, and simulate anticipated situations, such as with different modality SNRs. (N=10,000)

This dataset includes both synchronized modalities (e.g., lip movements) and unsynchronized modalities (e.g., image).



EXPERIMENTS

Evaluation metrics:

- **Speech recognition:** Word Error Rate (WER)
- **Impact of additional modalities:** We introduce a new metric for evaluating the impact of additional modalities in ASR: Relative WER Benefit (↑) = $(WER_A - WER_{X+A})/WER$

  A: audio, X: additional modalities added to audio-only model

This metric evaluates how much the WER is reduced relatively when additional modalities are incorporated.

Methodology:

We compute WER for all combinations of modalities (I+A→T, O+A→T, etc.) for each noise level in SNR=(+∞,20,10,5,0,-5,-10,-20,-∞)dB, and evaluate the relative WER benefit (%) for each combination.

Results:

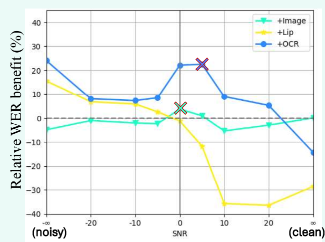


Figure 1: Relative WER benefit (%) of adding one more modality (I+A, L+A, and O+A)

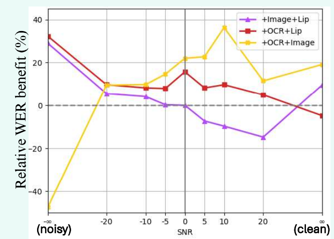


Figure 2: Relative WER benefit (%) of adding two more modalities (I+L+A, O+L+A, and O+I+A)

❑ Experiment I: The benefit of adding additional modalities to audio-only model (Fig. 1 & Fig. 2 & Fig. 4):

- ➢ **Integrating more modalities can improve ASR accuracy;**
- ➢ **OCR modality provide the best complementary benefit;**
- ➢ **In general, 3-modality models works better than 2-modality models.**

❑ Experiment II: Trend of benefit provided by each modality across noise levels (Fig.1 & Fig. 4):

- ➢ **Unsynchronized modalities (image and OCR) provide the greatest benefit at medium SNRs (0dB~10dB);**
- ➢ **Synchronized modality (lip movements) has larger benefit when there's more noise.**

❑ Experiment III: The benefit of adding different (implicit/explicit) visual modalities (Fig. 3):

- ➢ **Better visual representation can lead to better supplementary benefit;**
- ➢ **Oracle OCR, which is the most abstract and accurate visual information, provides the greatest overall benefit.**
- ➢ **The model has difficulties with 2-D representations, even it's as perfect as raster representation.**

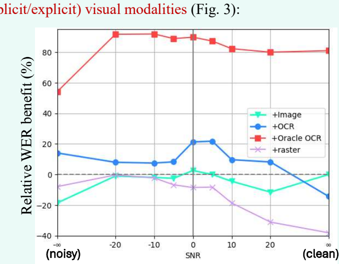
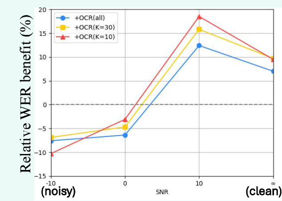


Figure 3: Relative WER benefit (%) of adding different visual modalities (I, O, Oracle OCR, and R)

Notations: audio (A), image (I), OCR (O), lip (L), raster (R)

SlideAVSR[2]: An audio-visual dataset of AI paper explanation videos, which include transcribed speech, synchronized slides, and OCR keywords.



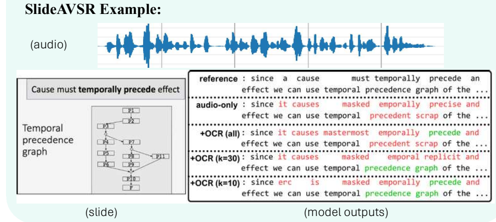
K value: top K words ranked by frequency of word occurrences in English Wikipedia (FQRanker)[2]. Only these K words will be kept as input.

Figure 4: Relative benefit (%) of adding filtered OCR with K values on SlideAVSR

❑ Experiment IV: Impact of irrelevant information (Fig. 4):

- ➢ **Irrelevant information may hurt the performance, filtering relevant or long-tail words can help. Model with OCR (K=10) has the best overall benefit on SlideAVSR.**

SlideAVSR Example:



CONCLUSIONS

✓ Fusing additional modalities enhances speech recognition performance.

✓ In different noise levels, unsynchronized modalities (image and OCR) exhibit a different trend from synchronized modalities (lip movements)

✓ Filtering relevant visual information enhances performance.

✓ More abstract and accurate visual modality improves accuracy more with supplementary visual information.

✓ Our work is the first to show the benefit of combining audio, image, and lip movements in one model for speech recognition.

FUTURE WORK

- Extend to other backbone language models of other architecture.
- Exploration of different visual encoders and visual modalities.
- Try other input (prompt) strategies like interleaving.
- Extend our findings to other real-world datasets.

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https://arxiv.org/pdf/2409.09221

References

[1] V. A. Trinh, R. Southwell, Y. Guan, X. He, Z. Wang, and J. Whitehill, "Discrete multimodal transformers with a pretrained large language model for mixed-supervision speech processing," arXiv preprint arXiv:2406.06582, 2024.

[2] H. Wang, S. Kurita, S. Shimizu, and D. Kawahara, "Slideavsr: A dataset of paper explanation videos for audio-visual speech recognition," arXiv preprint arXiv:2401.09759, 2024.