Sign Language Video Segmentation Using Temporal Boundary Identification

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Abstract

Sign language segmentation focuses on identifying temporal boundaries within sign language videos. As compared to previous segmentation techniques that have depended on frame-level and phrase-level segmentation, our study emphasizes on subtitle-level segmentation, using synchronized subtitle data to facilitate temporal boundary recognition. Based on Beginning-Inside-Outside (BIO) tagging for subtitle unit delineation, we train a sequence-to-sequence (Seq2Seq) model with and without attention for subtitle boundary identification. Training on optical flow data and aligned subtitles from BOBSL and YouTube-ASL, we show that the Seq2Seq model with attention outperforms baseline models, achieving improved percentage of segments, F1 and IoU score. An additional contribution is the development of an method for subtitle temporal resolution, aiming to facilitate manual annotation.

1 Introduction

Sign languages are the primary means of communication among both hard-of-hearing and deaf individuals globally. Sign languages are gestural natural languages incorporating facial expressions, body movements and hand gestures to communicate and express meaning (Sandler et al., 2008).

A persistent challenge in Sign Language (SL) research is the demanding and time-consuming nature of creating high-quality annotations for visual-spatial communication (Dreuw and Ney, 2008). This limitation hinders the development and evaluation of robust SL recognition and segmentation systems. Automating these processes offers a significant advantage by reducing or eliminating the effort needed for manual annotation.

Sign languages rely on complex spatial and temporal grammatical structures. A key challenge in SL segmentation is precise temporal localization, accurately identifying when linguistic components occur. Consecutive sentences can be signed with minimal pauses, making boundary detection difficult. Therefore, a model that can precisely identify transitions is essential.

Previous SL recognition studies focused on sign or word-level segmentation, isolating individual signs from pre-segmented clips (Chaaban et al., 2021; Renz et al., 2021a). However, continuous SL integrates sentences and phrases, making word-level methods insufficient for capturing full linguistic context. Segmenting into subtitle-like units is crucial for capturing complete linguistic context necessary for translation and interpretation.

Focusing on subtitle-level segmentation, we investigate the effectiveness of sequence-to-sequence (Seq2Seq) models with and without attention mechanisms for automated boundary detection, using optical flow features to integrate motion information, which has demonstrated efficacy in shallow models and action recognition tasks. Following state-of-the-art research (Moryossef et al., 2023), we use BIO (B=beginning, I=inside, O=outside) rather than IO tagging used in previous work to capture the smooth transitions between signs and phrases. The model is based on an a Seq2Seq encoder-decoder model with an attention mechanism, employing a bidirectional LSTM (BiLSTM) in the encoder, which analyzes the frame features in both forward and backward directions, enabling the model to capture both past and future context. Moreover, integrating an attention mechanism enables the model to focus on the most pertinent segments of the input sequence at each phase.

We evaluate our model on the BOBSL (Albanie et al., 2021) and YouTube-ASL (Uthus et al., 2023) datasets, demonstrating the effectiveness of our approach for subtitle-level SL segmentation. Our results show that the Seq2Seq model with attention outperforms baseline models, achieving improved percentage of segments, F1 and IoU scores. Furthermore, we find that the integration of BIO

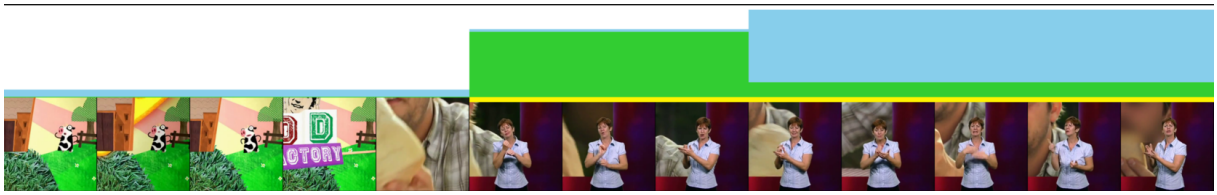

Figure 1: An illustration of BIO tagging on a subtitle from the BOBSL test set: 'If you've ever baked your own bread, you probably prefer this to the supermarket bread.' The model effectively detects subtitle boundaries and segments with BIO tags. Here the B tag (green) represents the start of the subtitle, the I tag (light blue) for continuation, and the O tag (white) for outside of the subtitle segment, based on the probability for each segment.

tagging is crucial for modeling sign boundaries, and that the Seq2Seq encoder-decoder architecture with attention mechanisms significantly enhances segmentation quality.

As part of our research, we present a method for subtitle temporal resolution, able to generate .srt files from model predictions including time-stamped segmentation. The suggested tool aims to facilitate the annotation of SL datasets.

2 Related work

In this section we are focusing on previous work seeking to determine boundaries between separate signs or linguistic parts. Farag and Brock (2019) address word boundary detection in Japanese Sign Language (JSL) by employing a binary random forest classifier on 3D joint positions. This frame-by-frame approach, evaluated on JSL and human activity datasets, achieves an F1 score of 0.89, effectively distinguishing between motion transitions and genuine gestures.

Renz et al. (2021a) explore automatic sign segmentation through two primary approaches. Initially, they propose a frame-level binary labeling method using I3D (Carreira and Zisserman, 2017) and MS-TCN (Farha and Gall, 2019), trained to minimize over-segmentation and reduce annotation costs. Building upon this, they introduce Changepoint-Modulated Pseudo Labelling for source-free domain adaptation, leveraging pseudo-labelling (Lee et al., 2013) to reduce model uncertainty in unlabelled data Renz et al. (2021b).

Bull et al. (2020b) explore SL segmentation through spatio-temporal modeling and transformer-based approaches. Initially, they propose a method to automatically identify temporal boundaries using an ST-GCN (Yan et al., 2018) combined with a BiLSTM, trained on 2D skeleton data from French SL (LSF) videos (Bull et al., 2020a). Subsequently, Bull et al. (2021) introduce a system that uses Transformers to simultaneously segment SL videos and align them with subtitles, employing BERT (Devlin et al., 2019) for subtitle encoding and CNNs for video representation.

Moryossef et al. (2023) address the limitations of binary frame classification in SL segmentation by integrating linguistic cues and adopting a Beginning-Inside-Outside (BIO) tagging scheme (Ramshaw and Marcus, 1995), inspired by Named Entity Recognition, to better define segment boundaries. Their task is to perform segmentation of signs and phrases, for which they also utilize optical flow and 3D hand normalization. Evaluated on the DGS Corpus (Hanke et al., 2020), their model demonstrates improved cross-lingual generalization. Contrary to this work, that focuses on phrase-level segmentation, our work focuses on sentence-level and subtitle-level segmentation. We find this granularity (a) more appropriate for capturing complete meaning units, accounting for long-distance reording and other linguistic phenomena that require long context (b) better fit to real-world use-cases (e.g. captioning) and NLP tasks (parallel corpus creation, machine translation).

3 Methods

3.1 Sequence-to-sequence modelling

Our proposed approach for subtitle-level SL segmentation follows these methods:

Optical Flow We use the RAFT method (Teed and Deng, 2020) to estimate optical flow calculating pixel displacement between frames of a certain distance (in our case, 10 frames apart). This captures the detailed motion patterns which is provided as features to the Seq2Seq model for the boundary detection.

BIO Tagging BIO tagging (B=beginning, I=inside, O=outside), inspired from NER is used to define and label segment boundaries (similar

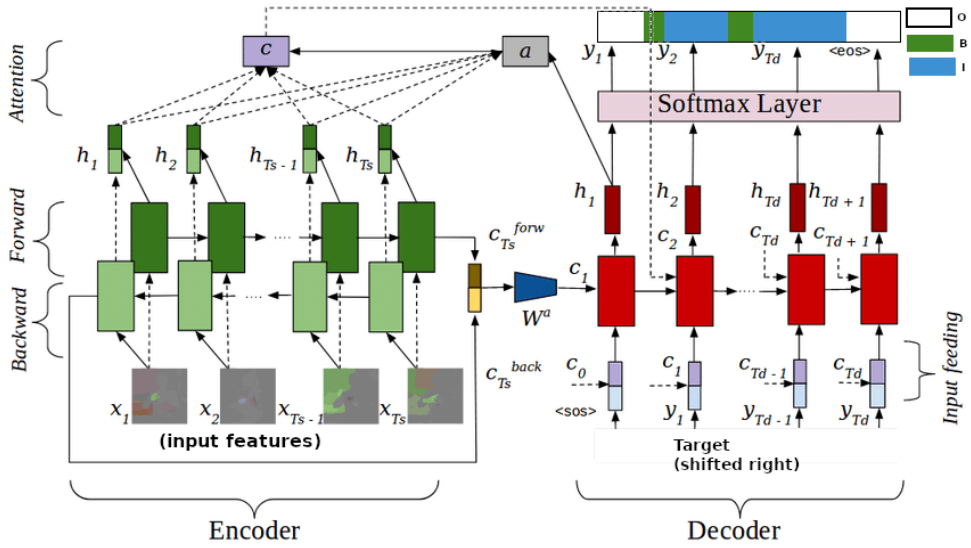

Figure 2: Seq2Seq Encoder-Decoder with Attention mechanism (Source: Chowdhury and Vig, 2018)

to Moryossef et al., 2023; Ramshaw and Marcus, 1995). The sentence boundary labels serve as target labels on the output of the Seq2Seq model.

Sequence Encoder and Autoregressive Encoder We adopt two encoder architectures to analyze feature sequences and capture temporal dependencies. A BiLSTM (Hochreiter and Schmidhuber, 1997) is employed to integrate preceding and subsequent context, capturing long-range dependencies. This serves as a baseline model. We integrate an autoregressive mechanism (Jiang et al., 2023; Moryossef et al., 2023), using two stacked encoders with sequential logit input for temporal coherence.

Seq2Seq Encoder-Decoder without attention utilizes a BiLSTM encoder and an LSTM decoder. The encoder analyzes the input sequence, producing context vectors (final hidden and cell states) that are transmitted to the decoder. The decoder subsequently produces output tokens derived from the preceding output and the encoder's final hidden state. However, this architecture depends on a static context vector, which may restrict its capacity to capture long-range dependencies.

Seq2Seq Encoder-Decoder with attention A primary constraint of conventional Seq2Seq encoder-decoder systems is their difficulty in effectively handling long input sequences. This is due to the model's dependence on a single context vector of a predetermined length to store and transmit the information from the input sequence to the decoder. For long input sequences, the fixed-size context vector may have difficulty preserving all the required details, particularly those related to long-range dependencies, leading to a decline in output quality. To overcome this constraint, the attention mechanism (Bahdanau, 2014) is incorporated into Seq2Seq models, specifically designed for RNN-based architectures (Figure 2).

3.2 Subtitle Temporal Resolution

For subtitle file generation, where accurately identifying subtitle categories is crucial, we employ sequence prediction methods. We find that beam search decoding with a beam width of 4 produces more precise and accurate model predictions compared to greedy search, after evaluating both methodologies. This process generates temporal interval tokens, indicating subtitle categories: no subtitle(O), start of subtitle(B), or continuation of subtitle(I).

1. The process starts by inputting a start token into the model, hence commencing the prediction sequence.

2. At each time step, we retain a collection of the leading sequences with the highest cumulative probability scores, limited to a certain beam width. In our experiments, we evaluated the beam widths 3, 4, 5 and 6, and determined that the beam width of 4 yielded optimal results for our purpose.

3. For every candidate sequence in the beam, the model predicts potential subsequent tokens, producing a probability value for each. The

cumulative score of each sequence is updated, indicating the probability of that sequence.

4. Among all expanded sequences, the highest-scoring sequences (up to the beam width) are retained, while the others are eliminated.

5. The search continues until the end-of-sequence (EOS) token is reached.

6. Upon reaching the end of the sequence, the optimal sequence is determined by the highest cumulative probability.

Algorithm 1 is a post-processing algorithm that maps model predictions obtained earlier to frame boundaries, which can subsequently be converted into subtitle timing generation. The detailed steps are provided in the Appendix A.1.

Input: $all\_predictions$, $all\_softmax\_outputs$, $sequence\_frames$
Output: $combined\_preds$: List of predictions with frame boundaries
Initialize $combined\_preds \leftarrow []$;
$current\_frame \leftarrow 0$;
foreach $(preds\_chunk, softmax\_chunk)$ *in* $(all\_predictions, all\_softmax\_outputs)$ **do**
  Initialize $probabilities \leftarrow []$;
  foreach $(pred, soft)$ *in* $(preds\_chunk, softmax\_chunk)$ **do**
    $probability \leftarrow soft[pred]$;
    Append $probability$ to $probabilities$;
  end
  $total\_prob \leftarrow$ sum$(probabilities)$;
  $frame\_lengths \leftarrow \left[\frac{d}{total\_prob} \cdot sequence\_frames \; \forall \; d \in probabilities\right]$;
  foreach $(pred, length)$ *in* $(preds\_chunk, frame\_lengths)$ **do**
    Append $(current\_frame, current\_frame + length, pred)$ to $combined\_preds$;
    $current\_frame \leftarrow current\_frame + length$;
  end
end
return $combined\_preds$;

Algorithm 1: Probabilities to Subtitle boundaries

3.3 Evaluation Metrics

F1 Score We compute the macro-averaged per-class F1 score at the segment level, using argmax to determine segment labels. This is our primary metric for validation, early stopping, and model selection.

Percentage of Segments (%) Following (Moryossef et al., 2023), we assess segment alignment accuracy by calculating the ratio of predicted segments to ground truth segments (1), with 100% indicating perfect alignment.

$$\%\text{ of Segments} \left(\frac{\text{Predicted Segments}}{\text{Ground Truth Segments}} \right) \times 100\% \quad (1)$$

Intersection over Union (IOU) IoU, as described in (Moryossef et al., 2023), measures segment overlap (2), indicating the model's ability to capture precise segment boundaries. A score of 1 signifies perfect overlap.

$$\text{IoU} = \frac{\text{Area of Intersection}}{\text{Area of Union}} \quad (2)$$

Efficiency We evaluate the efficiency of each model based on parameter count and training time (55 epochs) using V100 and RTXA6000 GPU.

4 Experimental Setup

4.1 Dataset

For our research, we employ the BOBSL and YouTube-ASL datasets. BOBSL comprises British Sign Language (BSL) interpreted footage from various BBC broadcasts, paired with English subtitles (Albanie et al., 2021), while the YouTube-ASL dataset provides a comprehensive collection of American Sign Language (ASL) videos with corresponding annotations (Uthus et al., 2023).

We use the manually-aligned subset of the BOBSL dataset, consisting of 60 videos, as other subsets exhibit inconsistencies. The videos, with a frame rate of 25 fps, are pre-divided into training (40 videos), validation (10 videos), and test (10 videos) sets. Most videos are either 30 or 60 minutes long, with an average duration of 45 minutes. This dataset features diverse genres, including comedy, drama, and entertainment, captures co-articulated signs, and offers a natural signing style. For the YouTube-ASL dataset, we use 70% of the dataset for training, 20% for validation, and 10% for testing. The videos in this dataset vary in duration, ranging from 40 seconds to 40 minutes, providing a diverse collection of lengths that supports effective model training and evaluation.

For our segmentation task, we preprocess video frames by resizing, normalizing, and grouping them into 375-feature segments based on annotations. This segmentation enables the model to learn temporal context and transitions, essential for accurate results.

4.2 Experiments

Our experiments are organized into 4 stages: feature extraction, baseline temporal modeling, and two variations of Seq2Seq encoder-decoder architectures. We first establish a robust feature representation using ResNet-101, then explore temporal modeling with BiLSTM and autoregressive encoders, and finally evaluate the to segmentation accuracy of Seq2Seq models with and without attention. Code and datasets (to the extent permitted by the licenses) will be available open source upon acceptance.

Feature Extraction Given the different nature of motion data compared to RGB, training 2DCNNs from scratch is often preferred. However, due to our limited data relative to ImageNet, we employ transfer learning with a ResNet-101 model pretrained on ImageNet (motivated by Yosinski et al. (2014)) for feature extraction.

As our objective is exclusively feature extraction rather than classification, we remove the final fully connected layer from the ResNet-101 model. An Adaptive Average Pooling layer is set to produce a constant spatial dimension in the network output. This setting guarantees the model's output will be a compact feature vector, irrespective of the input image dimensions. This layer generates a feature vector with the shape (2048,). Employing Adaptive Average Pooling enables preserving the high-level features of the ResNet model, while normalizing the output dimensions to a vector format. The input dimensions for each image are (224, 224, 3), where 224x224 denotes the spatial dimensions and 3 indicates the number of channels for RGB images.

For BOBSL we use their pre-computed optical flow features as input, which have been processed through a ResNet model to extract relevant features. For the Youtube-SL we use RAFT (Teed and Deng, 2020) to estimate optical flow, calculating pixel displacement between frames 10 frames apart.

Sequence Encoder and Autoregressive Encoder For temporal modeling, 2048-dimensional feature vectors are fed into a BiLSTM encoder. Each batch has 375 feature vectors, where each vector represents the features extracted from a single frame of the video segment. The sequence length is determined after testing multiple different values to achieve an appropriate balance between collecting temporal patterns and guaranteeing efficient processing. The BiLSTM predicts BIO labels for each frame, classifying them as B, I or O of the subtitle, effectively segmenting the video into SL segments.

Similarly, an autoregressive encoder processes the 375 feature vectors, incorporating logits from the current time step as input to the next, enhancing temporal coherence in the BIO label predictions.

Seq2Seq Encoder-Decoder without attention In the Seq2Seq model without attention, the input consists of 2048-dimensional features from ResNet-101, with a sequence length of 375 frames. To optimize efficiency, sequences are sorted by length, avoiding padding tokens. The BiLSTM encoder processes these sequence, generating a context vector that summarizes the input. The LSTM decoder then uses this context vector to predict segments corresponding to "B" (beginning), "I" (inside), or "O" (outside) within the SL sequence.

Seq2Seq Encoder-Decoder with attention Here a BiLSTM encoder (2 layers, 128 hidden units, dropout 0.2) to encode 375x2048 input sequences from ResNet-101. The decoder (2 LSTM layers, 128 hidden units, dropout 0.1) uses an attention mechanism to compute a weighted sum of the encoder outputs, forming a context vector (256 dimensions) at each decoding step. This context vector, combined with the previous output embedding (128 dimensions), is used to generate logits via a fully connected layer. A softmax operation is used to normalize these logits into a probability distribution over the output segments.

4.3 Model Training

4.3.1 Training Details

We train the BiLSTM and autoregressive encoders using the Adam optimizer with a learning rate of 1e-4 and a batch size of 16. Gradient clipping with a clip value of 1 is applied to overcome the exploding gradient. We use theReduceLROnPlateau, and an early stopping with patience=10 using both validation loss and the F1 score.

We train Seq2Seq encoder-decoder models, both with and without attention mechanisms, for segmenting SL into subtitle units. Preliminary tests using cross-entropy loss resulted in overfitting, adopting the transition to Negative Log-Likelihood Loss (NLLLoss) for improved management of class imbalance. Our preliminary hyperparameter search involves testing a range of LSTM layers (2, 4, 6, 8), fully connected layers (1, 2), hidden sizes (128, 256, 512, 1024), dropout rates (0, 0.1, 0.2, 0.3), optimizers (SGD, Adam), learning rates (1e-3, 1e-4,

1e-5), and batch sizes (9, 12, 16), we conclude hidden size 128, 4 LSTM layers, 1 FC layer, encoder dropout 0.2, and decoder dropout 0.1, optimal to both YouTube-ASL and BOBSL datasets.

4.4 Training Time

To optimize training efficiency, we employ a two-stage process: pre-extracting ResNet-101 features from optical flow images and storing them for direct loading during training, thus reducing computational overhead. The Seq2Seq Encoder-Decoder without attention trains in 14-16 hours, whereas the attention-based model requires around one day. Training on the BOBSL dataset is faster due to its limited size, whereas the extensive YouTube-ASL dataset requires longer training times to achieve adequate convergence.

4.5 Teacher Forcing and Scheduled Sampling

Teacher Forcing, where the decoder receives actual target outputs during training, can result in over-dependence on ground truth labels and instability during inference. To mitigate this, we employ Scheduled Sampling. This method randomly alternates between using actual labels (teacher forcing) and model predictions as decoder inputs during training, enabling the model to adapt to prediction errors.

5 Results

In this section, we present the results of our experiments, focusing on answering some key research questions.

What are the performance differences between Sequence Encoder and Autoregressive Encoder models in segmentation tasks?

On the BOBSL dataset, the Sequence Encoder achieves an F1 score of 0.58 and IoU of 0.60, with a segment percentage of 250%, 1.38 million parameters, and a 14-hour training time. On YouTube-ASL, it achieves an F1 of 0.56 and IoU of 0.58, with a segment percentage of 70%, 1.18 million parameters, and a 15-hour training time. The Autoregressive Encoder, on BOBSL, achieves an F1 of 0.55 and IoU of 0.51, with a segment percentage of 174%, 1.42 million parameters, and a one-day training time. On YouTube-ASL, it achieves an F1 of 0.47 and IoU of 0.50, with a segment percentage of 55%, 1.26 million parameters, and a one-day training time. Notably, the BOBSL dataset results in over-segmentation for both models, while the YouTube-ASL dataset results in under-segmentation. To address these challenges, we move to a subtitle-level prediction strategy using Seq2Seq models. Due to differences in datasets and the specific nature of our subtitle segmentation task, a direct comparison with previous work is not feasible.

How can the Seq2Seq Encoder-Decoder model with and without attention improve subtitle generation for SL in longer, multi-sentence videos?

We evaluate the ability of Seq2Seq models, with and without attention, to improve subtitle generation for SL videos. Using F1 Score, IoU, and segment percentage on the BOBSL dataset, we compare model performance. The datasets' video lengths allow us to analyze each model's capacity to handle continuous SL sequences, focusing on performance differences and strengths.

For the BOBSL dataset as shown in Table 2, the Seq2Seq Encoder-Decoder without attention demonstrates moderate segmentation accuracy with an F1 score of 0.58 and reasonable overlap recognition with an IoU of 0.70, but exhibits significant over-segmentation, with a segment percentage of 216%. In contrast, the Seq2Seq model with attention attains an F1 Score of 0.60, signifying moderate precision in identifying and segmenting relevant SL sequences. This is supported by an IoU of 0.74, highlighting the model's ability to identify overlapping regions between predicted and ground-truth segments. The model attains best segment percentage of 103%. The addition of attention increases the model's parameters to 7.8 million and training time to about 2 days, from 3.1 million parameters and 15 hours for the model without attention.

On the YouTube-ASL dataset as in Table 3, the Seq2Seq model without attention achieves an F1 score of 0.55 and an IoU of 0.58, indicating poor segmentation and overlap recognition. The model demonstrates under-segmentation, identifying only 87% of the segments. It has 3.1 million parameters and trains in 19 hours, suggesting optimization is needed. However, he Seq2Seq model with attention demonstrates a balanced performance with an F1 score of 0.60 and moderate overlap recognition (IoU: 0.62). The model identifies 95% of segments, indicating slight under-segmentation.

The observed performance differences between the datasets can be attributed to their distinct structural characteristics. For example, the BOBSL dataset consists of full sentences, where inter-

Model	Dataset	F1	IOU	%	# Params	Time
Sequence Encoder	BOBSL	0.58	0.60	2.50	1.38M	∼ 14h
	YouTube-ASL	0.56	0.58	0.70	1.18M	∼ 15h
Autoregressive Encoder	BOBSL	0.55	0.51	1.74	1.42M	∼ 1d
	YouTube-ASL	0.47	0.50	0.55	1.26M	∼ 1d

Table 1: Test evaluation metrics for our BOBSL and YouTube-ASL dataset using Sequence Encoder and Autoregressive Encoder model. A Comparative Analysis of F1, IOU and % of segments across Sequence Encoder and Autoregressive Encoder.

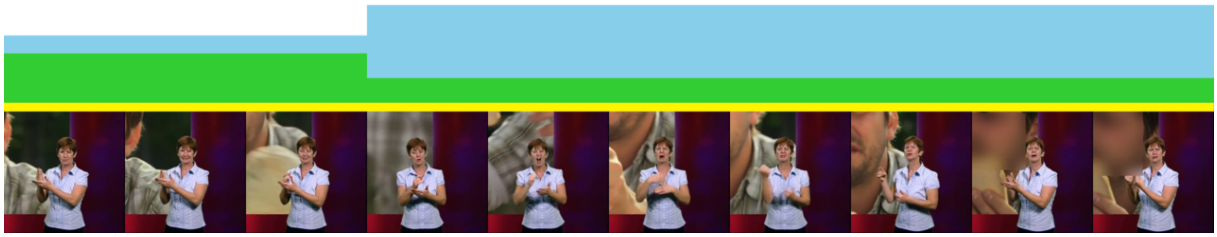

Figure 3: Continuation of the sequence from Figure 1, where the model correctly labels the new subtitle with the "beginning" and "inside" tags as it moves smoothly between subtitles without pausing.

Model	F1	IOU	%	# Params	Time
Seq2Seq Encoder-Decoder w/o attention	0.58	0.70	2.16	3.1M	∼ 15h
Seq2Seq Encoder-Decoder w/ attention	**0.60**	**0.74**	**1.03**	7.8M	∼ 2d

Table 2: Test evaluation metrics for our BOBSL dataset using the proposed Seq2Seq Encoder-Decoder model with and without attention. A Comparative Analysis of F1, IOU and % of segments across two models.

Model	F1	IOU	%	# Params	Time
Seq2Seq Encoder-Decoder w/o attention	0.55	0.58	0.87	3.1M	∼ 19h
Seq2Seq Encoder-Decoder w/ attention	**0.60**	**0.62**	**0.95**	3.0M	∼ 2d

Table 3: Test evaluation metrics for our YouTube-ASL dataset using the proposed Seq2Seq Encoder-Decoder model with and without attention. A Comparative Analysis of F1, IOU and % of segments across two models.

preters typically make clear pauses between them, aiding the model's segmentation task. In contrast, the YouTube-ASL dataset contains subtitles that may span across multiple sentences or include two sentences within a single subtitle, which may cause greater challenges for segmentation. This difference in structure could explain the model's superior performance on the BOBSL dataset, and it may be assumed that this structural difference affects the segmentation task on the YouTube-ASL dataset.

How does the subtitle temporal resolution affect the quality of generated .srt files for sign language?

To assess the quality of generated .srt files, we manually evaluate the model's accuracy in capturing subtitle timing and segmentation, as shown in Table 4. This table compares the original and model-generated subtitle start and end times. This case study illustrates the model's overall performance on the BOBSL dataset, revealing its strengths and limitations in boundary detection, segmentation accuracy, and alignment with natural speech flow. The model demonstrates promising capabilities, achieving closer boundaries in specific segments, though perfect matches remain challenging.

The model effectively delineates subtitle boundaries in segments like [Subtitle 8, 9, 13, 14], closely aligning generated timings with actual subtitles. For example, Subtitle [8] and [9] correctly separate paused segments, while [13] and [14] accurately capture continuous signing. This demonstrates the model's ability to perceive subtle subtitle transitions beyond simple pauses. However, achieving exact timing matches is difficult due to our segment-level analysis, resulting in minor discrepancies. Furthermore, the model introduces temporal discrepancies in other segments, notably subtitles that

succeed [10] and those before [13], leading to artificial interruptions and fragmented subtitles. This inconsistency in segmentation accuracy highlights the challenge of achieving frame-level precision without frame-level segmentation, and disrupting the natural flow.

To what extent can the segmentation tool accurately recognize and delineate significant subtitle boundaries within continuous SL sequences? To illustrate model performance, we present comparative case studies. In Figure 1, the model accurately segments the BOBSL dataset video, correctly identifying subtitle boundaries. It accurately predicts non-signing periods (white), the start of subtitle segments (green "B" tag), and the continuation of segments (light blue "I" tag). This demonstrates the model's ability to label the beginning and continuation of signing subtitles without false boundaries. Similarly, in Figure 3, the model effectively detects transitions between subtitles, even without pauses, using high probability scores for "B" and "I" tags. This highlights the model's ability to identify boundaries based on natural signing structure rather than just pauses.

Despite general efficiency, the model occasionally misidentifies subtitle boundaries, failing to consistently distinguish signing from non-signing activity. In Figure 4, the model incorrectly assigns a high probability to the "I" label, indicating signing when there is none. This error may stem from feature ambiguity, where subtle motion in non-signing segments, such as raising and removing a hat, is misconstrued as signing. Additionally, an imbalance in training data may bias the model towards the "I" label, particularly with minimal or unintentional movements. In Figure 5, the model oversegments, failing to recognize transitions between distinct signing periods, further highlighting the difficulty in distinguishing between signing and non-signing behaviors.

6 Conclusion

SL segmentation presents unique challenges due to its temporal and spatial complexity, including subtle transitions and variability across users. This study addresses subtitle-level SL segmentation using Seq2Seq models. A key contribution is an automated system for generating .srt subtitle files with accurate temporal boundaries. We adapt and improve the Encoder-Decoder model with attention specifically for subtitle-level segmentation. Utilizing optical flow and ResNet features, our model enhances temporal alignment and transition management. Our focus on subtitle boundaries distinguishes our approach from frame-level studies. Our Seq2Seq models achieve strong F1, IoU, and segmentation accuracy, emphasizing the importance of temporal boundary identification and attention mechanisms in subtitle-level SL segmentation.

Limitations

Our proposed approach, while effective, has several limitations. We haven't directly compared to the phrase-based SoTA but this is due to limitations of the available annotated datasets, and we are strong on our opinion that subtitle-level segmentation is the ideal one. Its evaluation is restricted to BOBSL and YouTube-ASL datasets with English subtitles, potentially limiting its generalizability to the broader linguistic diversity of global sign languages. Furthermore, the model's primary reliance on optical flow makes it susceptible to noisy or inadequate motion data, such as during occlusions or subtle movements. Achieving a perfect one-to-one mapping between predicted and actual subtitle timing also remains a challenge. Finally, the study's reliance on manually labeled subtitle boundaries introduces potential noise and imprecision due to the inherent difficulty in their exact delineation. Future research should explore incorporating diverse input features like OpenPose, applying the model to synchronize subtitles with continuous signing, and testing on more varied sign language datasets to enhance generalizability.

Ethical considerations

In our work, we present experiments on the British Sign Language and American Sign Language which should be seen and respected as the primary languages of the respective language communities. Although we perform this research aiming to provide equal access to language technology for sign language users, the fact that the majority of the researchers in NLP are hearing people entails the risk of developments that are not in accordance with the will of the respective communities, and therefore it is required that every research step takes them in constant consideration. In order to mitigate this, in our broader research we have included members of the Deaf/deaf and hard of hearing communities as part of the research team, consultants and participants in user studies and workshops and we have

been in co-operation with related unions and communication centers. It should also be noted, that our experiments are part of a broader series of research projects, and the results presented here should by no means considered ready for production and be used as final products without the agreement of the communities. The use of the dataset follows their respective licenses and limitations and every follow-up work should adhere to those.

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A Appendix

A.1 Algorithm to Map Probabilities to Subtitle Boundaries

1. **Model Predictions:** Collect raw predictions and their corresponding confidence scores (softmax probabilities) for each segment.

2. **Normalize Probabilities:** Compute the proportion of each prediction by dividing its probability by the total probability of all predictions in the sequence.

$$\text{Normalized Probability}_i = \frac{\text{Probability}_i}{\text{Total Probability}}$$

3. **Frame Allocation:** Assign frames to each segment using the normalized probability and the total number of frames in the sequence.

$$\text{Frames}_i = \text{Normalized Probability}_i \times \text{Sequence Frames}$$

4. **Frame Mapping:** Calculate the start and end frame for each segment iteratively.

$$\text{End Frame}_i = \text{Start Frame}_i + \text{Frames}_i$$

Start the first segment at frame 0, and for subsequent segments, the start frame is the end frame of the previous segment.

5. **Convert to Time:** Map the calculated start and end frames to time using the frame rate (FPS).

$$\text{Time} = \frac{\text{Frame}}{\text{Frames per Second}}$$

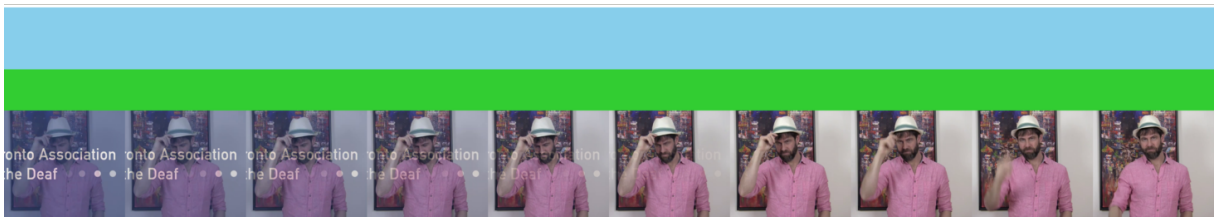

Figure 4: Failure instance in which the model incorrectly assigns a high probability to the "Inside" (I) label, indicating that signing activity is occurring.

Actual subtitle	**Model generated subtitle**
00:00:20.410 --> 00:00:21.813 Bug free?	00:00:20,930 --> 00:00:21,054 [Subtitle 8]
00:00:21.816 --> 00:00:22.676 No.	00:00:22,657 --> 00:00:24,055 [Subtitle 9]
00:00:22.774 --> 00:00:24.748 Insect free?	00:00:24,055 --> 00:00:26,047 [Subtitle 10]
00:00:24.748 --> 00:00:25.722 Brilliant.	00:00:26,047 --> 00:00:28,027 [Subtitle 11]
00:00:25.883 --> 00:00:31.710 Well, I'm going to reveal the secrets behind supermarket food, by making the ingredients that go into a sandwich.	00:00:28,027 --> 00:00:30,000 [Subtitle 12]
00:00:48.453 --> 00:00:55.707 If you've ever baked your own bread, you probably prefer this to the supermarket bread.	00:00:48,646 --> 00:00:55,638 [Subtitle 13]
00:00:55.707 --> 00:01:01.220 But the problem with this stuff is that it goes rock hard in a day or so, while the supermarket bread...	00:00:55,638 --> 00:01:01,140 [Subtitle 14]

Table 4: Comparison of Original Subtitles with Model-Generated Subtitles for BOBSL dataset

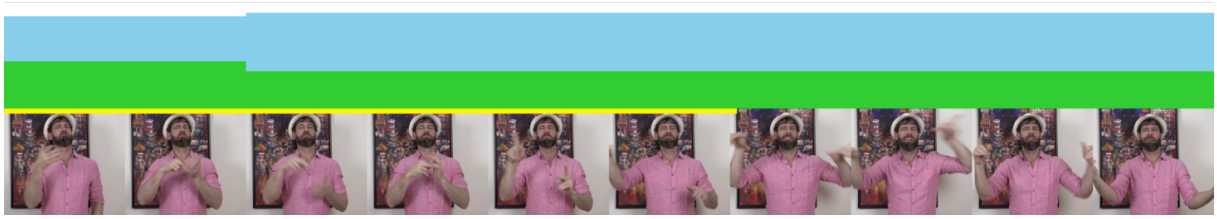

Figure 5: Failure instance where the model incorrectly oversegments the subtitles, predicting a single subtitle instead of two distinct ones, thereby assigning a high probability to the "Inside" (I) label and indicating continuous signing activity.