



# ALIGNATT: Using Attention-based Audio-Translation Alignments as a Guide for Simultaneous Speech Translation

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## Abstract

Attention is the core mechanism of today's most used architectures for natural language processing and has been analyzed from many perspectives, including its effectiveness for machine translation-related tasks. Among these studies, attention resulted to be a useful source of information to get insights about word alignment also when the input text is substituted with audio segments, as in the case of the speech translation (ST) task. In this paper, we propose ALIGNATT, a novel policy for simultaneous ST (SimulST) that exploits the attention information to generate source-target alignments that guide the model during inference. Through experiments on the 8 language pairs of MuST-C v1.0, we show that ALIGNATT outperforms previous state-of-the-art SimulST policies applied to offline-trained models with gains in terms of BLEU of 2 points and latency reductions ranging from 0.5s to 0.8s across the 8 languages.

**Index Terms:** simultaneous speech translation, direct speech translation, attention, alignment

## 1. Introduction

Simultaneous speech translation (SimulST) involves the generation, with minimal delay, of partial translations for an incrementally received input audio. In the quest for high-quality output and low latency, recent developments led to the advent of direct methods, which have been demonstrated to outperform the traditional cascaded (ASR + MT) pipelines in terms of both quality and latency [1]. Early works on direct SimulST require the training of several models which were optimized for different latency regimes [2, 3, 4], consequently resulting in high computational and maintenance costs. With the aim of reducing this computational burden, the use of offline-trained direct ST models for the simultaneous inference has been recently studied [5] and is becoming popular [6, 7, 8] due to its competitive performance compared to dedicated architectures specifically developed for SimulST [1]. Indeed, this approach enables an offline ST model to work in simultaneous by applying, only at inference time, a so-called *decision policy*, which is in charge to determine whether to emit a partial hypothesis or wait for more audio input. As a result, no specific adaptation is required either for the SimulST task or to achieve different latency regimes.

Along this line of research, we propose ALIGNATT, a novel policy for SimulST that exploits the audio-translation alignments obtained from the attention weights of an offline-trained model to decide whether to emit or not a partial translation.

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Our policy is based on the idea that, if the candidate token is aligned with the last frames of the input audio, the information encoded can be insufficient to safely produce that token. The audio-translation alignments are automatically generated from the attention weights, whose representativeness has been extensively studied in linguistics-related tasks [9, 10, 11], including word-alignment in machine translation [12, 13, 14].

All in all, the contributions of our work are the following:

- We present ALIGNATT, a novel decision policy for SimulST that guides an offline-trained model during simultaneous inference by leveraging audio-translation alignments computed from the attention weights;
- We compare ALIGNATT with popular and state-of-the-art policies that can be applied to offline-trained ST models, achieving the new state of the art on all the 8 languages of MuST-C v1.0 [15], with gains of 2 BLEU points and a latency reduction of 0.5-0.8s depending on the target languages;
- The code, the models, and the simultaneous outputs are published under Apache 2.0 Licence at: <https://github.com/hlt-mt/fbk-fairseq>.

## 2. ALIGNATT policy

ALIGNATT is based on the source audio - target text alignment obtained through the attention scores of a Transformer-based model [16]. In the Transformer, encoder-decoder (or cross) attention  $A_C$  is computed by applying the standard dot-product mechanism [17] as follows:

$$A_C(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V$$

where the matrices  $K$  (key) and  $V$  (value) are obtained from the encoder output and consequently depend on the input source  $\mathbf{x}$ , the matrix  $Q$  (query) is obtained from the output of the previous decoder layer (or from the previous output tokens in case of the first decoder layer), and consequently depends on the prediction  $\mathbf{y}$ , and  $d_k$  is a scaling factor. Cross attention can be hence expressed as a function of  $\mathbf{x}$  and  $\mathbf{y}$ , obtaining  $A_C(\mathbf{x}, \mathbf{y})$ . Exploiting the cross attention  $A_C(\mathbf{x}, \mathbf{y})$ , the alignment vector  $Align$  is computed by considering, for each token  $y_i$  of the prediction  $\mathbf{y} = [y_1, \dots, y_m]$ , the index of the most attended frame (or encoder state)  $x_j$  of the source input  $\mathbf{x} = [x_1, \dots, x_n]$ :

$$Align_i = \arg \max_j A_C(\mathbf{x}, y_i)$$

This means that, for every predicted token  $y_i$ , we have a unique aligned frame  $x_j$  of index  $Align_i$ .

Our policy (Figure 1) exploits the obtained alignment  $Align$  to guide the model during inference by checking whether

each token  $y_i$  attends to the last  $f$  frames or not. If this condition is verified, the emission is stopped, under the assumption that, if a token is aligned with the most recently received audio frames, the information they provide can be insufficient to generate that token (i.e. the system has to wait for additional audio input). Specifically, starting from the first token, we iterate over the prediction  $y$  and continue the emission until:

$$\text{Align}_i \notin \{n - f + 1, \dots, n\}$$

which means that we stop the emission as soon as we find a token that mostly attends to one of the last  $f$  frames. Thus,  $f$  is the parameter that directly controls the latency of the model: smaller  $f$  values mean fewer frames to be considered inaccessible by the model, consequently implying a lower chance that our stopping condition is verified and, in turn, lower latency. The process is formalized in Algorithm 1.

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#### Algorithm 1 ALIGNATT

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**Require:**  $\text{Align}, f, y$   
 $i \leftarrow 1$   
 $\text{prediction} \leftarrow [ ]$   
 $\text{stop} \leftarrow \text{False}$   
**while**  $\text{stop} \neq \text{True}$  **do**  
  **if**  $\text{Align}_i \in \{n - f + 1, \dots, n\}$  **then**  
     $\text{stop} \leftarrow \text{True}$    ▷ inaccessible frame  
  **else**  
     $\text{prediction} \leftarrow \text{prediction} + y_i$   
     $i \leftarrow i + 1$   
  **end if**  
**end while**

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Since in SimulST the source speech input  $x$  is incrementally received and its length  $n$  is increased at every time step  $t$ , applying the ALIGNATT policy means applying Algorithm 1 at each timestep to emit (or not) the partial hypothesis until the input  $x(t)$  has been entirely received.

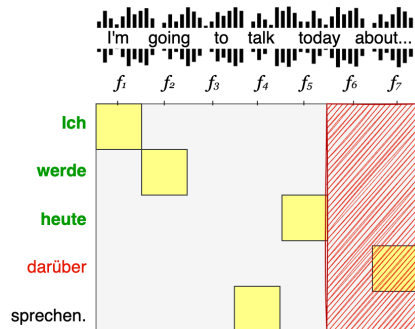
### 3. Experimental Settings

#### 3.1. Data

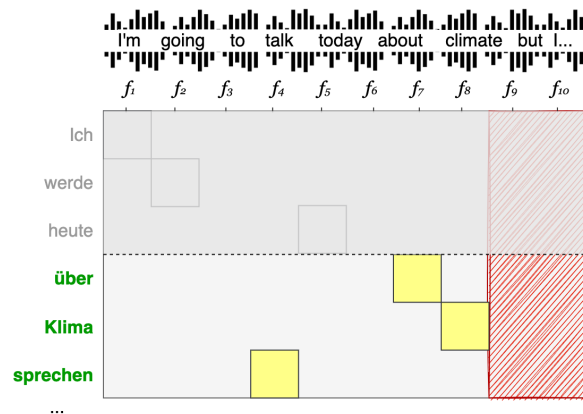
We train one model for each of the 8 languages of MuST-C v1.0 [15], namely English (en) to Dutch (nl), French (fr), German (de), Italian (it), Portuguese (pt), Romanian (ro), Russian (ru), and Spanish (es). We filter out segments longer than 30s from the training set to optimize GPU RAM consumption. We also apply sequence-level knowledge distillation [18] to increase the size of our training set and improve performance. To this aim, we employ NLLB 3.3B [19] as the MT model to translate the English transcripts of the training set into each of the 8 languages, and we use the automatic translations together with the gold ones during training. As a result, the final number of target sentences is twice the original one while the speech input remains unaltered. The performance of the NLLB 3.3B model on the MuST-C v1.0 test set is shown in Table 1.

Model	de	es	fr	it	nl	pt	ro	ru	Avg
NLLB	33.1	38.5	46.5	34.4	37.7	40.4	32.8	23.5	35.9

Table 1: BLEU results on all the language pairs of MuST-C v1.0 *tst-COMMON* of NLLB 3.3B model.



(a) The emission stops when “Ich werde heute” has been generated because the token “darüber” (“about”) is aligned with an inaccessible frame (in striped red).



(b) After “Ich werde heute”, also “über Klima sprechen” is emitted since no token is aligned with inaccessible frames.

Figure 1: Example of the ALIGNATT policy with  $f = 2$  at consecutive time steps  $t_1$  (a) and  $t_2$  (b).

#### 3.2. Architecture and Training Setup

The model is made of 12 Conformer [20] encoder layers and 6 Transformer decoder layers, having 8 attention heads each. The embedding size is set to 512 and the feed-forward layers are composed of 2,048 neurons, with  $\sim 115M$  parameters in total. The input is represented by 80 log Mel-filterbank audio features extracted every 10ms with a sample window of 25, and pre-processed by two 1D convolutional layers of striding 2 to reduce the input length by a factor of 4 [21]. Dropout is set to 0.1 for attention, feed-forward, and convolutional layers. The kernel size is 31 for both point- and depth-wise convolutions in the Conformer encoder. The SentencePiece-based [22] vocabulary size is 8,000 for translation and 5,000 for transcript. Adam optimizer with label-smoothed cross-entropy loss (smoothing factor 0.1) is used during training together with CTC loss [23] to compress audio input representation and speed-up inference time [24]. Learning rate is set to  $5 \cdot 10^{-3}$  with Noam scheduler and 25,000 warm-up steps. Utterance-level Cepstral Mean and Variance Normalization (CMVN) and SpecAugment [25] are also applied during training. Trainings are performed on 2 NVIDIA A40 GPUs with 40GB RAM. We set 40k as the maximum number of tokens per mini-batch, update frequency 4, and 100,000 maximum updates ( $\sim 28$  hours). Early stopping is applied during training if validation loss does not improve for 10 epochs. We use the bug-free implementation of fairseq-ST [26].

Model	Ext. Data		de	es	fr	it	nl	pt	ro	ru	Avg
	Speech	Text									
Fairseq-ST [21]	-	-	22.7	27.2	32.9	22.7	27.3	28.1	21.9	15.3	24.8
ESPnet-ST [27]	-	-	22.9	28.0	32.8	23.8	27.4	28.0	21.9	15.8	25.1
Chimera [28]	✓	✓	27.1	30.6	35.6	25.0	29.2	30.2	24.0	17.4	27.4
W-Transf. [29]	✓	-	23.6	28.4	34.6	24.0	29.0	29.6	22.4	14.4	25.8
XSTNet [29]	✓	✓	27.8	30.8	38.0	26.4	31.2	32.4	25.7	<b>18.5</b>	28.9
LNA-E,D [30]	✓	✓	24.3	28.4	34.6	24.4	28.3	30.5	23.3	15.9	26.2
LightweightAdaptor [31]	-	-	24.6	28.7	34.8	25.0	28.8	31.0	23.7	16.4	26.6
E2E-ST-TDA [32]	✓	✓	25.4	29.6	36.1	25.1	29.6	31.1	23.9	16.4	27.2
STEMM [33]	✓	✓	<b>28.7</b>	31.0	37.4	25.8	30.5	31.7	24.5	17.8	28.4
ConST [34]	✓	-	25.7	30.4	36.8	26.3	30.6	32.0	24.8	17.3	28.0
ours	-	✓	28.0	<b>31.5</b>	<b>39.0</b>	<b>27.3</b>	<b>31.8</b>	<b>32.9</b>	<b>26.3</b>	18.4	<b>29.4</b>

Table 2: BLEU results on MuST-C v1.0 *tst-COMMON*. “Ext. Data” means that external data has been used for training: “Speech” means that either unlabelled or labelled additional speech data is used to train or initialize the model, “Text” means that either machine-translated or monolingual texts are used to train or initialize the model. “Avg” means the average over the 8 languages.

### 3.3. Terms of Comparison

We conduct experimental comparisons with the other SimulST policies that can be applied to offline systems, thus policies that do not require training nor adaptation to be run, namely:

- **Local Agreement (LA)** [6]: the policy used by [35] to win the SimulST task at the IWSLT 2022 evaluation campaign [1]. With this policy, a partial hypothesis is generated each time a new speech segment is added as input, and it is emitted, entirely or partially, if the previously generated hypothesis is equal to the current one. We adapted the docker released by the authors to Fairseq-ST [21]. Different latency regimes are obtained by varying the speech segment length  $T_s$ .
- **Wait-k** [36]: the most popular policy originally published for simultaneous machine translation and then adapted to SimulST [2, 4]. It consists in waiting for a predefined number of words ( $k$ ) before starting to alternate between writing a word and waiting for new output. We employ adaptive word detection guided by the CTC prediction to detect the number of words in the speech as in [4, 5].
- **EDATT** [37]: the only existing policy that exploits the attention mechanism to guide the inference. Contrary to our policy that computes audio-text alignments starting from the attention scores, in EDATT the attention scores of the last  $\lambda$  frames are summed and a threshold  $\alpha$  is used to trigger the emission. While  $\alpha$  handles the latency,  $\lambda$  is a hyperparameter that has to be empirically determined on the validation set. This represents the main flaw of this policy since, in theory,  $\lambda$  has to be estimated for each language. Here, we set  $\lambda = 2$  following the authors’ finding.

### 3.4. Inference and Evaluation

For inference, the input features are computed on the fly and Global CMVN normalization is applied as in [3]. We use the SimulEval tool [38] to compare ALIGNATT with the above policies. For the LA policy, we set  $T_s = [10, 15, 20, 25, 30]^1$ ; for the wait-k, we vary  $k$  in  $[2, 3, 4, 5, 6, 7]^2$ ; for EDATT, we set  $\alpha = [0.6, 0.4, 0.2, 0.1, 0.05, 0.03]^3$ ; for ALIGNATT, we vary  $f$  in  $[2, 4, 6, 8, 10, 12, 14]$ . Moreover, to be comparable with

<sup>1</sup>Smaller values of  $T_s$  do not improve computational aware latency.

<sup>2</sup>We do not report results obtained with  $k = 1$  since the translation quality highly degrades.

<sup>3</sup>These are the same values indicated by the authors of the policy.

EDATT, for our policy we extract the attention weights from the 4<sup>th</sup> decoder layer and average across all the attention heads. All inferences are performed on a single NVIDIA TESLA K80 GPU with 12GB of RAM as in the IWSLT Simultaneous evaluation campaigns [39, 1]. We use sacreBLEU ( $\uparrow$ ) [40]<sup>4</sup> to evaluate translation quality and Length Adaptive Average Lagging [41] – or LAAL ( $\downarrow$ ) – to measure latency.<sup>5</sup> As suggested by [3], we report the computational-aware version of LAAL<sup>6</sup> that accounts for the real elapsed time instead of the ideal one, consequently providing a more realistic latency measure.

## 4. Results

In this section, we present the results of our offline systems trained for each language pair of MuST-C v1.0 to show their competitiveness compared to the systems published in literature (Section 4.1) and the results of the ALIGNATT policy compared to the other policies presented in Section 3.3 (Section 4.2).

### 4.1. Offline Results

To provide an upper bound to the simultaneous performance and show the competitiveness of our models, we present in Table 2 the offline results of the systems trained on all the language pairs of MuST-C v1.0 compared to systems published in literature that report results for all languages. As we can see, our offline systems outperform the others on all but 2 language pairs, en→{es, fr, it, nl, pt, ro}, achieving the new state of the art in terms of translation quality. BLEU gains are more evident for en→fr and en→it, for which we obtain improvements of about 1 BLEU point, while they amount to about 0.5 BLEU points for the other languages.

Concerning the other 2 languages (de, ru), our en→ru model achieves a similar result (18.4 vs 18.5 BLEU) with that obtained by the best model for that language (XSTNet [29]), with only a 0.1 BLEU drop. Moreover, our system reaches a slightly worse but competitive result for en→de (28.0 vs 28.7 BLEU) compared to STEMM [33], which instead makes use of a relevant amount of external speech data, and it also outperforms all the other systems for this language direction. On

<sup>4</sup>BLEU+case.mixed+smooth.exp+tok.13a+version.1.5.1

<sup>5</sup>Length Adaptive Average Lagging is a an improved speech version of Average Lagging [36], which accounts for both longer and shorter predictions compared to the reference.

<sup>6</sup>We present all the results with LAAL<sub>max</sub> = 3.5s.

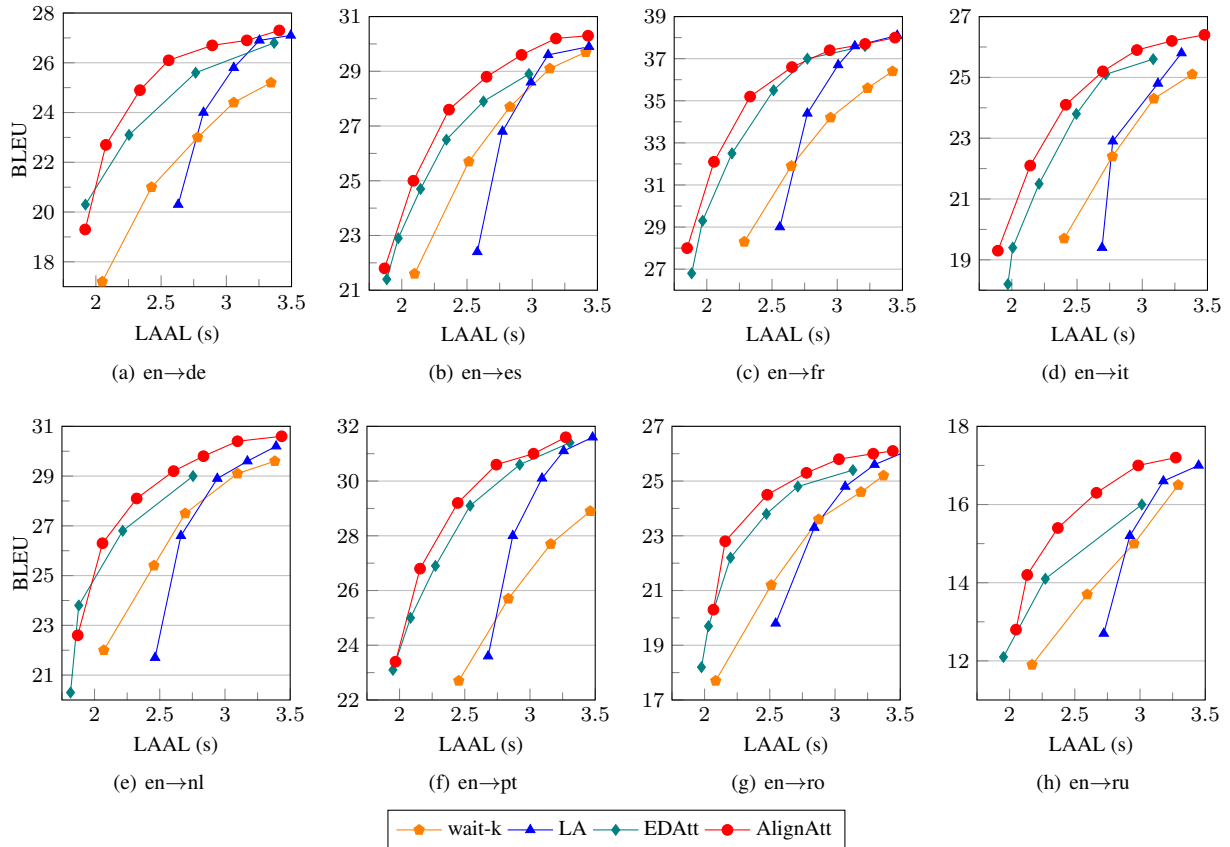


Figure 2: LAAL-BLEU curves for all the 8 language pairs of MuST-C *tst*-COMMON. ALIGNATT is compared to the SimulST policy presented in Section 3.3. Latency (LAAL) is computationally aware and expressed in seconds (s).

average, our approach stands out as the best one even if it does not involve the use of external speech data: it obtains an average of 29.4 BLEU across languages, which corresponds to 0.5 to 4.6 BLEU improvements compared to the published ST models.

#### 4.2. Simultaneous Results

Having demonstrated the competitiveness of our offline models, we now apply the SimulST policies introduced in Section 3.3 to the same offline ST model for each language pair of MuST-C v1.0. Figure 2 shows the results in terms of latency-quality trade-off (i.e. LAAL (↓) - BLEU (↑) curves).

As we can see, our ALIGNATT policy is the only policy, together with EDATT, capable of reaching a latency lower or equal to 2s for all the 8 languages.<sup>7</sup> Specifically, LA curves start at around 2.5s or more for all the language pairs, even if they are able to achieve high translation quality towards 3.5s, with a 1.2 average drop in terms of BLEU across languages compared to the offline inference. Similarly, the wait-k curves start at around 2/2.5s but are not able to reach high translation quality even at high latency (LAAL approaching 3.5s), therefore scoring the worst results. Compared to these two policies, ALIGNATT shows a LAAL reduction of up to 0.8s compared to LA and 0.5s compared to wait-k. Despite achieving lower latency as ALIGNATT, the EDATT policy achieves worse translation quality at almost every latency regime compared to our

<sup>7</sup>The maximum acceptable latency limit is set between 2s and 3s from most works on simultaneous interpretation [42, 43].

policy, with drops of up to 2 BLEU points across languages. These performance drops are particularly evident for en→de and en→ru, where the latter represents the most difficult language pair also in offline ST (it is the only language with less than 20 BLEU on Table 2). The evident differences in the ALIGNATT and EDATT policy behaviors, especially in terms of translation quality, prove that, despite both exploiting attention scores as a source of information, the decisions taken by the two policies are intrinsically different. Moreover, ALIGNATT is the closest policy to achieving the offline results of Table 2, with less than 1.0 BLEU average drop versus 1.8 of EDATT.

We can conclude that, on all the 8 languages of MuST-C v1.0, the ALIGNATT policy achieves a lower latency compared to both wait-k and LA, and an improved translation quality compared to EDATT, therefore representing the new state-of-the-art SimulST policy applicable to offline ST models.

## 5. Conclusions

We presented ALIGNATT, a novel policy for SimulST that leverages the audio-translation alignments obtained from the cross-attention scores to guide an offline-trained ST model during simultaneous inference. Results on all 8 languages of MuST-C v1.0 showed the effectiveness of our policy compared to the existing ones, with gains of 2 BLEU and a latency reduction of 0.5-0.8s, achieving the new state of the art. Code, offline ST models, and simultaneous outputs are released open source to help the reproducibility of our work.

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