Improving Sign Language Understanding with a Multi-Stream Masked Autoencoder Trained on ASL Videos

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Abstract

Understanding sign language remains a significant challenge, particularly for low-resource sign languages with limited annotated data. Motivated by the success of large-scale pretraining in deep learning, we propose Multi-Stream Masked Autoencoder (MS-MAE) — a simple yet effective framework for learning sign language representations from skeleton-based video data. Our approach begins with pretraining MS-MAE on the large-scale YouTube-ASL dataset, using a masked reconstruction objective to model sign sequences. The pretrained model is then adapted to multiple downstream tasks across different sign languages. Experimental results show that, after finetuning, MS-MAE achieves competitive or superior performance on a range of isolated sign language recognition benchmarks, including WLASL, ASL Citizen, Slovo, and the JSL Corpus. Furthermore, it demonstrates strong performance on sign language translation tasks, achieving results comparable to state-of-the-art methods on PHOENIX14T, CSL-Daily, and How2Sign. These findings highlight the potential of leveraging large-scale, high-resource sign language data to boost performance in low-resource sign language scenarios.

1 Introduction

Sign languages, which rely on hand movements, facial expressions, and body gestures to convey meaning, serve as a primary mean of communication within deaf communities. However, a significant communication gap persists between deaf and hearing populations. In response, research on sign language understanding, including Sign Language Recognition (SLR) (Li et al., 2020; Desai et al., 2023; Kapitanov et al., 2023) and Sign Language Translation (SLT) (Camgöz et al., 2018; Zhou et al., 2021a; Duarte et al., 2021), has garnered increasing attention, especially in the era of deep learning. Despite these advances, the development of sign language understanding systems is still hindered by the scarcity of large-scale, publicly available SL datasets.

To overcome this challenge, recent efforts have turned to the vast amount of sign language video content available online, particularly on YouTube. For instance, Youtube-ASL (YT-ASL) (Uthus et al., 2023) consists of 984 hours of annotated American Sign Language (ASL) videos. Meanwhile, YouTube-SL-25 (Tanzer and Zhang, 2024) expands the scope, collecting 3,207-hour videos spanning 25 different sign languages. These datasets have significantly accelerated progress in sign language understanding by enabling large-scale supervised pretraining strategies. The resulting pretrained models have proven effective in enhancing downstream tasks such as SLR and SLT.

Despite the significant contributions of YouTube-SL-25 toward the goal of "no language left behind" in sign language research, annotated resources for sign languages remain limited compared to those available for spoken language machine translation. Expanding annotated sign language datasets continues to be a major challenge. A more scalable way is to leverage unannotated data, as argued by (Rust et al., 2024). However, many sign languages still lack sufficient video resources for pretraining. This raises an important research question: Can knowledge learned from videos of known sign languages be transferred to unseen, low-resource sign languages? Addressing this question is crucial for making progress in adapting models to underrepresented sign languages. This study explores whether large-scale sign language video datasets from high-resource languages can be leveraged for effective representation learning and video encoder pretraining, with the goal of enhancing performance on downstream tasks in unseen sign languages.

Specifically, we introduce Multi-Stream Masked AutoEncoder (MS-MAE) designed to learn a strong sign language video encoder for sign language

videos. MS-MAE begins by extracting three distinct pose streams, including body, left hand, and right hand, and encoding each as a separate token sequence. These sequences are then concatenated into a single unified stream and passed through a transformer (Vaswani et al., 2017) encoder. During self-supervised pretraining, MS-MAE randomly masks a subset of tokens in each stream and tasks the model with reconstructing the masked portions. In our experiments, we first pretrain the video encoder only with videos from the YT-ASL dataset, and then test on two downstream tasks:

- Isolated SLR (ISLR), evaluated on ASL, Japanese Sign Language (JSL) and Russian Sign Language (RSL).
- SLT, evaluated on ASL, Chinese Sign Language (CSL) and German Sign Language (DGS).

Our contributions are as follows: (1) We propose a simple yet effective and efficient Multi-Stream Masked Autoencoder (MS-MAE) framework for training a sign language video encoder using large-scale, unlabeled sign language videos. (2) Through experiments, we demonstrate that finetuning our model pretrained exclusively on ASL videos achieves competitive performance compared to SOTA methods across multiple sign languages. Notably, freezing the encoder can still deliver strong results. (3) We further analyze our approach and find that pretraining on facial streams doesn't consistently improve the downstream performance. Besides, continual pretraining on the target training set is less effective with our framework.

2 Related Work

2.1 Transfer Learning of Supervised Pretraining

Data scarcity is a primary challenge in sign language processing, making transfer learning essential for enhancing both SLR and SLT performance. Several previous works employ either 2D CNNs (Camgöz et al., 2020) pretrained on image classification tasks or 3D CNNs (Sarhan and Frintrop, 2020; Chen et al., 2022a) pretrained on action recognition tasks, such as S3D (Xie et al., 2018) and I3D (Carreira and Zisserman, 2017), as backbone feature extractors. While these approaches have demonstrated effectiveness, their performance is constrained by a domain shift between action recognition and sign language understanding. This gap arises from differences in task granularity, with sign language understanding requiring finer temporal and spatial understanding, thereby limiting further performance gains.

Another line of research involves in-domain transfer, or cross-lingual transfer learning, where models trained on high-resource sign languages are finetuned to adapt to low-resource sign languages, yielding significant performance improvements, including (Bird et al., 2020; Holmes et al., 2023). However, annotated sign language data are difficult to obtain and hard to scale up, highlighting the need for approaches that can leverage unannotated data.

2.2 Self-supervised Learning in Sign Language Understanding

Self-supervised learning, which leverages large-scale unlabeled data, has achieved remarkable success in various fields. In the domain of sign language, several works have adopted masked prediction strategies, such as BEST (Zhao et al., 2023) and SHuBERT (Gueuwou et al., 2024). Others follow a masked reconstruction paradigm. Among these, SignBERT (Zhou et al., 2021b) and SignBERT+ (Hu et al., 2023) employ BERT (Devlin et al., 2019)-like encoder-only architectures. Meanwhile, approaches like MASA (Zhao et al., 2024), SSVP-SLT (Rust et al., 2024), and SignRep (Wong et al., 2025) adopt MAE (He et al., 2022)-like asymmetric encoder-decoder architectures. Specifically, MASA performs masked reconstruction on skeleton-based input. SSVP-SLT targets RGB input, which is computationally intensive and demands substantial resources—its longest pretraining run reportedly takes two weeks on 64 A100 GPUs. To address these challenges, the recent work SignRep introduces an approach that takes RGB inputs but reconstructs pose sequences. This design significantly reduces computational costs during pretraining and removes the need for skeleton estimation tools at inference time.

However, RGB videos remain computationally intensive to process, especially in the context of sign language, which is inherently information-dense. Additionally, transformer-based architectures further amplify this challenge. As a result, finetuning the entire model for some downstream tasks, particularly in SLT, becomes impractical, limiting potential performance gains. Moreover, RGB-based MAEs typically tokenize videos into

fixed-size patches. This patch-based tokenization can fragment critical visual cues across multiple tokens, potentially leading to low-efficiency learning.

In contrast, our pretraining framework operates on skeletal data in order to focus on the interaction among visual cues for efficient representation learning. Unlike MASA, which aggregates all visual cues within each frame as a single input unit, our pretraining framework leverages skeletal data by explicitly decoupling visual cues and passing them through a transformer concurrently, which is close to the strategy of SignBERT.

3 Method: Multi-Stream Masked AutoEncoder

An overview of MS-MAE is illustrated in Figure 1. We begin by extracting skeleton sequences from sign language videos and dividing them into separate streams corresponding to the left hand, right hand, and upper body. Each stream is then encoded into a sequence of tokens. Our framework adopts an MAE-like asymmetric encoder-decoder architecture for pretraining. Specifically, we randomly drop several time steps within each stream, and the unmasked tokens are fed into a transformer encoder. The encoder outputs are then padded with learnable mask tokens and passed to the decoder. The pretraining objective is to reconstruct the original skeleton sequences.

3.1 Multi-Stream Transformer

Our encoder architecture consists of an embedding layer followed by a standard transformer encoder. We utilize MediaPipe Holistic (Lugaresi et al., 2019) to extract skeletal data from sign language videos. Each pose sequence consists of three distinct streams—left hand, right hand, and upper body—denoted as $\mathcal{P} = \{(P_t^{\text{LH}}, P_t^{RH}, P_t^{B})\}_{t=1}^{n}$, where n is the total number of frames and each $P_t^p \in \mathbb{R}^{|K_p| \times D}$ contains the D-dimensional keypoints of part $p \in \{\text{LH}, \text{RH}, \text{B}\}$. In this work, we only use x- and y-coordinates of the keypoints, so $D = 2$. The term $|K_p|$ is the number of keypoints for each body part.

We flatten and project each stream frame-wise:

$$\begin{aligned} \boldsymbol{x}_k^{\text{B}} &= \text{Linear}_B(\text{flatten}(P_t^B)) \\ \boldsymbol{x}_k^{\text{LH}} &= \text{Linear}_H(\text{flatten}(P_t^{LH})), \\ \boldsymbol{x}_k^{\text{RH}} &= \text{Linear}_H(\text{flatten}(P_t^{RH})) \end{aligned} \tag{1}$$

where $t = 1, \cdots, n$.

Inspired by video transformers (Arnab et al., 2021; Tong et al., 2022) that leverage cubelet embeddings to encode spatio-temporal cubes, which can reduce computational cost through mitigating the redundancy of neighboring frames, we adopt the same strategy to reduce sequence length. Specifically, we use 1D convolutions with kernel size = stride = S to encode streams separately to ensure non-overlapping encoding:

$$\begin{aligned} \hat{\boldsymbol{x}}^B &= \text{Conv1D}_{\text{B}}(\boldsymbol{x}^{\text{B}}) \in \mathbb{R}^{(n/S) \times C} \\ \hat{\boldsymbol{x}}^{LH} &= \text{Conv1D}_{\text{H}}(\boldsymbol{x}^{\text{LH}}) \in \mathbb{R}^{(n/S) \times C} \\ \hat{\boldsymbol{x}}^{RH} &= \text{Conv1D}_{\text{H}}(\boldsymbol{x}^{\text{RH}}) \in \mathbb{R}^{(n/S) \times C} \end{aligned} \tag{2}$$

. Each stream is added to the same positional encoding, denoted as PE, so that the part token at the same time step can be correctly identified, and concatenated along the time channel into a single sequence as inputs to the transformer:

$$\begin{aligned} \text{Emb}^p &= \hat{\boldsymbol{x}}^p + \text{PE}[: n/S] \in \mathbb{R}^{(n/S) \times C} \\ \text{Emb} &= [\text{Emb}^{\text{B}}; \text{Emb}^{\text{LH}}; \text{Emb}^{\text{RH}}] \in \mathbb{R}^{(3n/S) \times C} \end{aligned} \tag{3}$$

, and feed Emb into a standard transformer encoder $\mathbf{Z} = \text{Transformer}(\text{Emb})$.

By keeping streams separate up through the patch embedding, self-attention can explicitly model both intra-stream dynamics (e.g. left-hand over time) and cross-stream dependencies (e.g. right-hand vs. body), and during pretraining, we may apply masking to individual streams rather than entire frames for more granular learning.

3.2 Pretrain

In the pretraining stage, we employ an asymmetric encoder–decoder MAE architecture tailored to our multi-stream setting. Let $\mathcal{P} = \{P_t^p\}_{p \in \{\text{B,LH,RH}\},\, t=1}^{n}$ denote the set of input pose sequences. We apply a $\text{PatchEmbed}(\cdot)$ function to each stream, producing cubelet tokens, which are augmented with positional encodings $\text{Emb}^p \in \mathbb{R}^{(n/S) \times C}$. A random fraction r of tokens in each stream is masked; we denote the sets of visible and masked indices as V_p and M_p, respectively.

1. **Encoding.** All unmasked token embeddings $\{\text{Emb}_i^p : i \in V_p,\ p \in \{B, \text{LH}, \text{RH}\}\}$ are passed through a transformer encoder to yield contextual representations $\mathbf{Z}_V \in \mathbb{R}^{\sum_p |V_p| \times C}$.

2. **Decoding.** For each masked index, we prepend a learnable mask token, concatenate

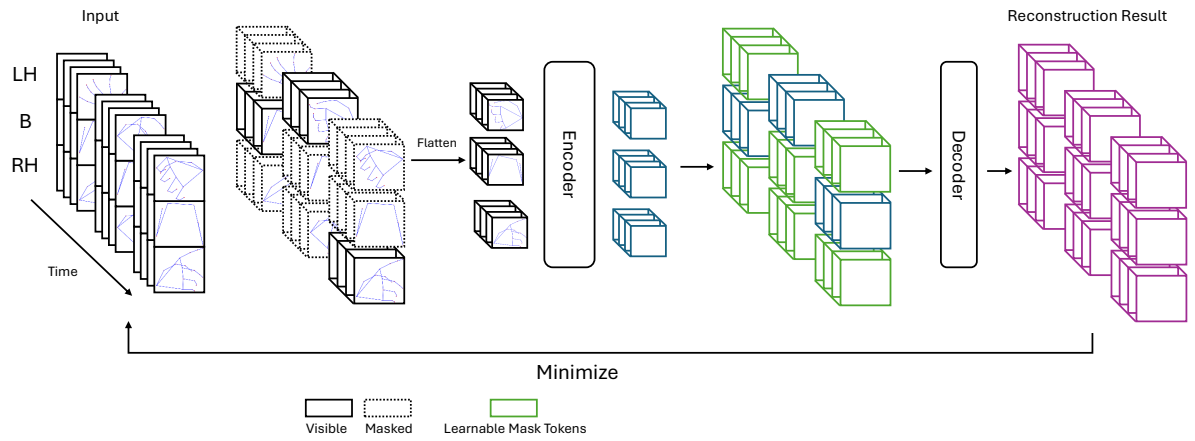

Figure 1: An overview of MS-MAE. Sign language videos are first converted into skeletal data using MediaPipe Holistic, and separated into left-hand, body, and right-hand streams. Each stream is divided into a sequence of spatiotemporal cubes. During pretraining, a portion of the tokens is masked, while the unmasked tokens are flattened and passed through an encoder to produce latent representations. These encoder outputs are concatenated with learnable mask tokens and fed into a decoder, which is trained to reconstruct the original input sequences.

the resulting embeddings with $\mathbf{Z}_V$ to form $\mathbf{Z} \in \mathbb{R}^{n \times C}$, and pass $\mathbf{Z}$ through a lightweight decoder. The decoder reconstructs outputs $\hat{\boldsymbol{t}}_i^p$ for all $i \in M_p$.

3. **Reconstruction target & loss.** For each masked token index k, the target is the original sequence of keypoints within the corresponding cubelet $\mathbf{t}_k^p = \left[P_{kS}^p,\ P_{kS+1}^p, \ldots, P_{kS+S-1}^p\right] \in \mathbb{R}^{S \times (D\,|K_p|)}$.

   We minimize the mean squared error $\mathcal{L} = \frac{1}{\sum_p |M_p|} \sum_p \sum_{k \in M_p} \left\| \hat{\boldsymbol{t}}_k^p - \text{flatten}(\mathbf{t}_k^p) \right\|_2^2$.

This architecture encourages the encoder to learn the dependencies among different visual cues at different time steps. When computing the loss, we ignore any missing keypoints in $\mathbf{t}_k^p$ due to MediaPipe failures, to avoid the model being misled by noisy and absent detections.

4 Experiment

4.1 Pretraining

We pretrain our model using the YT-ASL dataset, which contains ASL videos collected from YouTube. Subtitle information is not utilized, and sentence boundary information is assumed to be unavailable. We randomly sample 300 frames from a sequence of 600 consecutive frames (sampled at a rate of 2 frames per unit) during each pretraining step. We explore two masking strategies: full masking and random masking. In full masking, the same time steps are masked across all input streams, denoted as SameMask. In contrast, random masking applies different masked time steps to each stream while maintaining an equal number of masked tokens across streams, denoted as DiffMask.

Hyperparameters The encoder follows a Transformer architecture with $L = 8$, $H = 8$, and a hidden dimension of 512. The decoder uses a smaller Transformer encoder with $L = 4$, $H = 8$, and a hidden dimension of 512. We employ the AdamW optimizer (Loshchilov and Hutter, 2019) with a maximum learning rate of 8×10^{-4} and betas $(0.9, 0.95)$. A learning rate scheduler with warmup and cosine decay is used, with 2K warmup steps. The maximum number of optimization steps is set to 120K. We mask 50% of tokens for each stream in our experiments.

4.2 Isolated Sign Language Recognition

Dataset We evaluate effectiveness through ISLR, a classification task that predicts a single gloss from a video clip. Our experiment includes four ISLR datasets: WLASL (Li et al., 2020), ASL Citizen (Desai et al., 2023), Slovo (Kapitanov et al., 2023), and the JSL Corpus (Bono et al., 2014). WLASL, a widely used and challenging ISLR dataset for ASL, serves as the in-domain benchmark. ASL Citizen provides an additional large-scale ASL dataset for evaluation. To assess cross-lingual generalization, we include Slovo and the JSL Corpus, which represent RSL and JSL, respectively. Since the JSL Corpus is not originally de-

Table 1: Statistics of the used ISLR datasets.

Dataset	WLASL	ASL Citizen	Slovo	JSL Corpus
Gloss	2,000	2,731	1,001	696
Train	14,289	40,154	15,300	32,282
Valid	3,916	10,304	5,100	4,306
Test	2,878	32,941		4,676

signed for ISLR, we extract word-level annotations and exclude non-lexicalized signs, such as classifier constructions, non-manual markers, and mislabeled instances that do not correspond to valid lexical signs. Dataset statistics are summarized in Table 1.

Finetuning During finetuning, we prepend a learnable [CLS] token to the input pose sequences. The video features are obtained from the contextual embedding of the [CLS] token. We attach a classifier head to the [CLS] token's contextual embedding and optimize it using cross-entropy loss.

Hyperparameters We set the batch size to 128 and sample 32 frames per video as input. We use AdamW optimizer with a weight decay of 10^{-3}. A cosine learning rate scheduler is used with a 10-epoch linear warm-up and a peak learning rate of 5×10^{-5}. Training is conducted for 100 epochs. During training, we apply temporal augmentation by randomly sampling frames from each video. We also augment the pose data by randomly rotating, shearing, and scaling, as suggested by SignCLIP (Jiang et al., 2024), on all datasets except the JSL Corpus.

Comparison We compare our method with ST-GCN (Yan et al., 2018). We reproduce the result via the implementation from ST-GCN++ (Duan et al., 2022). We report top-k recall, where a prediction is considered correct if the target label appears among the top-k results. We evaluate performance with $k = 1, 5$. For WLASL, ASL Citizen and JSL Corpus, we choose the checkpoint with the best validation performance to evaluate on the test sets. For Slovo, which has no test set, we report the performance of the checkpoint with the best top-5 validation recall on the validation set.

4.2.1 Experiment Result

The experimental results are summarized in Table 2. Our model, pretrained on the large-scale YT-ASL dataset, consistently outperforms the pose-based ST-GCN baseline across all four benchmarks. Notably, on WLASL, our approach surpasses other masked reconstruction methods, including SignBERT and MASA. We attribute these improvements to two primary factors. First, pretraining on YT-ASL allows us to leverage a significantly larger and more diverse collection of sign language videos than those available in the public ISLR datasets used by SignBERT and MASA. Second, the separation of each modality stream enables more flexible and effective masking strategies. As shown in Table 2, the DiffMask outperforms SameMask, suggesting that applying different temporal masks to each stream during pretraining contributes to a more robust sign language video encoder.

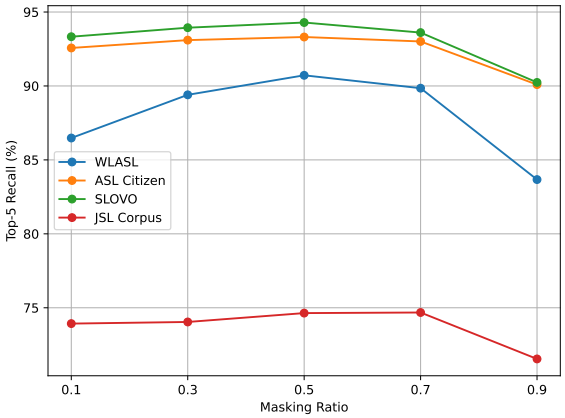

Figure 2: The correlations between top-5 recall and the masking ratio are similar across all ISLR datasets. The best performance is achieved by the masking ratio of 50%. The second best masking ratio is 30% or 70%, depending on the dataset.

Effect of Masking Ratio The correlation between the performance and the masking ratio is shown in Figure 2. We can observe that the trends are similar across all datasets. The masking ratio of 0.5 yields the best overall performance, while ratios of 0.3 or 0.7 achieve the second-best results, depending on the dataset. An extremely high ratio, 0.9, leads to performance degradation.

4.2.2 Frozen Video Encoder

To further evaluate the pretrained encoder, we conducted experiments by freezing the pretrained video encoder. Specifically, we freeze the pretrained model, apply average pooling to its contextual embeddings, and project the resulting features using a simple trainable linear layer. We utilized the checkpoint with a masking ratio of 0.5 for this experiment. Table 3 summarizes the results.

On the WLASL dataset, our learned representations outperform the baseline model. However, on other datasets, the performance declines. In SLOVO, the performance is slightly below the baseline, while in the ASL Citizen and JSL Corpus datasets, there is a drop of 10 points or more com-

Table 2: ISLR results across four benchmarks. * denotes the ST-GCN implementation reproduced from previous work, while the other ST-GCN result is from our own implementation. MR denotes Masking Ratio. Our method outperforms previous pose-based self-supervised learning approaches.

Method	WLASL		ASL Citizen		Slovo		JSL Corpus	
	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
ST-GCN* (Yan et al., 2018)	34.40	66.57	63.10	86.09				
ST-GCN (Yan et al., 2018)	41.70	74.36	70.67	90.72	64.94	87.71	46.17	70.87
SignBERT (Zhou et al., 2021b)	47.46	83.32						
MASA (Zhao et al., 2024)	49.06	82.90						
Ours (DiffMask, MR=0.5)	56.95	90.72	75.72	93.31	74.98	94.29	52.40	74.64
Ours (SameMask, MR=0.5)	52.05	87.21	71.87	91.23	72.24	94.14	51.26	72.43

pared to the baseline in top-1 recall. These findings indicate that the learned video encoder is effective without further finetuning.

Table 3: Result of freezing the pretrained model with a masking ratio of 50%. The results show that the pretrained model is effective even without further finetuning, although in most cases, the performance lags behind the baseline model.

Dataset	Method	Split	Rec@1	Rec@5
WLASL	ST-GCN++	test	41.70	74.36
WLASL	probe	test	42.88	74.77
ASL Citizen	ST-GCN++	test	70.67	90.72
ASL Citizen	probe	test	54.54	79.45
SLOVO	ST-GCN++	valid	64.94	87.71
SLOVO	probe	valid	60.12	85.61
JSL Corpus	ST-GCN++	test	46.17	70.87
JSL Corpus	probe	test	37.68	62.19

4.3 Sign Language Translation

We evaluate our approach on three SLT benchmarks: Phoenix14T (P14T) (Camgöz et al., 2018), CSL-Daily (Zhou et al., 2021a), and How2Sign (H2S) (Duarte et al., 2021), representing DGS, CSL and ASL, respectively. Dataset statistics are summarized in Table 6. In our experiment, we don't use gloss information. We integrate our pretrained sign language video encoder with the mBART translation model (Liu et al., 2020)[1] translation model. We fully finetune the mBART encoder while adapting the decoder using Low-Rank Adaptation (LoRA) (Hu et al., 2022) to avoid overfitting, with hyperparameters $\alpha = 32$ and $r = 32$. Training objective is cross-entropy loss. We employ the AdamW optimizer with a weight decay of 10^{-3}, and apply a cosine learning rate schedule with a 10-epoch warmup. We train for up to 100 epochs with a batch size of 32, applying gradient clipping to stabilize optimization. During training, 20% of video frames are randomly deleted or copied as temporal augmentation. We experiment with both freezing and finetuning the pretrained video encoder. Learning rates and gradient clipping norms vary depending on the dataset and encoder setting, which are shown in Table 5.

We report BLEU scores (Papineni et al., 2002) and ROUGE (Lin, 2004) metrics to evaluate translation quality. Specifically, we compute BLEU-1 and BLEU-4 using SacreBLEU (Post, 2018)[2], and report the ROUGE-L F1 score[3].

We compare our model against recent gloss-free approaches. For the P14T and CSL-Daily datasets, we evaluate performance relative to Sign2GPT (Wong et al., 2024), VAP (Jiao et al., 2024), C^2RL (Chen et al., 2024), and Sign-LLMs (Gong et al., 2024), which are language-supervised pretraining methods. For the How2Sign dataset, we compare our results with SSVP-SLT, an MAE-based method on RGB modality, and T5 models pretrained on YT-ASL with subtitle supervision (Uthus et al., 2023).

We explore two input strategies: (1) Flat concatenation: Tokens from all three input streams are concatenated into a single sequence and passed to mBART. (2) Per-time-step averaging: At each time step, embeddings from the three streams are averaged to produce a single fused embedding per time step. The resulting sequence is input to mBART.

4.3.1 Experimental Results

Results for P14T and CSL-Daily are shown in Table 4, and results for How2Sign are shown in Table 7. On CSL-Daily, our method outperforms

[1]https://huggingface.co/facebook/mbart-large-50-many-to-many-mmt

[2]For Chinese, we use the 'zh' tokenizer; for English and German, we use the '13a' tokenizer

[3]We adopted the ROUGE implementation from the official codebase of TwoStreamSLT (Chen et al., 2022b)

Table 4: Experimental results on P14T and CSL-Daily. Following the observation in (Jiao et al., 2024), the mBART tokenizer exhibits an inconsistent punctuation bug, particularly affecting evaluations in Chinese due to the use of full-width punctuation marks. To ensure a fair comparison, we report the results after correcting the bug, with the uncorrected results shown in parentheses.

		P14T			CSL-Daily		
Method	Modality	B1	B4	R	B1	B4	R
Sign2GPT (Wong et al., 2024)	RGB	45.43	19.42	45.23	34.80	12.96	41.12
Sign2GPT(Pseudo-Gloss Pretraining) (Wong et al., 2024)	RGB	49.54	22.52	48.90	41.75	15.40	42.36
VAP (Jiao et al., 2024)	Skeleton	53.07	26.16	51.28	52.98 (49.99)	23.65 (20.85)	51.09 (48.56)
SignLLMs (Gong et al., 2024)	RGB	45.21	23.40	44.49	39.55	15.75	39.91
C^2RL (Chen et al., 2024)	RGB	52.81	26.75	50.96	49.32	21.61	48.21
Ours (Flat Concatenation)	Skeleton	43.79	19.96	41.52	51.30 (48.31)	21.79 (19.15)	48.81 (46.31)
Ours (Flat Concatenation, Frozen Video Encoder)	Skeleton	39.26	17.92	37.91	47.30 (44.43)	19.80 (17.37)	45.37 (43.07)
Ours (Per-time-step averaging)	Skeleton	40.48	17.45	38.31	51.01 (47.98)	21.48 (18.94)	48.81 (46.29)

Table 5: Learning rates and gradient clipping norms for each dataset and encoder status.

	P14T & CSL-Daily		H2S	
Video Encoder Status	Frozen	Unfrozen	Frozen	Unfrozen
Learning Rate	1×10^{-3}	1×10^{-4}	3×10^{-4}	5×10^{-5}
Gradient Clipping	0.1		1.0	

Table 6: Statistics of the SLT datasets used in our experiments. For the H2S dataset, we use the manually re-aligned version provided on their homepage and exclude a very small subset of samples due to invalid time ranges.

Dataset	P14T	CSL-Daily	H2S
# Train	7,096	18,401	31,086
# Valid	519	1,077	1,738
# Test	642	1,176	2,349

Sign2GPT using only skeleton data. On How2Sign, it matches the performance of SSVP-SLT that has no Language Supervised Pretraining (LSP), while being more lightweight and computationally efficient. Compared to T5 with supervised pretraining on YT-ASL, our model achieves comparable performance without relying on subtitle data.

While the performance on P14T is weaker, we attribute this to the dataset's low video resolution and motion blur, which leads to inaccurate keypoint estimation. The pose quality gap between finetuning and pretraining stages may hurt the performance. This highlights a key limitation of skeleton-based pretraining: its reliance on high-quality pose data. The skeleton quality between pretraining and finetuning should be aligned.

While our encoder does not surpass all prior methods, it demonstrates the effectiveness of our method. It shows that the video encoder pretrained on only ASL videos can be generalized to other SLs. Additionally, our results show that flat concatenation of stream features outperforms per-time-step averaging, proving the effectiveness of separating the skeleton into multiple streams. Our following experiments will use the flat concatenation strategy as the default setup.

4.4 Analysis

4.4.1 Facial Information

Facial information plays a critical role in sign language understanding (Mukushev et al., 2020; Chaudhary et al., 2024). Facial expressions often serve grammatical purposes, while mouthing can help disambiguate signs that share similar manual gestures. However, it remains unknown whether facial information in ASL can also benefit understanding in other sign languages.

To investigate the impact of facial information, we experiment with different configurations for incorporating facial keypoints during pretraining and finetuning. The results are presented in Table 8. When facial keypoints are used only during finetuning, we observe slight performance gains on P14T and H2S, but a notable degradation on CSL-Daily. Moreover, incorporating facial keypoints during both pretraining and finetuning leads to slight improvements on P14T and a significant boost on H2S, compared to incorporating facial information in merely the finetuning stage. However, on CSL-Daily, the performance remains similar to that without facial information.

We think two key factors may influence the transferability of facial information. First is the varying importance of facial cues across benchmarks.

Table 7: Experiment results on How2Sign. SSVP-SLT-LSP means the method with language supervision pretraining.

Method	Modality	B1	B4	R
T5 (scratch) (Uthus et al., 2023)	Skeleton	14.96	1.22	
T5 (YT-ASL→ H2S) (Uthus et al., 2023)	Skeleton	37.82	12.39	
SSVP-SLT-LSP (PT + FT: YT-ASL + H2S) (Rust et al., 2024)	RGB	43.2	15.5	38.4
SSVP-SLT(PT: YT-ASL, FT:H2S) (Rust et al., 2024)	RGB	38.1	11.7	33.8
VAP (Jiao et al., 2024)	Skeleton	39.22	12.87	27.77
C^2RL (Chen et al., 2024)	RGB	29.07	9.37	27.02
Ours (Flat Concatenation)	Skeleton	33.14	10.84	27.99
Ours (Flat Concatenation, Frozen Video Encoder)	Skeleton	31.03	9.05	25.16
Ours (Per-time-step averaging)	Skeleton	31.57	9.92	26.78

Table 8: Results of varying stream setups during the pretraining and finetuning stages, denoted as PT and FT in the header. B, H, and F represent body, hands, and face, respectively. The best performance for each dataset is highlighted in bold.

Dataset	PT	FT	B1	B4	R
P14T	B,H	B,H	43.79	19.96	41.52
	B,H	B,H,F	44.56	21.12	42.59
	B,H,F	B,H,F	**45.98**	**21.66**	**43.76**
CSL-Daily	B,H	B,H	**51.30**	**21.79**	**48.81**
	B,H	B,H,F	48.69	19.88	45.52
	B,H,F	B,H,F	50.15	21.23	48.17
H2S	B,H	B,H	33.14	10.84	27.99
	B,H	B,H,F	38.56	12.67	28.72
	B,H,F	B,H,F	**42.47**	**15.40**	**35.43**

Table 9: Results of models further pretrained on the videos in the training set.

Dataset	Pretraining Schedule	Frozen	B1	B4	R
P14T	YT-ASL	✓	39.26	17.92	37.91
	YT-ASL→ P14T	✓	43.28	20.72	42.20
	YT-ASL		43.79	19.96	41.52
	YT-ASL→ P14T		44.73	20.84	42.96
CSL-Daily	YT-ASL	✓	47.30	19.80	45.37
	YT-ASL→ CSL-Daily	✓	48.44	19.88	46.72
	YT-ASL		51.30	21.79	48.81
	YT-ASL→ CSL-Daily		50.78	21.29	48.42
H2S	YT-ASL	✓	31.03	9.05	25.16
	YT-ASL→ H2S	✓	34.89	9.91	23.96
	YT-ASL		33.14	10.84	27.99
	YT-ASL→ H2S		36.32	11.92	28.07

Some datasets rely more heavily on facial features than others. Second is the diversity in face patterns across different sign languages, which limits cross-lingual transferability. For instance, while certain facial expressions may be shared across sign languages, mouthing patterns are often language-specific and thus less transferable. Further investigation of the exact reason is left for future work.

4.4.2 Continual Pretraining with videos in training set

We further perform continual pretraining using the training set of each target dataset, with results shown in Table 9. We observe that continual pretraining leads to performance improvements when the video encoder is frozen during finetuning. However, when the entire model is fully finetuned, the performance gains become less pronounced.

5 Conclusion

In this paper, we investigate using ASL videos to enhance the performance in other SLs. We propose a simple yet effective and efficient pretraining framework, MS-MAE, which concatenates the sequence from multiple skeleton streams along the temporal dimension. This architecture enables a flexible masking strategy that each stream may be masked at different time steps, allowing the model to learn richer spatiotemporal dependencies among different visual cues. The experimental results show that pretraining solely on ASL videos from scratch can enhance the performance in both ISLR and SLT tasks on different languages. In ISLR tasks, it achieves much better performance than other approaches pretrained only on the training set. On SLT benchmarks, it achieves a comparable performance with SOTA gloss-free RGB-based methods through fully finetuning, demonstrating the effectiveness of our pretraining strategy. Additionally, we conduct extensive ablation studies. Our results show that incorporating facial expression data during pretraining does not consistently improve performance. Moreover, continual pretraining on the training set yields better results under a frozen setting, while fully finetuned models show similar performance regardless of continual pretraining.

Limitations

In our proposed pretraining framework, separating visual cues results in significantly longer input

sequences, which increases the complexity of the transformer due to the quadratic nature of the self-attention mechanism. Although we have not yet conducted specific experiments to validate this, we hypothesize that without sufficient data, training such a framework effectively would be difficult. Besides, as mentioned in Section 4, the pose quality gap between pretraining and finetuning may lead to performance degradation, which is the inherent issue of skeleton-based methods. One future direction is to improve the robustness to noisy keypoints. Additionally, although skeletal modalities can substantially reduce computational demands during both pretraining and finetuning, they require extra preprocessing time to extract pose data.

Regarding our experiments, we acknowledge that the evaluation did not encompass a sufficiently diverse range of sign language categories, primarily due to the limited availability of datasets and computational resources. As a result, we were unable to thoroughly investigate the factors that contribute to improved cross-lingual transferability, and thus could not provide concrete guidelines for future work. Additionally, existing benchmarks are built under varying conditions, making it difficult to isolate the specific factors that influence model performance. For example, we did not control for confounding variables such as video quality, dataset scale, and dataset difficulty, which may have limited the strength and generalizability of our conclusions. In our future work, we will conduct more comprehensive experiments on other datasets.

Acknowledgments

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A Keypoints

In our experiments, we use MediaPipe Holistic for pose estimation and extract the following keypoints:

1. **Hands:** All 21 keypoints of each hand (indices 0–20).

2. **Body:** Upper-body keypoints with indices $\{11, 12, 13, 14, 15, 16\}$.

3. **Face:** Includes keypoints from the contour, mouth, nose, and eyes:

   Contour `234, 93, 132, 58, 172, 136, 150, 149, 176, 148, 152, 377, 400, 378, 379, 365, 397, 288, 361, 323`

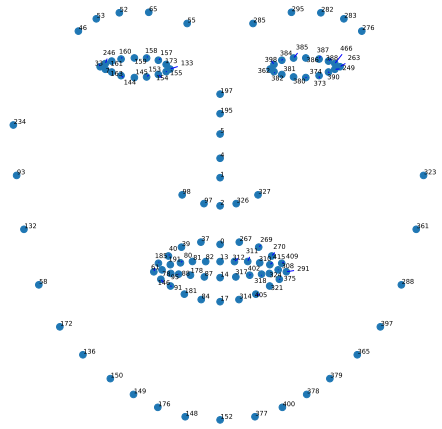

Figure 3: Face keypoints used in our experiments

Mouth `0, 267, 269, 270, 409, 291, 375, 321, 405, 314, 17, 84, 181, 91, 146, 61, 185, 40, 39, 37, 13, 312, 311, 310, 415, 308, 324, 318, 402, 317, 14, 87, 178, 88, 95, 78, 191, 80, 81, 82`

Nose `98, 97, 2, 326, 327, 1, 4, 5, 195, 197`

Eyes `46, 53, 52, 65, 55, 285, 295, 282, 283, 276, 33, 246, 161, 160, 159, 158, 157, 173, 133, 155, 154, 153, 145, 144, 163, 7, 362, 398, 384, 385, 386, 387, 388, 466, 263, 249, 390, 373, 374, 380, 381, 382`

An example showing face keypoints is shown in Figure 3.

B Computational Resource Usage

We conducted pretraining on 8 nodes, each equipped with an NVIDIA GH200 GPU, for approximately 14 hours. To ensure convergence, we used a total of 120,000 training steps. Our in-house experiments show that the checkpoint at 60% of training steps achieved performance comparable to the final checkpoint.

C Use of AI Assistance

In this research, we primarily used GitHub Copilot for coding and debugging, and ChatGPT for refining the writing of this paper.