

OmniFusion: Simultaneous Multilingual Multimodal Translations via Modular Fusion

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Abstract

There has been significant progress in open-source text-only translation large language models (LLMs) with better language coverage and quality. However, these models can be only used in cascaded pipelines for speech translation (ST), performing automatic speech recognition first followed by translation. This introduces additional latency, which is particularly critical in simultaneous ST (SimulST), and prevents the model from exploiting multimodal context, such as images, which can aid disambiguation. Pretrained multimodal foundation models (MMFMs) already possess strong perception and reasoning capabilities across multiple modalities, but generally lack the multilingual coverage and specialized translation performance of dedicated translation LLMs. To build an effective multimodal translation system, we propose an end-to-end approach that fuses MMFMs with translation LLMs. We introduce a novel fusion strategy that connects hidden states from multiple layers of a pretrained MMFM to a translation LLM, enabling joint end-to-end training. The resulting model, OmniFusion, built on Omni 2.5-7B as the MMFM and SeedX PPO-7B as the translation LLM, can perform speech-to-text, speech-and-image-to-text, and text-and-image-to-text translation. Experiments demonstrate that OmniFusion effectively leverages both audio and visual inputs, achieves a 1-second latency reduction in SimulST compared to cascaded pipelines and also improves the overall translation quality¹.

1 Introduction

In recent years, research in natural language processing (NLP) has increasingly shifted from unimodal foundation models (Touvron et al., 2023; Grattafiori et al., 2024) to multimodal foundation models (MMFMs) (Abdin et al., 2024; Goel

et al., 2025; Xu et al., 2025), as many tasks benefit from contextual information derived from multiple sources. Although unimodal systems can perform strongly in certain settings, further progress also requires models to be able to take advantage of additional contextual cues without degrading quality.

One representative task that can benefit from such multimodal integration is speech translation (ST), where the goal is to translate spoken input in a source language into a target language. Over the years, advances in data scale, modeling techniques, and architectural design have led to substantial improvements in ST quality across many language pairs and domains (Ahmad et al., 2024; Agostinelli et al., 2025). However, the use of multimodal context—such as visual information from images or presentation slides accompanying speech—remains relatively underexplored (Liu and Niehues, 2024; Gaido et al., 2024a; Sinhamahapatra and Niehues, 2025).

Although MMFMs are capable of processing multiple modalities jointly, their multilingual translation capabilities are generally weaker than those of specialized translation large language models (LLMs) (Alves et al., 2024; Cheng et al., 2025). As a result, directly using MMFMs for ST often yields inferior translation quality compared to approaches that rely on strong text-based translation components (Appendix: Table 4). They also do not cover several languages compared to specialized translation LLMs. Consequently, a practical solution is to adopt a cascaded pipeline, where automatic speech recognition (ASR) is first performed, followed by machine translation (MT). This modular setup allows each component to be optimized independently and integrated during inference (Ahmad et al., 2024; Agostinelli et al., 2025; Koneru et al., 2025). However, since the translation model operates solely on text, it cannot exploit contextual information from the original speech or visual input. Moreover, the cascaded design introduces

¹Code is available at <https://github.com/saikoneru/OmniFusion>

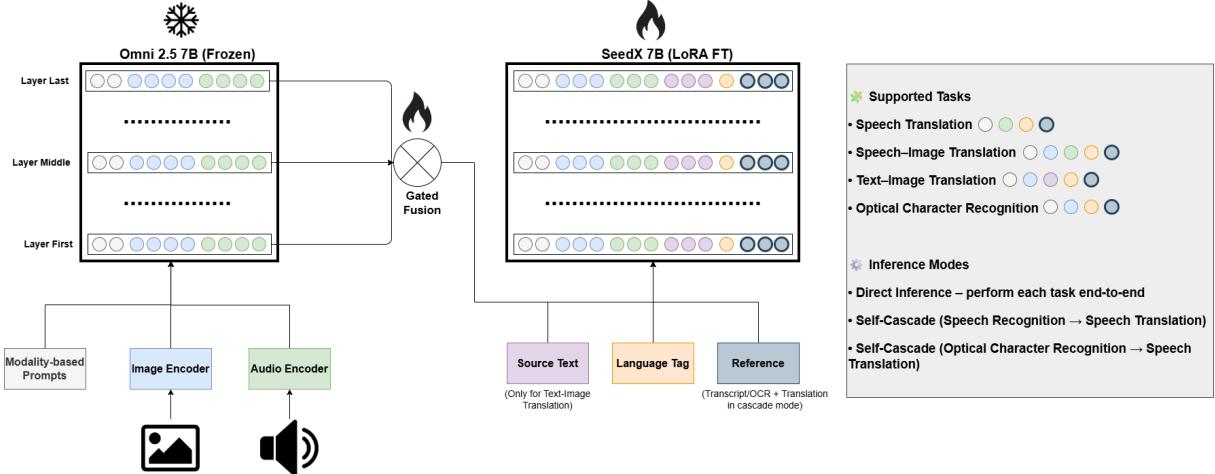


Figure 1: Architecture of OmniFusion with supported tasks and inference modes.

additional generation steps, leading to increased latency compared to end-to-end (E2E) models—an issue that is particularly critical for simultaneous ST (SimulST) applications (Agostinelli et al., 2025; Papi et al., 2025a).

Therefore, we aim to develop an E2E MMFM that excels in multimodality, multilinguality and efficient for SimulST. This can be achieved by extending the capabilities of a translation LLM to handle additional modalities. Few prior works have explored adding audio or image inputs to multilingual LLMs (Ambilduke et al., 2025; Viveiros et al., 2025). However, these approaches typically rely on training from scratch or only using pre-trained audio/vision encoders and do not leverage the higher-level representational capabilities of existing MMFMs. Furthermore, training is ineffective as the base LLM needs to learn the modality mapping from scratch.

In this work, we propose leveraging pre-trained MMFMs to introduce multimodal capabilities into a multilingual LLM with a E2E architecture. Rather than transferring only vision or audio encoders, we extract and utilize hidden-state representations from multiple layers of the MMFM to capture both the perceptual and reasoning components of multimodal understanding. Specifically, we adapt the translation LLM by incorporating hidden states from the first, middle, and last layers of the MMFM, thereby enabling the transfer of both low-level perception and high-level semantic understanding.

To further strengthen cross-modal alignment, we introduce Optical Character Recognition (OCR) as a bridge task for the image modality, analogous

to how ASR serves as an alignment mechanism for audio. This strategy allows the model to effectively leverage pre-trained multimodal representations while receiving direct cross-modal supervision.

We use Qwen Omni 2.5 7B (Xu et al., 2025) as the MMFM and SeedX 7B (Cheng et al., 2025) as the translation LLM to validate our approach on SimulST and multimodal MT tasks. We refer to the resulting fused model as **OmniFusion**.

Our main contributions are summarized as follows:

- We propose a gated fusion approach that extracts multimodal embeddings from MMFMs, allowing translation LLMs to fully utilize the pre-trained perceptual and interpretive capabilities of MMFMs.
- We show the benefit of using slides for context and achieve an improvement in latency of approximately 1 second in the SimulST scenario compared to cascaded fine-tuned models while having better quality. (Figure 2).
- We observe a reduction in the major and critical errors for offline ST through self-cascading and effective use of the image context (Table 2).
- We achieve state-of-the-art performance in the CoMMuTE benchmark for image-text translation highlighting the ability of the model to exploit images (Table 3).

2 Approach

We propose to fuse a MMFM with a task-specific translation LLM to leverage their complementary strengths and enable E2E training for improved latency. Furthermore, we aim to incorporate not only the perception capabilities of the MMFM but also its multimodal reasoning and understanding.

First, we describe the overall architecture and training process of our approach, considering a general input and output sequence independent of the specific task. We formally define the information flow, training loss, and the fusion of MMFM layers. Next, we detail the training tasks used to align multimodal representations from both image and audio modalities to the translation LLM. Finally, we discuss the training prompts that enable a self-cascading inference mode, allowing the model to enhance translation quality at the cost of increased latency. An overview of the architecture and supported tasks is in Figure 1.

2.1 Architecture

Let us denote the specialized translation LLM as \mathcal{M}_{NMT} and the MMFM as $\mathcal{M}_{\text{MMFM}}$, where both use a language model as their backbone. The \mathcal{M}_{NMT} is trained for translation via supervised fine-tuning with the following loss function:

$$\mathcal{L}_{\text{Trans}} = -\frac{1}{T_y} \sum_{t=1}^{T_y} \log P_\theta(y_t | y_{<t}, X), \quad (1)$$

$$X = (x_1, \dots, x_{L_x}), \quad y = (y_1, \dots, y_{T_y})$$

where $X = (x_1, \dots, x_{L_x})$ is the sequence of source tokens of length L_x , and $y = (y_1, \dots, y_{T_y})$ is the sequence of target tokens of length T_y .

For $\mathcal{M}_{\text{MMFM}}$, the image and audio modalities are first processed by modality-specific encoders and then projected to match the embedding dimension of $\mathcal{M}_{\text{MMFM}}$, denoted as D_{MMFM} . This projection allows the encoder outputs to be concatenated as a sequence of tokens, enabling the MMFM to operate similarly to a standard LLM, such as \mathcal{M}_{NMT} .

To fuse both the perception and higher-level understanding of the MMFM, we hypothesize that lower layers predominantly capture perceptual features, while higher layers encode more abstract reasoning as computation progresses. Accordingly, we extract the first, middle, and last hidden layers from the MMFM, denoted as:

$$\begin{aligned} h_t^{(1)} &= \text{MMFM}_{\text{layer } 1}(x_t), \\ h_t^{(\text{mid})} &= \text{MMFM}_{\text{layer mid}}(x_t), \\ h_t^{(\text{last})} &= \text{MMFM}_{\text{layer last}}(x_t), \\ h_t^{(1)}, h_t^{(\text{mid})}, h_t^{(\text{last})} &\in \mathbb{R}^{L_m \times D_{\text{MMFM}}}, t = 1, \dots, L_m \end{aligned} \quad (2)$$

where L_m is the length of the MMFM hidden states.

Directly concatenating these multi-dimensional representations into \mathcal{M}_{NMT} poses three challenges. First, the sequence length triples, significantly increasing computational and memory requirements. Second, the relevance of each layer may vary depending on the task, necessitating selective weighting. Third, the embedding dimension of $\mathcal{M}_{\text{MMFM}}$ may not match that of \mathcal{M}_{NMT} .

To overcome these challenges, we introduce a gated fusion layer that determines the contribution of each hidden state along the sequence length. Each hidden state is multiplied by its corresponding gate values, summed across layers, and then projected through an MLP to align the embedding dimension with that of the translation model:

$$\begin{aligned} W_{\text{gate}} &\in \mathbb{R}^{3 \times 3D_{\text{MMFM}}}, \\ [g_1, g_{\text{mid}}, g_{\text{last}}]_t &= \text{softmax}(W_{\text{gate}} \cdot h_t^{(1)} \oplus h_t^{(\text{mid})} \oplus h_t^{(\text{last})}), \\ m'_t &= g_1 \odot h_t^{(1)} + g_{\text{mid}} \odot h_t^{(\text{mid})} + g_{\text{last}} \odot h_t^{(\text{last})}, \\ m_t &= \text{MLP}(m'_t) \in \mathbb{R}^{L_m \times D_{\text{Trans}}}, \quad t = 1, \dots, L_x \end{aligned} \quad (3)$$

where D_{Trans} is the embedding dimension of \mathcal{M}_{NMT} and m_t is the fused multimodal representation at time step t .

The fused multimodal embeddings m_t can now be treated like additional token embeddings and concatenated with the \mathcal{M}_{NMT} token embeddings:

$$\begin{aligned} \tilde{x}_t &= m_t \oplus x_t, \\ \tilde{X} &= (\tilde{x}_1, \dots, \tilde{x}_{L_m+L_x}) \end{aligned} \quad (4)$$

Finally, the multimodal translation loss is computed by conditioning on the concatenated sequence \tilde{X} while predicting the target tokens:

$$\mathcal{L}_{\text{MM-Trans}} = -\frac{1}{T_y} \sum_{t=1}^{T_y} \log P_\theta(y_t | y_{<t}, \tilde{X}) \quad (5)$$

Where \tilde{X} is the multimodal input to the translation model.

2.2 Training

We have shown how MMFM internal representations can be extracted and integrated into our downstream model. However, leveraging these representations effectively also requires a training process that explicitly aligns multimodal features so that the LLM can exploit them. The exact alignment procedure depends on the downstream tasks we expect the fused model to perform after fine-tuning.

In this work, our goal is to obtain a translation model that can utilize both audio and image context. Therefore, we must make the translation LLM context-aware by training to exploit these representations. We consider 3 translation tasks in this work and are defined as follows:

- **Speech Translation (ST):** Generate a translation in the target language given only audio in the source language.
- **Speech-Image Translation (SIT):** Generate a translation in the target language given source-language audio together with an image that provides additional context (e.g., a slide corresponding to the spoken segment).
- **Text-Image Translation (TIT):** Generate a translation in the target language given the source text and an aligned image, such as in caption translation scenarios.

While we can train the model to perform translation directly, decomposing the task into intermediate steps can be beneficial. For example, translating English audio to German can be approached by first predicting ASR outputs and then producing the translation by continuing generation conditioned on the ASR hypothesis. This decomposition not only simplifies learning but also provides explicit alignment signals that help map audio representations into the LLM’s semantic space.

When vision input is available—particularly for slide-based scenarios—we additionally introduce OCR as a bridge task before generating the final translation. In this case, the model must predict both OCR text and the final translation using the same audio-visual representation. This encourages alignment between the modalities and explicitly informs the model that the visual context is meaningful and should be utilized.

During training, we stochastically decide—based on a specified probability for each data source—whether an example should

be trained in self-cascading mode and along which modality the cascade should occur. Furthermore, we provide modality-specific prompt to the MMFM for handling different modality combination scenarios. Pseudocode for building the prompt for each task during training is shown in Algorithm 1.

We also freeze the MMFM to preserve its pre-trained abilities while fine-tuning the translation LLM with LoRA (Hu et al., 2021). We use LoRA for computational benefits and not go Out-Of-Memory during fine-tuning.

3 Experimental Setup

3.1 Training Data

We aim to train the fused model to perform translation tasks across both speech and image modalities. An overview of the data sources is provided in Table 1.

For ST, we use subsets of Europarl-ST (Iranzo-Sánchez et al., 2020) and Covost-2 (Wang et al., 2020), sampling across multiple target languages. We limit training data to these subsets due to computational constraints and to demonstrate that full datasets are not strictly necessary.

To enable the model to exploit images when translating audio, we use the M3AV corpus (Chen et al., 2024), which contains English scientific talks paired with corresponding slides. The slides also include Paddle-OCR (Cui et al., 2025) predictions, allowing the model to be trained either to predict translations directly or via an intermediate OCR step for better alignment.

Since M3AV has limited language coverage, we augment the data by synthetically translating ASR transcripts into additional target languages (**M3AV-Aug**). This enables the model to handle ST with slides and supports the self-cascade mode, performing ASR first and then translation.

Finally, for TIT, we employ the Multi30k dataset (Elliott et al., 2016), which contains images paired with captions in multiple languages. This task encourages the model to go beyond OCR and to leverage visual content, including objects and scene understanding, for translation.

3.2 Models

Several MMFMs have been developed rapidly in recent years, showing significant improvements in both quality and efficiency (Abdin et al., 2024; Team et al., 2025). In our scenario, we require a

Dataset	# Examples	Language	Modality	Task
M3AV	122k	en	Speech, Image	ASR, OCR
		zh, fr, de, it, ja, ko, pt, ru,		
M3AV - Aug	122k	es, vi, ar, cs, hr, da, nl, fi, hu, id, ms, nb, no, pl, ro, tr	Speech, Image	ST, OCR
Europarl	260k*	de, es, fr, it, nl, pl, pt, ro	Speech	ST
Covost2		de, ja, tr, zh	Speech	ST
Coco-Captions	87k	cs, de, fr	Image	TIT

Table 1: Overview of data sources collected for E2E training. * We sample together 260k from the concatenated data uniformly across the language pairs. All the speech and text data are only available with English as the source language. Language code mapping is presented in Table 9.

model capable of processing both audio and image modalities, while also supporting cross-modal abilities. Accordingly, we select Qwen Omni 2.5B² (Xu et al., 2025), due to its strong multimodal capabilities and the potential to incorporate video in future experiments.

For the translation LLM, we choose the recently proposed SeedX PPO 7B³ (Cheng et al., 2025), which provides broad language coverage and strong translation performance compared to closed-source alternatives.

We use the training data mentioned above and denote the fine-tuned model as **OmniFusion** for the rest of the paper. While we report results using these specific models, it is important to note that our approach is not limited to these base LLMs. The proposed fusion strategy does not require massive pre-training or fine-tuning resources and can be adapted in more modest computing environments, such as university clusters. The training hyper-parameters are specified in Table 10. For validation, we used Covost-2 validation data and select the checkpoint with the least loss in 20k steps.

3.3 Evaluation: Data & Metrics

For evaluating the performance of multimodal Simul-ST systems, we require aligned audio-visual translation data. Additionally, we avoid using M3AV for testing, as it overlaps with our training data, monolingual and we aim to measure the model’s robustness on unseen domains.

Consequently, we use the MCIF test set (Papi

²Qwen/Qwen2 Audio.5-Omni-7B

³ByteDance-Seed/Seed-X-PPO-7B

et al., 2025b), which contains video and audio recordings of ACL talks in three target languages from English. We report latency with Average Lagging (Ma et al., 2020) and translation quality results on this dataset.

For TIT, we focus on test cases where the image is crucial for disambiguating the source sentence. For this, we use the CoMMuTE dataset (Futeral et al., 2023, 2025), which provides a small but multilingual targeted TIT test set.

We measure translation quality using XCOMET-XL (Guerreiro et al., 2024) for ST scenarios, as it offers high-quality evaluation and allows analysis of minor, major, and critical errors. For TIT, we use the COMET⁴ model (Rei et al., 2022) directly, without providing error spans, to evaluate aligned references.

4 Results

Our primary motivation for the proposed approach is to build an E2E ST system that is context-aware, efficient for SimulST and enabled to exploit additional image context. To validate this, we first evaluate the system in simultaneous scenarios by comparing latency and quality. Next, we report quality in offline scenarios and conduct an error analysis to contrast the E2E system with traditional cascaded systems fine-tuned on the same data. We then assess performance in TIT scenarios, benchmarking against other off-the-shelf multimodal translation models. Finally, we perform an ablation study to analyze the contributions of individual layers in the MMFM and present the key findings.

We also validate the proposed approach for a different model combination (Qwen-Audio (Chu et al., 2023) and Tower-Instruct (Alves et al., 2024)), analyze training with different layers and post-editing in our preliminary experiments and report the results in the Appendixes Table 4 and table 5.

4.1 Simultaneous Speech Translation

A SimulST system must generate translations incrementally as the source audio arrives, rather than waiting for the entire utterance to finish. The decision of whether to commit a token or read more audio is referred to as the *policy*. Since our E2E system does not natively support simultaneous translation, we adopt the widely used Local Agreement policy (Liu et al., 2020), which commits the longest

⁴Unbabel/wmt22-comet-da

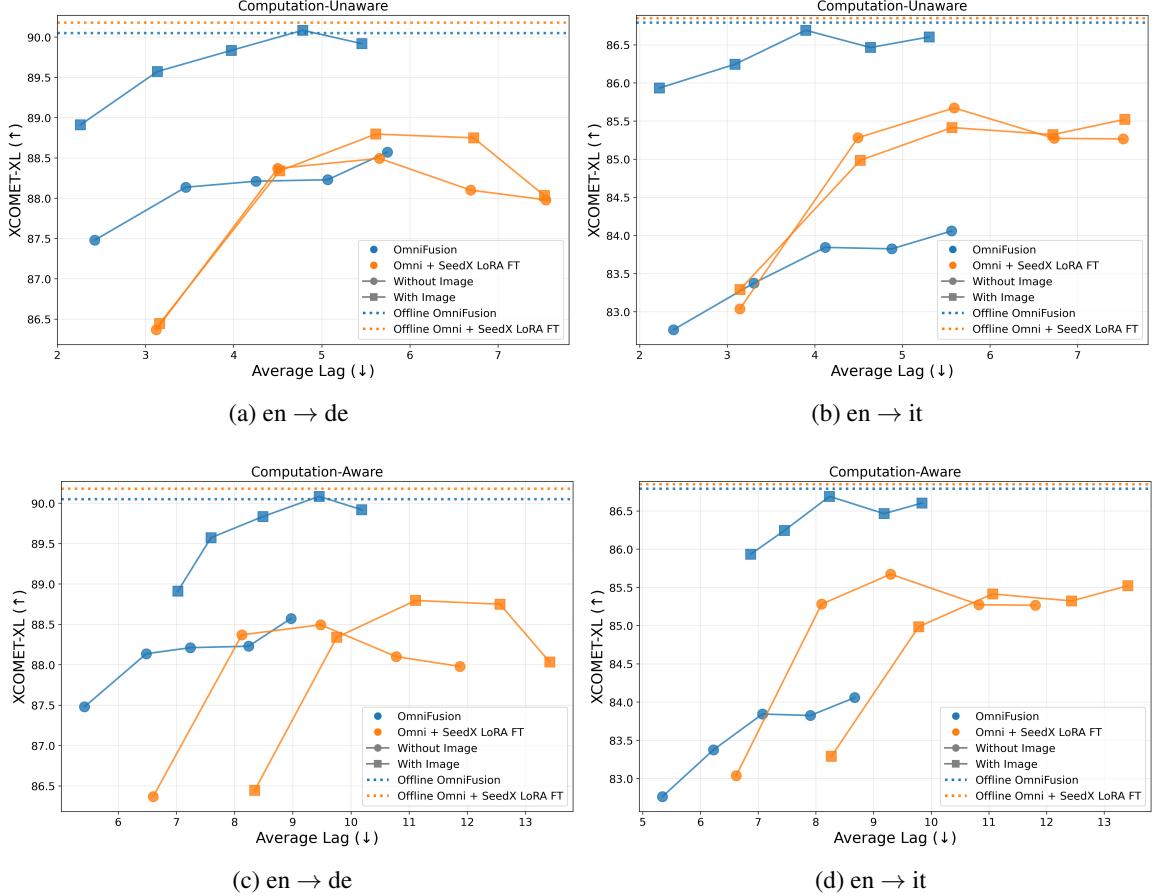


Figure 2: SimulST performance on $en \rightarrow de$ and $en \rightarrow it$. Average Lag (AL, lower is better) vs. XCOMET-XL quality score (higher is better). Results compare OmniFusion (E2E) against the fine-tuned cascaded baseline and the offline upper bound (**with Image**). Top figures are computation-unaware and bottom are computation-aware.

common prefix observed across consecutive predictions. Concretely, at each step we process the audio in fixed chunk sizes (a hyperparameter) and irreversibly emit the overlapping prefix between the current and previous hypotheses. After committing, subsequent tokens are force-decoded conditioned on the partial translation committed so far.

To fairly evaluate the proposed approach, we compare our E2E model OmniFusion against a strong cascaded counterpart built from the same pretrained components. We therefore fine-tune this cascaded baseline on the same data using LoRA adapters (Omni + SeedX LoRA FT). The effect of fine-tuning is discussed in more detail in Section 4.2. We experiment with chunk sizes of $[1, 1.5, 2, 2.5, 3]$ seconds, run inference both with and without images, and report computation-aware and computation-unaware AL together with XCOMET-XL scores for the $en \rightarrow de$ and $en \rightarrow it$ language pairs in Figure 2.

The results reveal several key insights. First, as expected, the offline ST systems (with images)

achieve the highest quality in both language pairs due to access to full context. Next, OmniFusion is consistently around 1 second faster than its cascaded counterpart across all chunk sizes while preserving comparable quality in the audio-only setting. When images are provided, OmniFusion delivers both the lowest latency and the highest quality, demonstrating that visual context is substantially more beneficial in the E2E model than in the cascaded baseline allowing it to commit high quality stable outputs earlier. Finally, we also see that in computation-aware settings, adding image causes delay due to processing and causes overhead than only-audio creating a trade-off between quality and latency.

We attribute the advantage of OmniFusion to two factors: (1) our fine-tuning strategy, which includes an OCR objective that tightly aligns image and audio representations, and (2) the inherent efficiency of the E2E architecture, which requires fewer decoding steps overall. In contrast, the cascaded pipeline with Local Agreement must wait for

Category	Config	Image	XCOMET-XL	Minor	Major	Critical	Total
Cascade Systems (ASR → MT) Omni + SeedX	No FT	✗	85.88	1212.3	773.0	74.3	2059.7
	No FT	✓	85.94	1191.3	759.3	74.7	2025.3
	LoRA FT	✗	86.42	1239.0	751.3	75.0	2065.3
	LoRA FT	✓	86.59	1202.3	766.3	55.7	2024.3
End-to-End (Direct ST) OmniFusion	Mid Fusion	✗	83.57	1114.0	1188.3	72.3	2374.7
	Mid Fusion	✓	85.98	1256.3	749.0	61.7	2067.0
	Gated Fusion	✗	83.98	1119.3	1188.0	62.7	2370.0
	Gated Fusion	✓	86.24	1255.7	736.0	57.0	2048.7
	Gated Fusion + Self-Cascade	✓	86.57	1231.0	719.0	55.3	2005.3

Table 2: Offline ST results averaged across en→zh, en→de, and en→it on the MCIF test. ✓ indicates models using image input. Bold indicates best XCOMET-XL and lowest error counts. Language-wise results are additionally reported in Table 6, 7 and 8.

stable ASR hypotheses before translation can even begin, making it slower than the E2E approach.

In conclusion, OmniFusion achieves better latency, leverages image context effectively, and has higher quality in SimulST scenarios, making it particularly well-suited for real-world applications such as live presentations and meetings where visual information is readily available.

4.2 Offline Speech Translation

Although SimulST is the primary focus of this work, we also evaluate the systems in the offline scenario, where latency is not a concern and the goal is to maximize translation quality. In this setting, we can leverage the self-cascade inference mode described in Section 2.2 to further boost performance.

To measure the contributions of fine-tuning and visual context, we first evaluate the cascaded baseline in four configurations: base vs. fine-tuned (LoRA FT) models, each tested with and without images. For the E2E OmniFusion model, we additionally train a variant that uses only the middle-layer fusion without gating to assess the need for the gating module. We then compare all E2E configurations (mid-only fusion and full gated fusion) both with and without images, and with/without self-cascade inference. Results are averaged across three target languages $en \rightarrow \{de, it, zh\}$ and reported in Table 2 using XCOMET-XL scores. We further include the detailed XCOMET-XL error categories, hypothesizing that E2E models may sacrifice minor fluency for substantially fewer major and critical errors.

The results yield several insights. In the cascaded pipeline, LoRA fine-tuning yields consistent gains (e.g., 85.94 → 86.59 with images), whereas adding images provides only marginal benefit. In contrast, the E2E OmniFusion model benefits sub-

stantially from both gated fusion (outperforming mid-only fusion) and image context showing the need for gating module and additional contextual information. Although the direct E2E translation score remains slightly below the best cascaded system, enabling self-cascade inference closes this gap almost entirely (cascaded LoRA FT: 86.59 vs. E2E gated fusion + self-cascade: 86.57). More importantly, error analysis reveals that our best E2E configuration produces the fewest critical and major errors (e.g., 719 vs. 751.3 for the strongest cascaded baseline). These findings demonstrate that OmniFusion, when equipped with image context and self-cascade inference, matches fine-tuned cascaded system in offline ST quality while offering significantly fewer severe translation errors

4.3 Text-Image Translation

Apart from ST, translating captions also relies on image context, where cascaded systems fail due to their inability for disambiguation. To demonstrate this, we evaluate several models on the CoMMuTE test set across multiple language pairs and report COMET scores in Table 3.

First, the audio-only Omni 2.5B exhibits the weakest multilingual performance, which reinforces our motivation for integrating it with a strong translation backbone. SeedX 7B obtains reasonable scores yet consistently trails all vision-capable models, confirming its limitation in the absence of image context. Among vision-aware systems, both Mid Fusion and Gated Fusion variants of our OmniFusion 14B achieve state-of-the-art or near-SOTA COMET scores, matching or surpassing vision-only models such as ZeroMMT 3.3B (Futeral et al., 2025) and TowerVision 9B (Viveiros et al., 2025) on most language directions.

Interestingly, and in contrast to ST, the Mid Fusion variant slightly outperforms Gated Fusion on

Model	Config	en → ar	en → cs	en → de	en → fr	en → ru	en → zh
Omni 2.5B	-	78.56	81.03	81.94	79.99	47.27	81.74
SeedX 7B	-	80.39	83.56	82.38	80.31	82.13	83.25
ZeroMMT 3.3B (Futeral et al., 2025)	-	80.64	86.69	83.54	83.40	83.87	77.85
TowerVision 9B (Viveiros et al., 2025)	-	70.85	86.62	84.97	84.29	85.81	85.24
OmniFusion 14B	Mid Fusion	80.98	87.49	85.14	84.97	85.69	85.15
OmniFusion 14B	Gated Fusion	80.81	87.58	84.88	84.28	84.62	84.34

Table 3: COMET scores (\uparrow) on the CoMMuTE dataset. Statistically significant top-performing results per language pair are highlighted in **bold**. ‘Config’ distinguishes the two OmniFusion variants (mid-layer fusion vs. gated fusion).

CoMMuTE. This suggests that, when the image serves primarily as supplementary context (as in caption translation) rather than the main information source (as in audio for spoken ST), using visual features at the middle layer alone may be sufficient, and the additional flexibility of gating offers no further advantage.

Importantly, unlike TowerVision which requires massive multimodal pretraining from scratch, OmniFusion can be built on top of existing strong pre-trained components. This makes our approach far more data- and training-efficient without compromising quality, by effectively exploiting the rich image–text alignment knowledge already present in the MMFM pretrained weights. These results underline the strength of our E2E design on visually grounded translation tasks where image context is essential.

4.4 Contribution of Layers

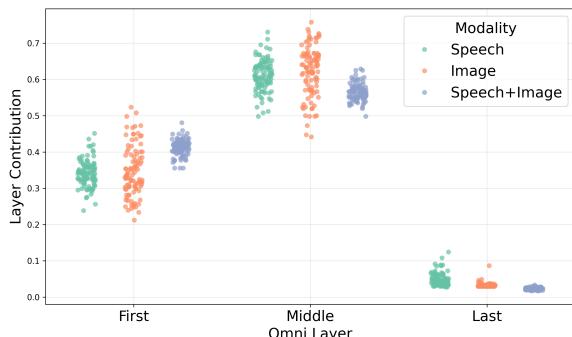


Figure 3: Analysis of the layer contribution from the MMFM in the gating module across modalities.

We presented a gating module in Section 2.1 for fusing information across layers of the MMFM. To better understand its behavior, we conduct an ablation study by examining the gate values assigned to

each MMFM layer during fusion. Specifically, we compute the average gate value across the three layers (first, middle, last), noting that the gate weights for each timestep sum to 1.

We run inference on 100 examples from the MCIF dataset—both speech-only and speech+image conditions—and on the CoMMuTE dataset for the image-only modality. The resulting average gate values are shown in Figure 3.

We observe that the first and middle layers receive consistently higher contributions, while the last layer contributes only marginally. This suggests that the majority of transferable multimodal processing occurs in the earlier half of the MMFM. Although the weak contribution of the last layer is not entirely clear, we hypothesize that these representations may be more language-specific, whereas the middle layers capture more language-agnostic features (Liu and Niehues, 2025).

5 Related Work

Multimodal MT: Translating captions has been widely explored in the MT field over the last decade (Specia et al., 2016; Elliott et al., 2017; Barrault et al., 2018). Several works focus on enabling NMT models to process images, either by training models from scratch (Vijayan et al., 2024) or by augmenting large pretrained models such as NLLB (Costa-Jussà et al., 2022; Futeral et al., 2025). Most recently, and in parallel to our work, Viveiros et al. (2025) extend Tower with image and video modalities through a computationally expensive multi-stage training pipeline.

While these efforts focus primarily on vision, an other line of direction is adding audio to translation LLMs (Ambilduke et al., 2025). A smaller line of work tackles the combination of vision and audio, such as Sinhamahapatra and Niehues (2025),

which exploits slides and speech for ASR. Building on this trend, there is also increasing interest in translating audio together with video (Anwar et al., 2023; Choi et al., 2024). In contrast to these works, our approach focuses on jointly using images and audio specifically for ST, while remaining efficient in both training and inference.

Simultaneous ST: Many real-world scenarios require real-time ST without waiting for the full source utterance. However, most research focuses on training models in offline settings and only later adapting them to SimulST. Such adaptation typically relies on predefined or learned translation policies, such as wait-k (Ma et al., 2019; Elbayad et al., 2020), which assumes a fixed token delay before committing to output. Other approaches include Local Agreement (Liu et al., 2020), which selects the most stable prefix across consecutive read steps or attention-based heuristics (Papi et al., 2023). More recently, several works explore leveraging LLMs for SimulST policy learning (Koshkin et al., 2024b,a; Guo et al., 2025; Fu et al., 2025). In our work, we use Local Agreement to validate the effectiveness of our approach and to compare against cascaded baselines. However, our method is compatible in theory with other SimulST policies, and integrating more advanced or LLM-driven strategies is a promising direction for future work.

Modality Fusion: With the rapid development of multimodal foundation models, a key challenge is how to effectively integrate speech and image modalities into text-centric LLMs. Some approaches (Abdin et al., 2024; Xu et al., 2025; Team et al., 2025) process each modality with separate encoders and merge them later within the LLM backbone. In contrast, models such as (Ye et al., 2025) enable early interaction between vision and audio modalities, facilitating better cross-modal alignment. Beyond the timing of modality interaction, ongoing research also investigates the design of modality projectors (Verdini et al., 2024; Gaido et al., 2024b) and the use of continuous versus discrete tokens for non-text modalities (Zhan et al., 2024; Li et al., 2025), balancing the trade-offs between latency and translation quality.

6 Conclusion

We proposed a novel approach to fuse a MMFM with a translation LLM, and validated its effectiveness across three key scenarios. First, we showed that the fused model achieves faster inference while

maintaining strong translation quality in SimulST settings, even when only partial source audio is available. Second, the model produces fewer major and critical translation errors, demonstrating more reliable linguistic accuracy. Third, we found that the model effectively leverages visual context for both speech and text translation, leading to consistent gains in multimodal settings. Finally, our layer-level analysis reveals that the first and middle MMFM layers contribute most to capturing semantic multimodal information, providing insight into where meaningful cross-modal representations emerge.

For future work, our fusion framework can naturally be extended to additional modalities. Since Omni already supports video processing, incorporating video embeddings would enable richer context for translation. Moreover, the fusion strategy is not limited to models for multimodal inputs but future extensions could target multimodal generation, allowing the system to produce not only text but also speech, images, or video as output.

Limitations

A primary limitation of our work is that Omni-Fusion is trained with fixed task-specific prompts across the three supported translation settings, and therefore does not exhibit general instruction-following capabilities. It remains unclear whether our fusion strategy can be extended to support more flexible, instruction-driven multimodal behavior. In addition, most of our experiments use English as the source language. Although we report zero-shot results in Table 4, we do not evaluate the Omni-Fusion model with vision inputs in multilingual zero-shot conditions.

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A Appendix

A.1 Layer Analysis, Zero-shot ability and APE - AudioTower

In our preliminary experiments, we focus exclusively on the audio modality and investigate fusing Qwen-Audio 7B (Chu et al., 2023) with Tower-Instruct 7B v0.2 (Alves et al., 2024). We train the fused model for ST using the same setup described earlier, but without gating, and we independently fuse the first, middle, and last layers of Qwen-Audio to assess their individual contributions. We then compare this fused model against several baselines. First, we evaluate both the out-of-the-box and fine-tuned versions of Qwen-Audio (Qwen2 Audio FT), trained end-to-end on the same ST data. We also include a standard cascaded setup using off-the-shelf ASR and MT models. Additionally, we evaluate an Automatic Post-Editing (APE)

Model	Mode	Hypothesis	Comet-22 (\uparrow)					
			en \rightarrow de	en \rightarrow zh	<u>zh</u> \rightarrow de	<u>es</u> \rightarrow it	<u>ja</u> \rightarrow ru	fr \rightarrow kr
Baselines								
Qwen2 Audio	E2E	–	81.24	78.20	73.59	83.38	70.70	71.26
Qwen2 Audio FT	E2E	–	84.82	85.57	80.22	84.17	67.69	77.09
Qwen2 Audio + Tower	Cascade	–	85.85	85.97	82.94	85.36	69.26	84.78
Tower APE	Cascade APE	Qwen2 Audio + Tower	85.96	85.77	82.59	85.21	47.43	70.67
Off-the-shelf ST models								
Tower-Spire	E2E	–	82.77	81.63	–	–	–	–
Tower-Spire	Self-Cascade	–	85.17	85.73	–	–	–	–
Seamless-M4T v2	E2E	–	85.63	80.05	70.22	77.78	70.58	78.91
E2E models								
AudioTower-Zero	E2E	–	85.13	83.97	76.62	83.98	68.71	81.64
AudioTower-Mid	E2E	–	86.02	85.03	80.62	84.86	74.47	83.26
AudioTower-Last	E2E	–	82.97	81.03	54.12	49.57	50.19	52.31
E2E + Speech-Aware APE model								
AudioTower-Mid	Cascade APE	Qwen2 Audio + Tower	86.34	85.99	83.42	85.96	78.26	84.59
AudioTower-Mid	E2E	Empty	85.77	84.79	80.39	85.27	74.67	82.71

Table 4: Offline ST results on FLEURS test set. Speech-Aware APE models use the hypothesis from a system and perform post-editing. Statistically significant top-performing results per language pair are highlighted in **bold**. Underlined languages are not seen during the fusing process as source/target.

Model	Mode	Hypothesis	Comet-22 (\uparrow)					
			en \rightarrow de	en \rightarrow zh	<u>zh</u> \rightarrow de	<u>es</u> \rightarrow it	<u>ja</u> \rightarrow ru	fr \rightarrow kr
Qwen2 Audio + Tower	Cascade	–	85.85	85.97	82.94	85.36	69.26	84.78
Whisper + Tower	Cascade	–	86.71	86.31	82.23	86.54	83.56	85.29
AudioTower-Mid	Cascade APE	Qwen2 Audio + Tower	86.34	85.99	83.42	85.96	78.26	84.59
AudioTower-Mid	Cascade APE	Whisper + Tower	87.09	86.34	82.81	86.60	84.38	84.95
Character-Error-Rate (\downarrow)								
Whisper	ASR	–	3.14	3.15	25.37	2.11	7.67	3.28

Table 5: Analysis of system combination by using Whisper to generate the hypothesis for post-editing on FLEURS test set. Statistically significant top-performing results per language pair are highlighted in **bold**. Underlined languages are not seen during the fusing process as source/target.

configuration in which Tower corrects translations generated by Qwen-Audio.

To contextualize performance, we further compare against other off-the-shelf ST systems such as Tower-Spire (Ambilduke et al., 2025) and Seamless-M4T (Barrault et al., 2023), which provides insight into multilingual generalization. Beyond the main fused model, we also train an APE variant of our fusion architecture that post-edits the outputs of cascaded systems. Unlike traditional APE, this Speech-Aware APE allows the model to use the source audio when correcting errors, enabling more informed revisions. For both APE variants, we generate synthetic APE tuples by running Qwen-Audio on the training data and fine-tune with LoRA.

We report results on the FLEURS test set in Table 4, including evaluations on zero-shot language directions not present on either the source or target side during training. First, while fine-tuning improves Qwen2 Audio, it still falls short of the out-

of-the-box cascaded setup across all languages, underscoring the strength of translation-centric LLMs. Tower-based APE is competitive for seen languages but struggles in harder zero-shot directions, such as $fr \rightarrow kr$. Off-the-shelf end-to-end ST models lag significantly behind cascaded systems as well.

Our proposed fused model (AudioTower) with middle-layer fusion achieves the strongest overall performance and even surpasses the cascaded baseline in several languages. Notably, both the first and middle layers show strong transfer to unseen languages, whereas the last layer collapses entirely—supporting the hypothesis that upper layers encode highly language-specific features, making them less suitable for cross-lingual contextual embeddings.

Finally, the APE variant of the fused model delivers the best results overall by combining the strong hypotheses of the cascaded pipeline with the ability to exploit the raw audio when correcting errors. We also test this APE model with empty

hypotheses and observe performance comparable to AudioTower-Mid, indicating its flexibility for multiple use cases.

Given the strong APE results, we additionally explore whether the model can correct outputs from different ASR systems. Using Whisper (Radford et al., 2023) for ASR, we evaluate the fused APE model on Whisper+Tower outputs and report results in Table 5. When Whisper+Tower produce the strongest cascaded baseline, using them as hypotheses likewise yields the highest APE performance—highlighting that Speech-Aware APE can be beneficial not only for E2E setups but also for offline cascaded scenarios.

A.2 Prompt Building

System Prompt for all modalities

You are Qwen, a virtual human developed by the Qwen Team, Alibaba Group, capable of perceiving auditory and visual inputs, as well as generating text and speech.

User Prompt (ST with/without Image)

Transcribe the audio using the image for context, and perform OCR on the image for correct spelling of keywords and names.

User Prompt (TIT)

Translate the following sentence into {tgt_lang} using the image for context. refers to the image. Use the image to determine formality, gender, keywords, and other details important for disambiguation:
{ex[src]}

Algorithm 1 Online Prompt building for examples in the training data to enable alignment and self-cascading inference mode.

Require: Example *ex*

```
// SeedX prompt (source text, language tag and reference)
1: src, tgt, img, aud, ocr, lang ← EXTRACT(ex)
2: suffix ← ⟨LANG(lang)⟩

3: if aud and not img then                                ▷ Speech only
4:   if RANDOM < 0.1 then
5:     inp ← ⟨en⟩
6:     lbl ← ASR(src)+⟨eos⟩+suffix+tgt+⟨eos⟩           ▷ English-Audio only in our dataset
7:   else
8:     inp ← suffix
9:     lbl ← tgt+⟨eos⟩                                    ▷ ASR Self-cascade
10:  end if

11: else if img and not aud then                          ▷ Image only
12:   if RANDOM < 0.05 then
13:     SWAP(src, tgt)
14:     suffix ← ⟨English⟩
15:   end if
16:   srcm ← MASK(src, prob_words = 0.2, mask_chance = 0.2) ▷ Mask 20% source words for
      20% of the time to pay attention to Image
17:   inp ← ⟨SRC⟩ srcm+⟨eos⟩+suffix
18:   lbl ← tgt+⟨eos⟩

19: else if img and aud then                            ▷ Audio + Image
20:   if RANDOM < 0.8 then
21:     if RANDOM < 0.1 then
22:       inp ← ⟨en⟩
23:       lbl ← ASR(src)+⟨eos⟩+suffix+tgt+⟨eos⟩
24:     else
25:       inp ← suffix
26:       lbl ← tgt+⟨eos⟩
27:     end if
28:   else
29:     inp ← ⟨OCR⟩
30:     lbl ← ocr+⟨eos⟩+suffix+tgt+⟨eos⟩                ▷ OCR Self-cascade
31:   end if
32: else
33:   error “no modalities”
34: end if

// Omni prompt (Multimodal prompt builder)
35: if aud and img then
36:   user ← “Transcribe with OCR and image context:” || img || aud
37: else if aud then
38:   user ← “Transcribe audio:” || aud
39: else
40:   user ← “Translate with image:” || img
41: end if
42: STORE(user,inp,lbl)
```

Category	Model Name	Image	XCOMET-XL	Minor	Major	Critical	Total
Cascade Systems (ASR → MT) Omni + SeedX	No FT	✗	89.66	2172	132	68	2372
	No FT	✓	89.49	2115	133	76	2324
	LoRA FT	✗	89.75	2209	128	67	2404
	LoRA FT	✓	90.18	2135	118	56	2309
End-to-End (Direct ST) OmniFusion	Mid Fusion	✗	88.44	2126	157	74	2357
	Mid Fusion	✓	90.03	2256	104	68	2428
	Gated Fusion	✗	88.09	2133	181	87	2401
	Gated Fusion	✓	89.90	2217	106	60	2383
	Gated Fusion + Self-Cascade	✓	90.05	2191	94	62	2347

Table 6: Offline ST results en→de on the MCIF test. ✓ indicates models using image input. Bold indicates best XCOMET-XL and lowest error counts.

Category	Model Name	Image	XCOMET-XL	Minor	Major	Critical	Total
Cascade Systems (ASR → MT) Omni + SeedX	No FT	✗	86.03	850	932	51	1833
	No FT	✓	86.11	862	891	67	1820
	LoRA FT	✗	86.76	884	855	54	1793
	LoRA FT	✓	86.85	868	855	55	1778
End-to-End (Direct ST) OmniFusion	Mid Fusion	✗	82.80	754	1065	93	1912
	Mid Fusion	✓	85.75	899	903	64	1866
	Gated Fusion	✗	84.06	745	1085	56	1886
	Gated Fusion	✓	86.79	914	847	48	1809
	Gated Fusion + Self-Cascade	✓	87.20	879	838	44	1761

Table 7: Offline ST results en→it on the MCIF test. ✓ indicates models using image input. Bold indicates best XCOMET-XL and lowest error counts.

Category	Model Name	Image	XCOMET-XL	Minor	Major	Critical	Total
Cascade Systems (ASR → MT) Omni + SeedX	No FT	✗	81.94	615	1255	104	1974
	No FT	✓	82.23	597	1254	81	1932
	LoRA FT	✗	82.74	624	1271	104	1999
	LoRA FT	✓	82.74	604	1326	56	1986
End-to-End (Direct ST) OmniFusion	Mid Fusion	✗	79.47	462	1343	50	1855
	Mid Fusion	✓	82.15	614	1240	53	1907
	Gated Fusion	✗	79.78	480	1298	45	1823
	Gated Fusion	✓	82.03	636	1255	63	1954
	Gated Fusion + Self-Cascade	✓	82.47	623	1225	60	1908

Table 8: Offline ST results en→zh on the MCIF test. ✓ indicates models using image input. Bold indicates best XCOMET-XL and lowest error counts.

Language	Code
Arabic	<i>ar</i>
Chinese	<i>zh</i>
Croatian	<i>hr</i>
Czech	<i>cs</i>
Danish	<i>da</i>
Dutch	<i>nl</i>
Finnish	<i>fi</i>
French	<i>fr</i>
German	<i>de</i>
Hungarian	<i>hu</i>
Indonesian	<i>id</i>
Italian	<i>it</i>
Japanese	<i>ja</i>
Korean	<i>ko</i>
Malay	<i>ms</i>
Norwegian	<i>no</i>
Norwegian Bokmål	<i>nb</i>
Polish	<i>pl</i>
Portuguese	<i>pt</i>
Romanian	<i>ro</i>
Russian	<i>ru</i>
Spanish	<i>es</i>
Turkish	<i>tr</i>
Vietnamese	<i>vi</i>

Table 9: Language codes used in paper following [Cheng et al. \(2025\)](#).

Hyperparameter	Value
Gradient checkpointing	True
Gradient checkpointing kwargs	{'use_reentrant': False}
Save steps	1000
Evaluation steps	1000
Save strategy	steps
Evaluation strategy	steps
Logging steps	5
Logging strategy	steps
Learning rate	1e-4
Train batch size (per device)	4
Eval batch size (per device)	4
Gradient accumulation steps	2
Weight decay	0.01
Save total limit	3
Max steps	20000
bf16	True
Push to hub	False
Metric for best model	loss
Remove unused columns	False
Label names	["labels"]
Dataloader num workers	1
DDP find unused parameters	True

Table 10: Huggingface trainer hyperparameters used for the model on 4 Nvidia A100 48GB GPU's with DDP training mode. Unspecified hyperparameters are set to default

Image	Cascaded FT Output	OmniFusion Output	Reference
 <p>DEPLAIN: A German Parallel Corpus with Intralingual Translations into Plain Language for Sentence and Document Simplification Regina Stodden, Omar Momen, Laura Kallmeyer Heinrich Heine University Düsseldorf, Germany ACL 2023</p>	<p>Hallo, willkommen zu unserer Präsentation von Deplain, einem neuen Korpus für die Identifizierung deutscher Texte auf Dokumenten- und Satzebene.</p>	<p>Hallo, willkommen zu unserer Präsentation von DEPLAIN, einem neuen Korpus für die deutsche Texterkennung auf Dokumentebene und auf Satzebene.</p>	<p>Herzlich willkommen zu unserer Präsentation von DEPLAIN, einem neuen Korpus für die deutsche Texterkennung auf Dokument- und Satzebene.</p>

Table 11: Example illustrating where OmniFusion is better than cascaded variant. Example taken from MCIF segment 1.