Towards Multimodal Simultaneous Neural Machine Translation

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Abstract

Simultaneous translation involves translating a sentence before the speaker’s utterance is completed in order to realize real-time understanding in multiple languages. This task is significantly harder than the general full sentence translation because of the shortage of input information during decoding. To alleviate this shortage, we propose multimodal simultaneous neural machine translation (MSNMT) which leverages visual information as an additional modality. Although the usefulness of images as an additional modality is moderate for full sentence translation, we verified, for the first time, its importance for simultaneous translation. Our experiments with the Multi30k dataset showed that MSNMT in a simultaneous setting significantly outperforms its text-only counterpart in situations where 5 or fewer input tokens are needed to begin translation. We then verified the importance of visual information during decoding by (a) performing an adversarial evaluation of MSNMT where we studied how models behave with incongruent input modality and (b) analyzing the image attention.

1 Introduction

Simultaneous translation is a natural language processing (NLP) task in which translation begins before receiving the whole source sentence. It is widely used in international summits and conferences where real-time comprehension is one of the most important aspects. Simultaneous translation is already a difficult task for human interpreters because the message must be understood and translated while the input sentence is still incomplete (Seeber, 2015). Consequently, simultaneous translation is even more difficult for machines. Previous works attempt to solve this task by predicting the sentence-final verb (Grissom II et al., 2014), or predicting unseen syntactic constituents (Oda et al., 2015). Given the difficulty of predicting future inputs based on existing limited inputs, Ma et al. (2019) proposed a simple simultaneous neural machine translation (SNMT) approach wait-k which generates the target sentence concurrently with the source sentence, but always k tokens behind, for given k satisfying latency requirements.

However, all existing approaches solve the given task only using the text modality, which may be insufficient to produce a reliable translation. Simultaneous interpreters often consider various additional information sources such as visual clues or acoustic data while translating (Seeber, 2015). Therefore, we hypothesize that using supplementary information, such as visual clues, can also be beneficial for simultaneous machine translation.

To this end, we propose Multimodal Simultaneous Neural Machine Translation (MSNMT) that supplements the incomplete textual modality with a visual modality, in the form of an image, during the decoding process to predict still missing information to improve the translation quality. Our research can be applied in various situations where visual

Figure 1: An overview of (a) vanilla NMT, (b) wait-k simultaneous NMT and (c) multimodal simultaneous machine translation based on wait-k approach incorporating visual clues for better En→De translation (here k = 3).
information is related to the content of speech such as presentations that use slides (e.g. TED Talks\textsuperscript{1}) and news video broadcasts\textsuperscript{2}, etc. Our experiments show that the proposed MSNMT method achieves higher translation accuracy by leveraging image information than the SNMT model that does not use images. To the best of our knowledge, we are the first to propose the incorporation of visual information to solve the problem of incomplete text information in SNMT.

The main contributions of our research are:

- We propose to combine multi-modal and simultaneous NMT and discover cases where such multimodal signals are beneficial for the end-task.
- We show that the MSNMT approach significantly improves the quality of simultaneous translation by enriching incomplete text input information using visual clues.
- By providing an adversarial evaluation for both text and image and a quantitative attention analysis, we showed that the models indeed depend on both textual and visual information.

2 Related Work

For simultaneous translation, it is crucial to predict the words that have not appeared yet to produce a translation. For example, it is important to distinguish nouns in SVO-SOV translation and verbs in SOV-SVO translation (Ma et al., 2019). SNMT can be realized with two types of policy: fixed and adaptive policies (Zheng et al., 2019). Most studies with adaptive policy to predict upcoming tokens include explicit prediction of the sentence-final verb (Grissom II et al., 2014; Matsubara et al., 2000) and unseen syntactic constituents (Oda et al., 2015). Such dynamic SNMT models (Gu et al., 2017; Dalvi et al., 2018; Arivazhagan et al., 2019), which decide to READ/WRITE in one model, have the advantage of using input text information as effectively as possible due to the lack of such information in the first place. Meanwhile, Ma et al. (2019) proposed a simple wait-\(k\) method with fixed policy, which generates the target sentence only from the source sentence that is delayed by \(k\) tokens. However, their models for simultaneous translation so far rely only on the source sentence.

In addition, in this research, we concentrate on the wait-\(k\) approach with fixed policy, so that the amount of input textual context can be controlled to better analyze whether multimodality is effective in SNMT.

Multimodal NMT (MNMT) for full-sentence machine translation has been developed to enrich text modality by using visual information (Hitschler et al., 2016; Specia et al., 2016). While the improvement brought by visual features is moderate, their usefulness is proven by Caglayan et al. (2019). They showed that MNMT models are able to capture visual clues under limited textual context, where source sentences are synthetically degraded by color deprivation, entity masking, and progressive masking. However, they use an artificial setting where they deliberately deprive the models of source-side textual context by masking. However, our research has discovered an actual end-task and has shown the effectiveness of using multimodal data. Also, in their progressive masking experiments, they use a model exposed to only \(k\) words. In our case, a model eventually sees all text, generating each target tokens after taking every new source token after waiting for \(k\) words to start translating.

In MNMT, visual features are incorporated into standard machine translation in many ways. Doubly-attentive models are used to capture the textual and visual context vectors independently and then combine these context vectors in a concatenation manner (Calixto et al., 2017) or hierarchical manner (Libovický and Helcl, 2017). Some studies use visual features in a multitask learning scenario (Elliott and Kádár, 2017; Zhou et al., 2018). Also, recent work on MNMT has partly addressed lexical ambiguity by using visual information (Elliott et al., 2017; Lala and Specia, 2018; Gella et al., 2019) showing that using textual context with visual features outperform unimodal models.

In our study, visual features are extracted using image processing techniques and then integrated into an SNMT model as additional information, which is supposed to be useful to predict missing words in a simultaneous translation scenario. To the best of our knowledge, this is the first work that incorporates external knowledge into an SNMT model.

\begin{footnotesize}
\textsuperscript{1}https://interactio.io/
\textsuperscript{2}https://www.a.nhk-g.co.jp/bilingual-english/broadcast/nhk/index.html
\end{footnotesize}
3 Multimodal Simultaneous Neural Machine Translation Architecture

Our main goal in this paper is to investigate if image information would bring improvement on an SNMT. As a result, two separate tasks could benefit from each other by combining them. In order to do that, we chose to keep our experiments as pure as possible, without using additional data, or other types of models. It will allow us to control the amount of input textual context, so we can easily analyze the relationship between the amount of textual and visual information.

In this section, we describe our MSNMT model, which is composed by combining an SNMT (Ma et al., 2019) framework and a multimodal model (Libovický and Helcl, 2017) (Figure 1 (c)). We base our model on the RNN architecture (Libovický and Helcl, 2017; Caglayan et al., 2017a). The models take a sentence and its corresponding image as inputs. The decoder of the MSNMT model outputs the target language sentence using a simultaneous translation mechanism by attaching attention not only to the source sentence but also to the image related to the source sentence.3

3.1 Simultaneous Translation

We first briefly review standard NMT to set up the notations (see also Figure 1, (a)). The encoder of standard NMT model always takes the whole input sequence $X = (x_1, ..., x_n)$ of length $n$ where each $x_i$ is a word embedding and produces source hidden states $H = (h_1, ..., h_n)$. The decoder predicts the next output token $y_i$ using $H$ and previously generated tokens, denoted $Y_{<t} = (y_1, ..., y_{t-1})$. The final output is calculated using the following equation:

$$p(Y|X) = \prod_{t=1}^{\|Y\|} p(y_t|X, Y_{<t}) \quad (1)$$

Different from standard neural translation, in which each $y_i$ is predicted using the entire source sentence $X$, the simultaneous translation needs to translate concurrently with the growing source sentence. We incorporate the wait-k approach (Ma et al., 2019) for our simultaneous translation model (Figure 1, (b)). Instead of waiting for the whole sentence before translating, this model waits for only the first $k$ tokens and starts to generate each target token after taking every new source token one by one. It stops taking new input tokens once the whole input sentence is on board. For example, if $k = 3$, the first target token is predicted using the first 3 source tokens, and the second target token using the first 4 source tokens. The wait-k decoding probability $p_{wait-k}$ is:

$$p_{wait-k}(Y|X) = \prod_{t=1}^{\|Y\|} p(y_t|X_{\leq g(t)}, Y_{<t}) \quad (2)$$

Where $g(t)$ is the wait-k policy function which decides how much input text to read and translate, $X_{\leq g(t)} = (x_1, ..., x_{g(t)})$ and $g(t)$ is $0 \leq t \leq n$. $g(t)$ is defined as follows:

$$g(t) = \min\{k + t - 1, n\} \quad (3)$$

When $k + t - 1$ is over source length $n$, $g(t)$ is fixed to $n$, which means the remaining target tokens (including current step) are generated using the full source sentence. For full sentence translation, $g(t)$ is constant $g(t) = n$.

3.2 Multimodal Translation

We use a hierarchical attention combination technique (Libovický and Helcl, 2017) to incorporate visual and textual features into an MNMT model. This model calculates the independent context vectors from the textual features $h^{txt} = (h_1^{txt}, ..., h_n^{txt})$ and the visual features $h^{img} = (h_1^{img}, ..., h_m^{img})$, which are extracted by the textual encoder and the image processing model, respectively. It then combines the resulting two vectors using a second attention mechanism, which helps to perform simultaneous translation taking into account visual information.

Specifically, we compute the context vectors $e_{i,j}^{f}$ for each image ($f = img$) and text ($f = txt$) modality independently using the following equations:

$$e_{i,j}^{f} = \Omega^{f}(s_i, h_{j}^{f}) \quad (4)$$

$$\alpha_{i,j}^{f} = \frac{\exp(e_{i,j}^{f})}{\sum_{l=1}^{\|h^{f}\|}\exp(e_{i,l}^{f})} \quad (5)$$

$$c_{i}^{f} = \sum_{j=1}^{\|h^{f}\|}\alpha_{i,j}^{f}h_{j}^{f} \quad (6)$$

where $\Omega^{f}$ is a feedforward network for each modality $f$; $s_i$ is $i$-th decoder hidden state.
We project these image and text context vectors into a common space and compute another distribution over the projected context vectors and their corresponding weighted average using the second attention:

\[ c_i^t = \Psi(s_i, c_i^t) \]  \hspace{1cm} (7)

\[ \beta_i^t = \exp(\tilde{c}_i^t) \]  \hspace{1cm} (8)

\[ \tilde{c}_i = \sum_{r \in \{\text{img}, \text{txt}\}} \beta_i^r W^r c_i^r \]  \hspace{1cm} (9)

where \( \Psi \) is a feedforward network. Equation 8 calculates the second attention to combine the image and text vectors. \( W^r \) is a weight matrix used to compute the context vector \( \tilde{c}_i \) calculated from image and text features.

The final hypothesis \( Y \) has the probability:

\[ p_{\text{mnmt}}(Y|X, Z) = \prod_{t=1}^{|Y|} p(y_t|X, Z, y_{<t}) \]  \hspace{1cm} (10)

where \( Z \) represents input image features.

### 3.3 Multimodal Simultaneous Neural Machine Translation

In this subsection, we describe the structure of the MSNMT model, which is a combination of the models described in Sections 3.1 and 3.2. The method for calculating the image context vector is the same as for MNMT; however, the text context vector (Equation 6) for the \( t \)-th step is calculated as follows:

\[ c_i^{\text{txt}} = \sum_{j=1}^{g(t)} \alpha_{i,j}^{\text{txt}} h_j^{\text{txt}} \]  \hspace{1cm} (11)

Thus \( c_i^{\text{txt}} \) is calculated from the input text prefix determined by \( \text{wait-}k \) policy function \( g(t) \). Then we apply the second attention to \( c_i^{\text{txt}} \) and \( c_i^{\text{img}} \) in order to calculate \( \tilde{c}_i \) (Equation 9).

The decoding probability becomes as follows:

\[ p_{\text{msnmt}}(Y|X, Z) = \prod_{t=1}^{|Y|} p(y_t|X_{\leq g(t)}, Z, y_{<t}) \]  \hspace{1cm} (12)

### 4 Experimental Setup

#### 4.1 Dataset

We used the train, development, and test sets from the Multi30k (Elliott et al., 2016) dataset published in the WMT16 Shared Task, which is a benchmark dataset generally used in multi-modal machine translation research (Libovický and Helcl, 2017; Caglayan et al., 2019). In addition to the test set provided by WMT16 (test2016), we also experimented on the test set from WMT17 Shared Task (test2017).

We experiment with our model in six translation directions consisting of 4 languages: English (En), German (De), French (Fr) and Czech (Cs). All language pairs include En on either of the sides. Data split for all pairs were as follows: training set, 29,000 sentence pairs; development set, 1,014 sentence pairs; 1,000 and 1,071 sentence pairs for tests 2016 and 2017, respectively. The average sentence length of this dataset is 12-13 tokens.

We limit the vocabulary size of the source and the target languages to 10,000 words. All sentences are preprocessed with lower-casing, tokenizing and normalizing the punctuation using the Moses script.\(^5\) Note that we provided experiments on word-level without using subwords such as BPE.

Visual features are extracted using pre-trained ResNet (He et al., 2016). Technically, we encode all images in Multi30k with ResNet-50 and pick out the hidden state in the relu4f layer as a 14 × 14 1,024-dimension visual features.

### 4.2 Systems

We compare the following models:

1. **Captioning:** We experimented on image captioning in order to examine the effect of using visual clues only to produce adequate translations. In this setting, instead of an input sentence, we used only one \(<\text{cpt}>\) token for each image of Multi30k to produce its description using MSNMT architecture.

2. **SNMT:** We use only text modality for training data as a baseline for each \( \text{wait-}k \) model.

3. **MSNMT:** We use image modality along with text modality for a training data for each \( \text{wait-}k \) model.

To train the above models, we utilize attention NMT (Bahdanau et al., 2015) with a 2-layer unidirectional GRU encoder and a 2-layer conditional

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\(^4\)Involving other types of data for training are out of the scope of this paper, however, they will be the next steps of this research.

\(^5\)We applied preprocessing using task1-tokenize.sh from https://github.com/multi30k/dataset.
Table 1: METEOR scores of SNMT (S) and MSNMT (M) models for six translation directions on test2016. Results are the average of three runs. Bold indicates the best METEOR score for each wait-\(k\) for each translation direction. “†” indicates statistical significance of the improvement over SNMT.

| wait-\(k\) | En→De | De→En | En→Fr | Fr→En |
|------------|--------|--------|--------|--------|
| S | M | S | M | S | M | S | M |
| 1 | 12.76 | 20.41 | 10.64 | 13.86 | 14.08 | 19.84 | 10.54 | 13.46 | 7.81 | 9.97 | 13.25 | 15.39 |
| 3 | 25.94 | 26.66 | 16.03 | 17.45 | 26.74 | 28.54 | 16.29 | 18.02 | 12.56 | 13.40 | 17.84 | 18.36 |
| 5 | 30.85 | 31.30 | 19.99 | 20.55 | 34.82 | 35.92 | 20.32 | 21.29 | 15.89 | 16.31 | 22.78 | 23.22 |
| 7 | 36.69 | 36.80 | 25.01 | 25.35 | 44.49 | 44.75 | 25.10 | 25.73 | 19.09 | 19.29 | 27.69 | 28.02 |
| 9 | 42.90 | 42.34 | 28.98 | 29.04 | 53.63 | 53.62 | 30.18 | 30.29 | 22.36 | 22.34 | 31.47 | 30.96 |
| Full | 54.80 | 53.92 | 36.59 | 35.59 | 73.28 | 72.00 | 43.09 | 42.27 | 29.25 | 28.79 | 36.14 | 35.39 |

Table 2: METEOR scores of SNMT (S) and MSNMT (M) models for four language pairs on test2017. Results are the average of three runs. Bold indicates the best METEOR score for each wait-\(k\) for each translation direction. “†” indicates statistical significance of the improvement over SNMT.

| wait-\(k\) | En→De | De→En | En→Fr | Fr→En |
|------------|--------|--------|--------|--------|
| S | M | S | M | S | M | S | M |
| 1 | 7.32 | 16.19 | 9.83 | 11.92 | 12.65 | 17.65 | 8.75 | 12.05 |
| 3 | 20.79 | 21.47 | 13.91 | 15.43 | 22.53 | 24.59 | 14.03 | 15.59 |
| 5 | 25.00 | 25.74 | 17.44 | 19.13 | 30.36 | 30.96 | 17.72 | 19.06 |
| 7 | 31.64 | 31.85 | 22.65 | 23.48 | 41.85 | 42.15 | 23.05 | 23.77 |
| 9 | 37.78 | 37.11 | 26.84 | 27.03 | 51.48 | 51.84 | 28.94 | 29.28 |
| Full | 47.91 | 47.29 | 33.44 | 32.32 | 67.83 | 65.89 | 40.41 | 39.92 |

Table 3: METEOR scores of Captioning models into four target languages on test2016. Results are the average of three runs.

| wait-\(k\) | En→De | De→En | En→Fr | Fr→En |
|------------|--------|--------|--------|--------|
| S | M | S | M | S | M | S | M |
| 12.36 | 18.65 | 17.71 | 8.76 |

GRU decoder. We use the open-source implementation of the nmt-pytorch toolkit v3.0.0 (Caglayan et al., 2017b). The hyper-parameters not mentioned in this table were set to the default values in nmt-pytorch. We incorporated early-stopping: when the METEOR score (Denkowski and Lavie, 2011) did not increase on the development set for 10 epochs, the training was stopped.

5 Results

In this section, we report METEOR scores, which is a widely used evaluation metric in MNMT, on our test sets for each wait-\(k\) model. Statistical significance (\(p < 0.05\)) on the difference of BLEU scores was tested by Moses’s bootstrap-hypothesis-difference-significance.pl. “Full” means that the whole input sentence is used as an input for the model. All reported results are the average of three runs using three different random seeds.

Tables 1-2 illustrate the METEOR scores of MSNMT and SNMT models on test2016 and test2017, respectively. For all language pairs, MSNMT systems show significant improvements over SNMT systems when input textual information is scarce (\(k \leq 5\)). Note that the difference of METEOR scores between MSNMT and SNMT grows larger as the input sentence gets shorter. On the other hand, the availability of more tokens during the decoding process (\(k \geq 5\)) leads to the text information becoming sufficient in most cases.

The results of Captioning in Table 3 compared to those in Table 1 show that using only visual information is not enough for translation. The cause is that captioning does not consider the actual text and only describes the image itself.

6 Analysis

In this section, we provide a thorough analysis to further investigate the effect of visual data to produce a simultaneous translation by: (a) providing
Table 4: Image Awareness results on test2016. METEOR scores of MSNMT Congruent (C) and Incongruent (I) settings for six translation directions. Results are the average of three runs. **Bold** indicates the best METEOR score for each **wait-k** for each translation direction.

| wait-k | En→De | De→En | En→Fr | Fr→En | En→Cs | Cs→En |
|--------|--------|--------|--------|--------|--------|--------|
|        | C      | I      | C      | I      | C      | I      |
| 1      | 20.41  | 14.83  | 13.86  | 9.60   | 13.46  | 9.34   |
| 3      | 26.66  | 23.50  | 17.45  | 14.86  | 28.54  | 24.47  |
| 5      | 31.30  | 29.01  | 20.55  | 18.84  | 35.92  | 32.30  |
| 7      | 36.80  | 35.17  | 25.35  | 24.05  | 44.75  | 42.60  |
| 9      | 42.34  | 41.39  | 29.04  | 28.30  | 53.62  | 52.03  |
| Full   | 53.92  | 53.43  | 35.59  | 35.37  | 72.00  | 71.74  |

Table 5: Text Awareness results on test2016. METEOR scores of SNMT (S) and MSNMT (M) models for six translation directions. Results are the average of three runs. **Bold** indicates the best METEOR score for each **wait-k** for each translation direction.

| wait-k | En→De | De→En | En→Fr | Fr→En | En→Cs | Cs→En |
|--------|--------|--------|--------|--------|--------|--------|
|        | S      | M      | S      | M      | S      | M      |
| 1      | 11.33  | 16.29  | 8.65   | 11.21  | 10.99  | 15.82  |
| 3      | 12.46  | 13.04  | 7.48   | 9.07   | 10.28  | 12.62  |
| 5      | 11.01  | 12.27  | 6.93   | 8.41   | 9.49   | 11.20  |
| 7      | 10.47  | 11.59  | 6.69   | 7.64   | 8.98   | 10.40  |
| 9      | 10.09  | 10.48  | 6.47   | 7.04   | 8.73   | 9.68   |
| Full   | 9.86   | 9.89   | 6.30   | 6.49   | 8.69   | 8.96   |

adversarial evaluation; and (b) visualizing attention.

6.1 Adversarial Evaluation

In order to determine whether MSNMT systems are aware of the visual context (Elliott, 2018), we perform two different versions of adversarial evaluation on test2016:

**Image Awareness.** We present our system with correct visual data with its source sentence (Congruent) as opposed to random visual data as an input (Incongruent) (Elliott, 2018). For that purpose, we reversed the order of 1,000 images of test2016, so there will be no overlapping congruent visual data. Then we reconstruct image features for those images to use as an input to a model.

**Text Awareness.** We present our system with incorrect source sentences but with the correct visual information in order to determine the impact of visual data to produce correct translations for noisy text input. Similarly, we used the same shuffling technique as above for the text data.

Results of image awareness experiments are shown in Table 4. We can see the large difference in METEOR scores between MSNMT congruent and incongruent settings when the input text information is incomplete which implies that our proposed model learns to extract information from images for translation. The interesting part is for a full translation, where scores for the incongruent setting outperform or are very close to those of the congruent setting. The reason is that when textual information is enough, visual information becomes not that relevant in some cases.

From the results of the text awareness experiments (see Table 5) we can draw the following conclusions. The fact that MSNMT models handle noisy text input better than SNMT models implies that the proposed model can leverage visual information. For both SNMT and MSNMT, the METEOR score degrades as the number of available first k tokens increases. We assume that the more
| Source | a black dog and a brown dog with a ball.  
| Target | ein schwarzer und ein brauner hund mit einem ball.  
| Captioning | zwei hunde spielen im gras.  (Two dogs are playing in the grass.)  
| S \(\text{wait-3}\) | ein schwarzer hund und ein brauner hund springt über einen zaun.  (a black dog jumps over a fence.)  
| M \(\text{wait-3}\) | ein schwarzer hund und ein brauner hund rennen auf einem feld.  (a black dog and a brown dog run on a field.)  
| S full | ein schwarzer hund und ein brauner hund mit einem ball.  (a black dog and a brown dog with a ball.)  
| M full | ein schwarzer hund und ein brauner hund mit einem ball.  (a black dog and a brown dog with a ball.)  

| Source | a baseball player in a black shirt just tagged a player in a white shirt.  
| Target | eine baseballspielerin in einem schwarzen hemd fängt eine spielerin in einem weißen hemd.  
| Captioning | ein mann in einem weißen trikot macht einen trick auf dem boden und hält dabei einen anderen mann.  (a man in a white jersey is doing a trick on the floor while holding another man.)  
| S \(\text{wait-3}\) | ein baseballspieler in einem roten trikot versucht den ball zu fangen, während der schiedsrichter zuschaut.  (a baseball player in a red jersey tries to catch the ball while the referee is watching.)  
| M \(\text{wait-3}\) | ein baseballspieler versucht, einen ball zu fangen.  (a baseball player is trying to catch a ball.)  
| S full | ein baseballspieler in einem schwarzen hemd hat einen spieler in einem weißen hemd.<unk>.  (a baseball player in a black shirt has a player in a white shirt <unk>.)  
| M full | ein baseballspieler in einem schwarzen hemd hat gerade einen spieler in einem weißen hemd.<unk>.  (a baseball player in a black shirt has just one player in a white shirt <unk>.)  

Table 6: Examples of En→De translations from test2016 using SNMT (S) and MSNMT (M) models. In () are shown their English meanings. *Italic* shows the correct translation outputs.

![Figure 3](image1.png)  
(a) \(\text{wait-3}\)  
(b) Full

Figure 3: Attention visualization for MSNMT outputs for Figure 2a at each decoding step of En→De translation (see Table 6).

![Figure 4](image2.png)  
(a) \(\text{wait-3}\)  
(b) Full

Figure 4: Attention visualization for MSNMT outputs for Figure 2b at each decoding step of En→De translation (see Table 6).

Noise is given as input, the more a model gets confused. However, visual information makes a model more robust to the introduced noise. MSNMT models also consider textual information, as models have lower performance as the input tokens are more restricted (opposed to Table 1, columns M).
6.2 Visual Attention

As an example, we sampled sentences and their images from test2016 (Figure 2) to compare the outputs of our systems. Table 6 lists their translations generated by Captioning, SNMT (S) and MSNMT (M) models. In the first example, Captioning did not capture “a ball” and “a black dog and a brown dog” presented in the source sentence. An SNMT model with wait-3 predicted an erroneous “zaun (fence)” which is not present neither in source text nor in a corresponding image. On the other hand, the MSNMT model was able to capture both input text and visual information and generates a richer output. When a full sentence is given as an input, both MSNMT and SNMT translated it correctly. In the second example, none of the models generated correct translations. For example, Captioning and SNMT models generated words that do not present in either of inputs, such as “schiedsrichter (referee)” or “trick (trick).” Also, our MSNMT models failed to capture the gender of the source gender-neutral word “player” and translated it into “spieler” instead of “spielerin,” although it was obvious from the visual information.

For a more detailed analysis, first, we visualized attention on the image of the above example at each decoding step for \(k=3\) and “Full” input scenarios (see Figures 3-4). Given a piece of incomplete text information, the proposed MSNMT model attends to the different parts of an image. For example, when decoding a token “brauner,” MSNMT attends more on a brown dog, and when decoding “rennen,” the model attends to the legs of the dogs (see Figure 3a). Also, in the other example, MSNMT focuses on a player while decoding “baseballspieler.”

We hypothesize that the MSNMT model is trying to find a piece of useful information from the image. In contrast, when an input text is fully given, MSNMT attends only localized parts of the image. These results show us, once again, that the visual data can enrich an incomplete input sentence and be used to produce more accurate translation with low latency in most cases.

Furthermore, we investigate how much attention is given to the visual information in each \(\text{wait} - \text{k}\) model. For that purpose, we simply calculate the average score of the second attention (Equation 8) to the visual features for each decoding step for all sentences. Figure 5 reports averages of second attention scores for visual features on test2016 for six translation directions. We can see that for the lower \(k\) values the MSNMT model utilizes image information more.

7 Conclusion

In this paper, we proposed a multimodal simultaneous neural machine translation approach which takes advantage of visual information as an additional modality to compensate for the shortage of input text information in the simultaneous neural machine translation. We showed that in a \(\text{wait} - k\) setting our model significantly outperformed its text-only counterpart in situations where only a few input tokens are available to begin translation. Furthermore, we showed the importance of the visual information for simultaneous translation, especially in small \(k\) settings, by performing a thorough analysis on the Multi30k data. We hope that our proposed method can be explored even further for various tasks and datasets.

In this paper, we created a separate model for each value of \(\text{wait} - k\). However, in future work, we plan to experiment on having a single model for all \(k\) values (Zheng et al., 2019). Furthermore, we acknowledge the importance of investigating MSNMT effects on more realistic data (e.g. TED), where the utterance does not necessarily match a shown image while speaking and/or where its context can not be guessed from the shown image.

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Table 7: Hyperparameter values of SNMT and MSNMT models.

| Parameter       | SNMT & MSNMT |
|-----------------|--------------|
| Enc., Dec. dim. | 320          |
| Emb. dim.       | 200          |
| Dropout         | 0.5          |
| Dropout for emb.| 0.4          |
| Tied embedding  | 2-way        |
| Max length      | 100          |
| Optimizer       | adam         |
| Learning rate   | 0.0004       |
| Batch size      | 64           |
| wait-k          | 1, 3, 5, 7, 9, Full |

Table 8: BLEU scores of SNMT (S) and MSNMT (M) models for six translation directions on test2016. Results are the average of three runs. **Bold** indicates the best BLEU score for each wait-k for each translation direction. "†" indicates statistical significance of the improvement over SNMT.

A Hyperparameters

Table 7 lists the hyperparameters of the SNMT and MSNMT models used in our experiments. We use the same hyperparameters, except for unique ones, for SNMT and MSNMT for a fair comparison.

B BLEU scores

Tables 8-10 show BLEU scores of models used in our experiments (corresponding METEOR scores are shown in Tables 1-3).
### Table 9: BLEU scores of SNMT (S) and MSNMT (M) models for four language pairs on test2017. Results are the average of three runs. **Bold** indicates the best BLEU score for each \textit{wait-}k for each translation direction. "†" indicates statistical significance of the improvement over SNMT.

| \( k \) | \( \text{En} \rightarrow \text{De} \) | \( \text{De} \rightarrow \text{En} \) | \( \text{En} \rightarrow \text{Fr} \) | \( \text{Fr} \rightarrow \text{En} \) |
|-------|-------|-------|-------|-------|
|       | S     | M     | S     | M     | S     | M     | S     | M     |
| 1     | 0.09  | †2.30 | 2.39  | †4.77 | 1.62  | †4.52 | 2.33  | †5.43 |
| 3     | 5.61  | †6.83 | 7.40  | †9.09 | 8.72  | †10.37| 9.02  | †10.49|
| 5     | 9.50  | 9.33  | 13.08 | †14.22| 16.93 | 17.40 | 15.16 | †16.59|
| 7     | 14.94 | 14.57 | 20.10 | †20.99| 27.23 | 27.20 | 23.55 | 23.73 |
| 9     | 20.80 | 20.15 | 25.50 | 25.08 | 35.99 | 36.08 | 32.01 | 31.59 |
| Full  | 26.62 | 26.34 | 32.72 | 31.10 | 50.36 | 48.70 | 46.01 | 45.31 |

### Table 10: BLEU scores of Captioning models into four target languages on test2016. Results are the average of three runs.

| \( \rightarrow \text{En} \) | \( \rightarrow \text{De} \) | \( \rightarrow \text{Fr} \) | \( \rightarrow \text{Cs} \) |
|-------|-------|-------|-------|
| 5.68  | 3.80  | 4.97  | 2.77  |

Table 10: BLEU scores of Captioning models into four target languages on test2016. Results are the average of three runs.