Video-guided Multimodal Machine Translation: A Survey of Models, Datasets, and Challenges

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Abstract

In recent years, machine translation has evolved with the integration of multimodal information. Infusion of multi-modality into translation tasks decreases ambiguation and enhances translation scores. Common modalities include images, speech, and videos, which provide additional context alongside the text to be translated. While multimodal translation with images has been extensively studied, video-guided machine translation (VMT) has gained increasing attention, particularly since (Wang et al., 2019) first explored this task. In this paper, we provide a comprehensive overview of VMT, highlighting its unique challenges, methodologies, and recent advancements. Unlike previous surveys that primarily focus on image-guided multimodal translation, this work explores the distinct complexities and opportunities introduced by video as a modality.

1 Introduction

Multimodal Machine Translation (MMT) improves translation by incorporating more context. This context can be in the form of images, audio and video. This infusion of extra context helps in disambiguation of translated text and makes it more meaningful and accurate. MMT often mimics the way human translators annotate data. They take into account all the information that emanates from all modalities while translating the sentence in source language to target language. While MMT mostly focuses on images being the additional modality to the source text sentence, Video-guided machine translation has been picking immense interest as compared to other MMT techniques due to its ability to provide richer, more dynamic contextual information than images.

VMT takes advantage of the temporal and multimodal nature of videos, which combine visual, auditory, and textual data into a single cohesive source of information. Unlike static images, videos capture sequences of events, actions, and interactions, offering a more comprehensive understanding of the context. This makes video-based MMT particularly effective for tasks such as translating instructional videos, movies, or multimedia content, where temporal alignment and multimodal fusion are critical. For example, in a cooking video, the translation of a spoken instruction (e.g., *"chop the onions"*) can be disambiguated by the visual demonstration of the action, ensuring the translation is both accurate and contextually appropriate. In Fig. 1 the presence of the word "bin" tarnslates to "trash bin" in chinese after observing the context from the given video.

Figure 1: An example with the noun sense ambiguity problem in the VMT model by (Wang et al., 2019)

The importance of video-guided MMT lies in its ability to address several limitations of traditional text-based and image-guided translation systems. Videos provide temporal continuity which enable models to capture the progression of events and actions over time. Second, the integration of multiple modalities (text, audio, and video) allows for more robust disambiguation of ambiguous terms or phrases. VMT has practical applications in real-world scenarios, such as cross-lingual video captioning, multimedia content localization, and assistive technologies for the hearing impaired.

In this paper, we provide a comprehensive survey of video-guided MMT, focusing on its methodologies, challenges, and advancements. Unlike previ-

ous surveys that primarily focus on image-guided MMT, this work highlights the unique aspects of video-guided MMT and its growing importance in the field. We systematically categorize and analyze state-of-the-art approaches, datasets, and evaluation metrics, while also identifying key open problems and future research directions.

Our contributions are:

1. A novel taxonomy for video-guided multimodal machine translation, which systematically categorizes existing VMT approaches. (Section 4)

2. Comprehensive comparisons of methods, datasets, and state-of-the-art systems provided. (Section 6)

3. Identifing key challenges and future research directions are discussed to guide further advancements in Video guided MT. (Section 8)

2 Background and Preliminaries

Machine translation involves translating texts from one language to another language. From statistical to neural MT has undergone pioneering transformations. We discuss below various stages of MT developments connecting it with VMT.

2.1 Neural Machine Translation

Neural Machine Translation (NMT) has evolved significantly through key innovations in neural architectures. (Sutskever et al., 2014) pioneered sequence-to-sequence learning using LSTMs, demonstrating that reversing source sentences improved translation by shortening dependencies, achieving a BLEU score of 34.8 on English-French tasks. (Bahdanau et al., 2016) introduced attention mechanisms, enabling dynamic focus on relevant source segments and addressing long-sequence limitations. (Luong et al., 2015) refined this with global and local attention models. The transformer architecture (Vaswani et al., 2023) eliminated recurrence entirely, using self-attention for superior parallelization. Subword segmentation techniques like byte-pair encoding improved rare-word handling (Sennrich et al., 2016) through compositional translation units. Multilingual NMT systems achieved zero-shot translation via shared parameters and language tokens, revealing interlingual representations (Wu et al., 2016).

2.2 Image Guided Machine Transaltion

Image-guided machine translation (IMT), which uses visual information as an additional modality, gained momentum with the introduction of the Multi30K dataset by (Elliott et al., 2016). However, the scarcity of paired image-text datasets led to alternative approaches such as retrieval-based image machine translation (Fang and Feng, 2022; Tang et al., 2022a; Zhang et al., 2020), which retrieves relevant images, and text-to-image-guided machine translation (Calixto et al., 2019; Li et al., 2022a; Long et al., 2021; Yuasa et al., 2023; Guo et al., 2023), where synthetic images are generated from text.

2.3 Other Forms

Beyond IMT, text-in-image machine translation (Chen et al., 2023; Lan et al., 2023; Ma et al., 2022, 2024, 2023) focuses on translating text embedded within images. Another development in MMT is simultaneous machine translation (SiMT) (Haralampieva et al., 2022; Imankulova et al., 2020; Ive et al., 2021), which generates translations before receiving the full input to reduce latency while maintaining quality.

In all of the above cases videos are not a part of the modeling. Therefore video-guided machine translation has emerged which incorporates temporal information alongside visual and textual data for improved translation accuracy.

3 Problem Formulation

The task of VMT involves contextually appropriate translations of source language text by utilizing additional modalities such as video and audio. Formally, given a source language text $S = \{s_1, s_2, \ldots, s_n\}$ and a corresponding video frame sequence $V = \{v_1, v_2, \ldots, v_m\}$ (which may include associated audio $A = \{a_1, a_2, \ldots, a_k\}$), the goal is to produce a target language translation $T = \{t_1, t_2, \ldots, t_p\}$ that is linguistically accurate and contextually aligned with the multimodal input. The objective of video-guided MT is to learn a mapping function f that maximizes the likelihood of the target translation T given the source text S, video V, and audio A, expressed as

$$f(S, V, A) = \arg\max_{T} P(T \mid S, V, A).$$

This involves optimizing model parameters to minimize the discrepancy between the predicted translation $\hat{T}$ and the ground truth T, typically using

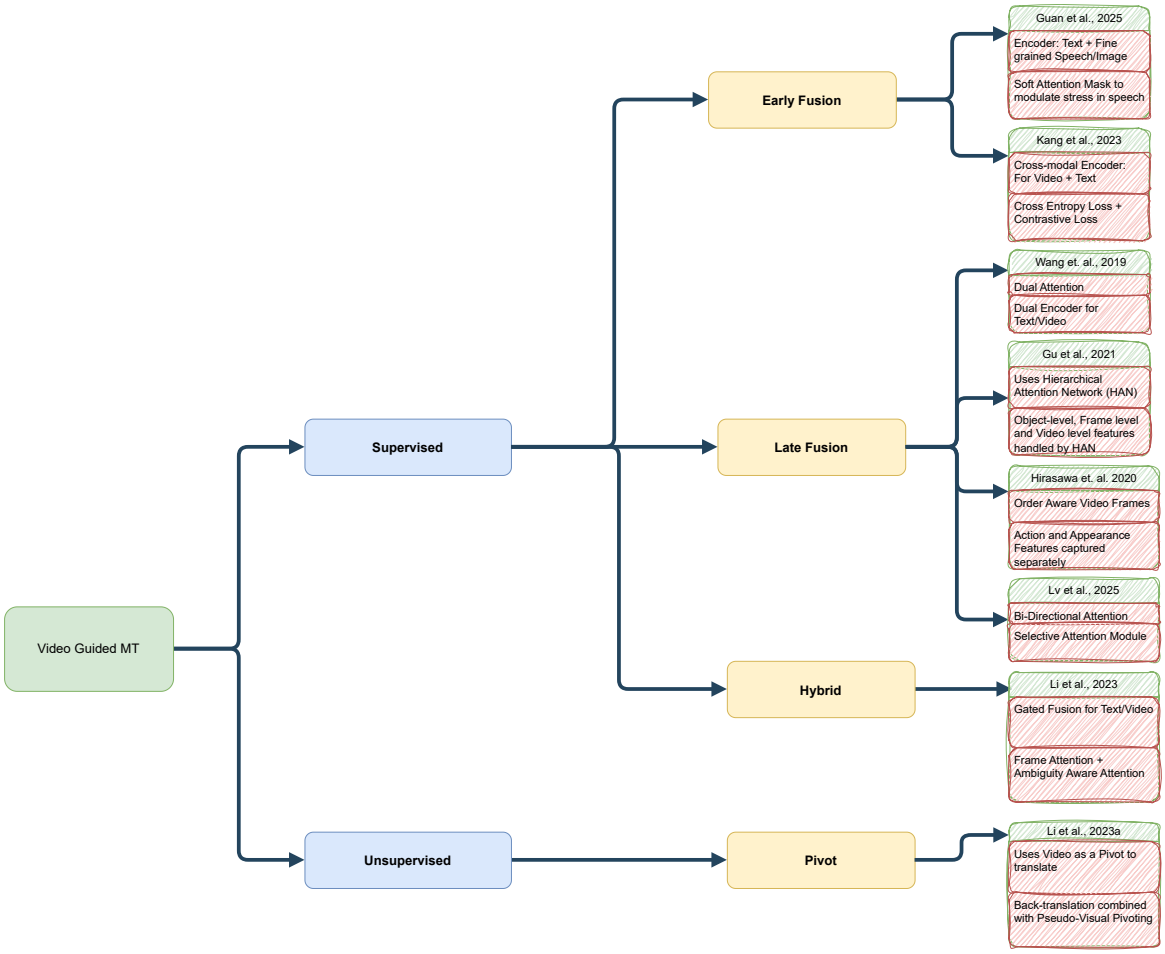

Figure 2: Taxonomy for Video Guided Machine Translation

cross-entropy loss or other sequence-level objectives. The integration of video and audio modalities introduces unique challenges, such as temporal alignment and scalability, which distinguish video-guided MT from traditional text-based or image-guided MT and necessitate specialized approaches to effectively harness the rich, dynamic information provided by multimodal inputs.

Video-guided multimodal MT leverages multiple modalities (text, video, and audio) to improve translation quality. The approaches can be broadly categorized based on how they handle modality fusion. Below and in Fig. 2, we present a taxonomy of these approaches, with supervised approaches focusing on **Late Fusion**, **Early Fusion**, **Hybrid Fusion** and unsupervised approaches focusing on **Video Pivoting**.

4 Video Guided Machine Translation.

4.1 Late Fusion

The early approaches in VMT utilized separate encoders for video and text modalities and combined them at a later stage in the VMT pipeline.

(Wang et al., 2019) designed a multimodal sequence to sequence model with temporal attention and source attention for videos and text embeddings respectively.

(Hirasawa et al., 2020) introduce a novel approach to video representation in machine translation by incorporating positional encodings, making the model aware of the temporal order of frames. They further enhance the video representation by distinguishing between two types of features: action and appearance. The action features, captured by a dedicated video encoder, focus on motion information crucial for disambiguating verbs in the translation process. Conversely, appearance features, extracted by an image encoder, provide detailed information about objects and scenes within each frame, aiding in the disambiguation of nouns. This dual-feature approach allows the model to better align visual cues with textual elements.

(Gu et al., 2021) introduce a novel approach to video representation inspired by Hierarchical Attention Networks (HAN) (Miculicich et al., 2018). Their model divides video input processing into two distinct components: motion representation and spatial representation. For capturing motion dynamics, they employ a pretrained I3D (Carreira and Zisserman, 2017) network. The spatial aspect is handled by a specialized HAN, which constructs a multi-level representation hierarchy: object-level, frame-level, and video-level. In this special HAN, each successive level of representation serves as a helper for the higher level, allowing for a progressively more comprehensive understanding of the video's spatial content. The object-level features inform the frame-level representation, which in turn contributes to the overall video-level understanding. This hierarchical approach enables the model to capture both fine-grained spatial details and broader contextual information. For generating the translated sentence, the authors utilize a GRU (Gated Recurrent Unit) (Chung et al., 2014) network as the decoder.

(Lv et al., 2025). integrates the selective attention module and the bidirectional attention module by taking inspiration from (Li et al., 2021) and (Tang et al., 2022b). Their architecture utilizes two encoders each for video and source text and fuses the obtained representations using a cross modal bidirectional attention mechanism. The fused representations are then decoded into target-language subtitles using an autoregressive transformer decoder. An empirical evaluation across multiple domains reveals that the model's performance notably diminishes in out-of-domain scenarios.

4.2 Early Fusion

This fusion occurs when different modalities are embedding together before being passed on to a shared encoder:

(Kang et al., 2023)introduces a cross-modal encoder that jointly processes video and text representations. The model enhances video features with positional encodings to capture temporal information. This cross-modal architecture enables the model to focus on relevant parts of both text and video inputs, facilitating more effective multimodal understanding. The training process incorporates two key objectives: cross-entropy loss in the decoder for sequence generation, and a novel cross-modal contrastive learning (CTR) objective. The CTR objective is designed to learn shared semantics between video and text modalities, encouraging similar video-text pairs to have closer representations while pushing dissimilar pairs apart in the embedding space.

(Guan et al., 2025) introduces the FIAT architecture, a uni-modal encoder that integrates multiple fine-grained inputs for video-guided translation. The model incorporates various types of tags, including entities, audio sentiments, locations, ex-

Models	Datasets	Modelling Approaches	En-Zh	Zh-En
(Wang et al., 2019)	VaTex	Dual Attention and Dual Encoder for Text/Video	29.1	26.4
(Hirasawa et al., 2020)	VaTex	Order-aware video frames using positional embeddings.	35.4	-
(Gu et al., 2021)	VaTex	Hierarchical Attention Network (HAN) applied at object, frame, and video levels.	35.9	-
(Li et al., 2023b)	EVA	Introduces Frame Attention and Ambiguity-Aware Attention.	-	27.6
(Li et al., 2023a)	Vatex	Uses Video as Pivot between languages	29.6	26.6
(Kang et al., 2023)	VaTex BigVideo	Introduces additional contrastive loss.	37.6 44.8	-
(Guan et al., 2025)	TriFine	Uses fine-grained speech features with soft attention masks.	38.06	25.51
(Lv et al., 2025)	TopicVD	Uses selective attention and Bi-Attention on Text and Videos.	29.33	-

Table 1: Overview of Multimodal Translation Models, Approaches, and BLEU scores in En-Zh and Zh-En Directions

pressions, and video captions, alongside source subtitles. The cross-modal encoder processes these diverse inputs jointly, allowing for complex interactions between different modalities. To capture nuanced speech information, the architecture employs a soft attention mask that incorporates stress patterns from the audio. This attention mechanism helps the model focus on emphasized parts of speech, improving the accuracy and naturalness of translations.

4.3 Hybrid Fusion

(Li et al., 2023b) introduce SAFA (Selective Attention with Frame Attention) that integrates two key innovations: frame attention and selective attention. The frame attention mechanism, inspired by gated fusion techniques, encourages the model to focus on the most relevant video frames, particularly central frames where subtitles typically appear. This is implemented through a frame attention loss. The selective attention component dynamically determines when to leverage visual information for translation, especially useful for handling ambiguous text. To further enhance the model's ability to handle ambiguity, SAFA incorporates an ambiguity-aware loss, encouraging heavier reliance on video information for ambiguous text while prioritizing textual cues for non-ambiguous cases.

4.4 Unsupervised Methods

(Li et al., 2023a) uses videos to serve as a "universal pivot" to bridge language pairs without parallel corpora, with spatial-temporal graphs providing fine-grained visual grounding for both close and distant language pairs. Video pivoting in MMT leverages visual content from videos as an intermediary to align source and target languages in unsupervised settings. This approach addresses the challenge of latent space alignment between languages by exploiting the shared visual-semantic information in videos, which provide richer spatial-temporal context than static images. The core mechanism involves multimodal back-translation combined with pseudo-visual pivoting, where models learn a shared multilingual embedding space.

Table 1 presents a comparison between all existing approaches.

5 Video Encoders

Recent advances in video encoding architectures have significantly expanded the toolkit for video understanding in VMT tasks moving beyond traditional 3D CNNs and ResNet-based approaches to specialized transformer architectures and cross-modal alignment strategies. Transformer-based models like VideoSwin Transformer (Liu et al., 2021) introduced locality-constrained spatiotemporal attention through shifted window mechanisms which reduced computational costs by 20× compared to 3D CNNs through hierarchical feature processing. Concurrently, ViViT (Arnab et al., 2021) demonstrated pure-transformer efficacy by factorizing spatial-temporal tokens and leveraging image-pretrained weights through temporal adaptation of vision transformers. Contrastive learning frameworks such as CLIP4Clip (Luo et al., 2021) adapted image-text pretrained CLIP models for video retrieval via parameter-free similarity calculation and temporal alignment modules and jointly optimized video-text embeddings. This paradigm was extended by VideoCLIP(Xu et al., 2021), which incorporated hard negative mining during contrastive pretraining to boost zero-shot performance on video QA and aslo enabled temporal localization without task-specific fine-tuning. Emerging foundational encoders like VideoPrism (Zhao et al., 2024) unified global-local video understanding through hybrid contrastive and masked autoencoding pretraining. For multimodal integration, VideoGPT+ (Maaz et al., 2024b) introduced dual spatial-temporal pathways combining ViT-L/14 image encoders with TimeSformer (Bertasius et al., 2021) video models via adaptive pooling gates. The MERV (Chung et al., 2025) framework advanced specialized knowledge fusion by spatiotemporally aligning features from DINOv2 (Oquab et al., 2024), ViViT (Arnab et al., 2021)(temporal), and SigLIP (Zhai et al., 2023) encoders through cross-attentive mixing, boosting VideoLLM performances. These architectures collectively address VMT's core requirements - balancing spatial-temporal resolution, cross-modal alignment, and computational efficiency - while providing adaptable frameworks for integrating domain-specific visual knowledge into translation pipelines.

6 Datasets

Table 2 presents all the datasets used in Video-guided machine Translation.

Vatex datset introduced in (Wang et al., 2019) is one of the most widely used benchmarks for video-guided multimodal machine translation. It

consists of multilingual video descriptions and is designed to facilitate research in video captioning and translation. The dataset contains over 41,000 videos collected from the MSR-VTT (Xu et al., 2016) dataset, with each video annotated with 10 English descriptions and their corresponding translations in Mandarin Chinese. The videos cover a diverse range of topics, including sports, music, and everyday activities, making it a robust resource for training and evaluating multimodal MT models.

EVA (Li et al., 2023b)is a large-scale resource focused on subtitle ambiguity. It contains 852,000 Japanese-English and 520,000 Chinese-English parallel subtitle pairs, each aligned with corresponding video clips sourced from movies and TV episodes. EVA also features a specially curated evaluation set where subtitle ambiguity is guaranteed and the accompanying video is necessary for disambiguation, directly addressing a major limitation of prior MMT datasets.

How2 (Sanabria et al., 2018) was one of the first datasets addressing multimodal language understanding. It contains 79,114 instructional videos along with English subtitles and aligned Portuguese subtitles. All the clips contain the summary of the event occurring in the clip.

VISA (Li et al., 2022b) contains clips from movies and TV along with parallel subtitles in English and Japanese. All subtitles are ambiguous and fall into either the "Polysemy" or "Ambiguous" category. Hence, any translation task involving these subtitles must rely on the corresponding video clip for context.

BigVideo (Kang et al., 2023) is a large-scale dataset specifically focusing on video subtitle translation. It contains 4.5 million English-Chinese sentence pairs aligned with 156,000 unique videos, totaling 9,981 hours of content. It is currently the largest video-guided machine translation dataset available. BigVideo contains two specially annotated test sets: Ambiguous and Unambiguous. The Ambiguous set contains source inputs that require video context for accurate translation, while the Unambiguous set includes self-contained text suitable for translation without visual cues.

The **MAD-VMT** (Shurtz et al., 2024) (Movie Audio Descriptions for Video-guided Machine Translation) dataset is derived from the MAD dataset, which contains transcribed audio descriptions of movies typically used for visually impaired audiences. To create MAD-VMT, the English transcriptions from MAD were machine-translated into Chinese using Google Translate. This approach was adopted to increase the amount and lexical diversity of both source and target language pretraining data for video-guided machine translation tasks.

TopicVD (Lv et al., 2025) is a topic-based dataset designed for VMT of documentaries, addressing the lack of large-scale, diverse video data in long-form videos. It consists of 256 documentaries spanning eight topics - Economy, Food, History, Figure, Military, Nature, Social, and Technology-comprising 285 hours of video and 122,930 Chinese-English parallel subtitle pairs, with contextual information for each video-subtitle pair. The dataset enables research on domain adaptation as experiments show that visual and contextual information significantly enhance translation performance, especially in in-domain scenarios.

Trifine (Guan et al., 2025) is a comprehensive tri modal dataset designed for vision-audio-subtitle analysis and translation tasks. It features a parallel corpus of English-Chinese subtitles, complemented by fine-grained audio labels such as audio sentiment and stress, as well as video labels including location, entities, expressions, and actions.

7 Previous Surveys

(Shen et al., 2024) explores Multimodal Machine Translation in detail covering various aspects like Image-guided MT, In-Image MT, Video-guided MT and Chat Multimodal MT. It explores image-guided MT in utmost detail, underlining its modelling approaches and datasets in detail. It also touches upon various works which analyze the extent of the importance of images in improving the translations. However, the (Shen et al., 2024) doesn't explore the intricacies of video-guided MT by going into the depth of modeling and taxonomy of VMT. Similarly, (Paul et al., 2024) surveys MMT papers related to Indian Languages with Image-guided MT in focus.

8 Challenges and Future Directions

This section discusses about various challenges in VMT and also points towards possible future research directions

8.1 Challenges

Information Redundancy and Computational Overhead According to (Guan et al., 2025),

Dataset	Language	Clips	Secs	Sen	Domain	Genre	AM	FT	S	A-S Alignment	TB
How2	En-Pt	186K	5.8	186K	Instruction	Short Video	×	×	✓	✓	×
VATEX	En-Zh	41K	10	129K	Captions	Short Video	×	×	✓	×	×
VISA	En-Ja	40K	10	40K	Subtitle	Film and Television	✓	×	×	×	×
EVA	En-Zh/Ja	1.4M	10	1.4M	Subtitle	Film and Television	✓	×	×	×	×
BigVideo	En-Zh	3.3M	8	4.5M	Subtitle	Short Video	✓	×	×	×	×
MAD-VMT	En-Zh	193K	-	193K	Caption	Movies	×	×	×	×	×
Trifine	En-Zh	2.4M	10	2.4M	Subtitle	Short Video	✓	✓	✓	✓	×
TopicVD	En-Zh	122K	8.4	122K	Subtitle	Documentary	×	×	×	✓	✓

Table 2: Overview of Video Based Machine Translation Datasets. "Secs" denote the duration of each clip. "Sen" denote the number of sentences in the dataset. "AM" denote the availability of ambiguity-aware dataset. "FT" denotes the availability of fine-grained tags of the dataset. "S" denotes the availability of Audio. "A-S" alignment indicates whether the Audio-Video are aligned. "TB" denotes topic based segragation of the dataset.

VMT requires selecting multiple frames to extract coarse-grained visual features. However, not all frames contribute equally to translation quality, leading to increased computational overhead. The inclusion of redundant frames can also introduce regularization issues, impacting model performance.

Audio Integration in VMT While VMT primarily relies on visual cues for translation, incorporating audio is crucial. Audio provides essential contextual information, such as speaker intent, tone, and background sounds, which significantly enhance translation accuracy. However, effectively fusing audio with video representations remains a challenge. (Guan et al., 2025) has only introduced a trimodal dataset with audio and fine grained tags.

Data Scarcity in Low-Resource Languages VMT models require triplet data—video, source text, and target text—for training. However, such datasets are scarce, particularly for low-resource languages and underrepresented language families. This data bottleneck limits the scalability and generalization of VMT models. Table 2 shows that most video-guided MT datasets consist of English and Chinese data with no representation from other language families.

8.2 Future Directions

Integrating World Knowledge using Video LLMs Enhancing VMT with external world knowledge, such as named entities (famous personalities, cultural references) and idiomatic expressions, could improve translation accuracy. Techniques like knowledge graph integration or retrieval-augmented generation could be explored. Pretrained large-scale multimodal models, trained on extensive text-image corpora, could be fine-tuned for VMT. Video LLMs like (Maaz et al., 2024b), (Cheng et al., 2024) and (Maaz et al., 2024a) inherently capture rich cross-modal representations and have instruction following ability making them valuable for video-guided translation tasks which may involve reasoning.

High-Quality Multilingual and Domain-Specific Datasets Developing large-scale, high-quality datasets across multiple language families and diverse domains is essential for improving VMT. This would address current data scarcity challenges and enhance translation performance in various contexts. Only (Lv et al., 2025) currently has domain specific segregation of data in English and Chinese.

Real-Time Translation with Low Latency Achieving real-time video-guided translation with minimal latency is a key goal. Optimizations such as efficient frame selection, lightweight transformer architectures, and parallelized inference pipelines could be explored to enable low-latency, high-accuracy translations. Recently (Chen et al., 2024) attempted to cruch stream video using Video LLMs. However, they lose out on better representation for spatial and temporal features.

9 Conclusion

In this paper, we provide a comprehensive overview of video-guided machine translation (VMT). We begin by discussing the background and evolution of multimodal machine translation (MMT) to VMT. Next, we present a taxonomy of various VMT approaches based on their model design. We then review the datasets commonly used for VMT research. Finally, we discuss the key challenges in VMT and explore potential future directions for advancing this task.

Limitations

Since video-guided machine translation is an emerging field, any survey on this topic must be

continuously updated to reflect new research developments. As new datasets, models, and approaches are introduced, the landscape of VMT evolves rapidly, making it challenging to maintain a comprehensive and up-to-date overview.

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