Audio captioning is the task of automatically creating a textual description for the contents of a general audio signal. Typical audio captioning methods rely on deep neural networks (DNNs), where the target of the DNN is to map the input audio sequence to an output sequence of words, i.e. the caption. Though, the length of the textual description is considerably less than the length of the audio signal, for example 10 words versus some thousands of audio feature vectors. This clearly indicates that an output word corresponds to multiple input feature vectors. In this work we present an approach that focuses on explicitly taking advantage of this difference of lengths between sequences, by applying a temporal sub-sampling to the audio input sequence. We employ a sequence-to-sequence method, which uses a fixed-length vector as an output from the encoder, and we apply temporal sub-sampling between the RNNs of the encoder. We evaluate the benefit of our approach by employing the freely available dataset Clotho and we evaluate the impact of different factors of temporal sub-sampling. Our results show an improvement to all considered metrics.

Index Terms— audio captioning, recurrent neural networks, temporal sub-sampling, hierarchical sub-sampling networks

1. INTRODUCTION

Audio captioning is the task of automatically describing the contents of a general audio signal, using natural language [1][2]. It can be considered an inter-modal translation task, where the contents of the audio signal are translated to text [2][3]. Audio captioning offers the ability for developing methods that can learn complex information from audio data, like spatiotemporal relationships, differentiation between foreground and background, and higher and abstract knowledge (e.g. counting) [2][4].

Audio captioning started in 2017 [1] and all published audio captioning methods (up to now) are based on deep neural networks (DNNs) [3][5]. The usual set-up of methods is according to sequence-to-sequence architectures, where an encoder (usually based on recurrent neural networks, RNNs) takes a sequence of audio feature vectors as an input, and a decoder (also usually RNN-based) takes as an input the output of the encoder and outputs a sequence of words. A common element to sequence-to-sequence architectures is the alignment of the input and output sequences [6][7][8]. Three main alternative techniques have been proposed for the alignment of the input and output sequences, namely the employment of a fixed-length vector representation of the output of the encoder [6], the usage of attention mechanism [7][8], and self-attention [9]. The former two approaches have been widely adopted in the audio captioning field. Specifically, [1] presents a method that employs an RNN encoder, an RNN decoder, and an attention mechanism between the encoder and encoder, to align the input and output sequences. Study [3] used again an RNN encoder and an RNN decoder, but the alignment of the input and output sequences performed with the usage of a fixed-length vector. This vector was the mean, over time, of the output of the encoder. Finally, [8] presented an approach for audio captioning, employing the attention mechanism presented in [8].

Although the above-mentioned techniques seem to be essential for the audio captioning task, they are applied only at the output of the encoder. This means that the encoder processes the whole input audio sequence, and only at its output there is the association (through the alignment mechanisms) of the different parts of the input sequence with the different parts of the output sequence. If we could adopt a policy for effectively collate sequential parts of the input sequence, then we might be able to let the encoder learn better, entities that exhibit long time presence, i.e., long temporal patterns that correspond to one output class like the sound of a car and the word “car”. This need for DNNs has been identified at least since 2012 [10] and the hierarchical sub-sampling networks were introduced, and also adopted more recently, e.g. [11].

In this paper we employ the hierarchical sub-sampling networks and we present a novel approach for audio captioning methods employing multi-layered and RNN-based encoders. We draw inspiration from the empirical observation that each word in the caption corresponds to multiple time-steps of the input sequence to a DNN-based audio captioning method, and we hypothesize that the performance of the method could be enhanced by reducing the temporal length of the sequence after each RNN layer in an RNN-based encoder. To assess our hypothesis and our method, we employ a method that is not using temporal sub-sampling, and we alter it by solely employing the sub-sampling. The obtained results show that, indeed, temporal sub-sampling can enhance the performance of the audio captioning methods.

The rest of the paper is organized as follows. In Section 2 we present our method and the temporal sub-sampling method. In Section 3 we present the followed evaluation procedure, and the obtained results are in Section 4. Section 5 concludes the paper.
2. PROPOSED METHOD

Our proposed method employs a multi-layered, bi-directional RNN-based encoder, an RNN-based decoder, accepts as an input a sequence of $T$ audio feature vectors with $F$ features, $X \in \mathbb{R}^{T \times F}$, and outputs a sequence of $S$ vectors $Y = [y_1, \ldots, y_s]$, where each vector $y_i \in [0, 1]^D$ contains the predicted probability for each of the $D$ words available to the method, where $D$ is the amount of unique words in the captions of the training dataset. After each bi-directional RNN layer in the encoder (except the last one), our method applies a temporal sub-sampling of the output sequence of the bi-directional RNN layer before use the sequence as an input for the next bi-directional RNN layer in the encoder. Figure 1 illustrates the method. Our method is otherwise the same as the baseline method of the DCASE 2020 automated audio captioning task (task 6) enhanced with the of temporal sub-sampling of the latent representations in the encoder.

2.1. Encoder with temporal sub-sampling

Our encoder consists of $L_{enc}$ bi-directional RNNs, where $\text{RNN}^{l}_{enc}$ and $\bar{\text{RNN}}^{l}_{enc}$ are the $l$-th forward and backward RNNs of the encoder, respectively. $\text{RNN}^{1}_{enc}$ and $\bar{\text{RNN}}^{1}_{enc}$ process the input sequence $X$ as

$$\overrightarrow{\text{h}}_{l,t} = \text{RNN}^{l}_{enc}(x_t, \overrightarrow{\text{h}}_{l,t-1})$$

and

$$\overleftarrow{\text{h}}_{l,t} = \text{RNN}^{l}_{enc}(x_t, \overleftarrow{\text{h}}_{l,t-1}),$$

where $\overrightarrow{\text{X}}_t$ is the $t$-th feature vector of the time-reversed $X$, $\overrightarrow{\text{h}}_{l,t}, \overleftarrow{\text{h}}_{l,t} \in [-1, 1]^F$ are the outputs of the $\text{RNN}^{l}_{enc}$ and $\bar{\text{RNN}}^{l}_{enc}$ respectively, for the $t$-th time-step. $\overrightarrow{\text{h}}_{l,0} = \overleftarrow{\text{h}}_{l,0} = [0]^F$, and $\Xi$ is the amount of output features of each of the RNNs of the $l$-th bi-directional RNN of the encoder. Then, the outputs of the $\text{RNN}^{1}_{enc}$ and $\bar{\text{RNN}}^{1}_{enc}$, $\overrightarrow{\text{h}}_{1,t}$ and $\overleftarrow{\text{h}}_{1,t}$ respectively, are concatenated as

$$\text{h}_{l,t} = [\overrightarrow{\text{h}}_{1,t}, \overleftarrow{\text{h}}_{1,t}]^T,$$

and $H_l = [h_{1,1}, \ldots, h_{1,T}]$. Then, for $2 \leq l \leq L$, our method applies a temporal sub-sampling to $H_{l-1}$, as

$$H_{l-1}' = \{h_{l-1}'_{i, \{0,1,\ldots,\lfloor(T_l-1)/M\}\}}_{i=0}^{H_l \lfloor l/M \rfloor},$$

where $T_l$ is the amount of time-steps of $H_{l-1}'$, $M \in \mathbb{N}^*$ is the sub-sampling factor, and $\lfloor \cdot \rfloor$ is the floor function. Figure 2 illustrates the sub-sampling process.

Then, $H_{l-1}'$ is given as an input to $\text{RNN}^{l}_{enc}$ and $\bar{\text{RNN}}^{l}_{enc}$, similarly to Eqs. (1), (2), and (3), obtaining $H_l^+$, $H_l$, is obtained by a residual connection between $H_{l-1}'$ and $H_{l-1}'$, as

$$H_l = H_{l-1}' + H_{l-1}',$$

where $H_l \in \mathbb{R}^{T_l \times D}$ is the output of the $l$-th bi-directional RNN layer of the encoder. By utilizing Eq. (4), we enforce the RNNs of the encoder to squeeze the information in the input sequence to a smaller output sequence, effectively making the RNNs to learn a time-filtering and time-compression of the information in the input sequence [10] [11]. This is can be proven beneficial in the case of audio captioning, since one output class (i.e. one word) corresponds to multiple input time-steps. By temporal sub-sampling, we are enforcing the encoder to express the learnt information with lower temporal resolution, effectively providing a shorter sequence but with each of its time-step to represent longer temporal patterns [10]. The above presented scheme of temporal sub-sampling, results in reducing the length of the input audio sequence to $M^{-L-1}$ times. For example, a sub-sampling factor of $M = 2$ and $L = 3$ RNN layers results in reducing the length of the input audio sequence $2^2$ times (a reduction of 75.0%).

Finally, the output of the encoder. $z \in \mathbb{R}^{\Delta}$, is formed as

$$z = H_{L-1}'_{L},$$

That is, $z$ is the last time-step of the output sequence $H_L$ of the $L$-th bi-directional RNN of the encoder.

2.2. Decoder and optimization

The decoder of our method consists of an RNN and a linear layer followed by a softmax non-linearity (the latter two will collectively referred to as classifier). The decoder takes as an input the $z$ for every time step as

$$u_s = \text{RNN}_{dec}(z, u_{s-1}),$$

where $u_s \in [0, 1]^F$ is the output of the $\text{RNN}_{dec}$ for the $s$-th time-step of the decoder, with $u_s = [0]^F$. $u_s$ is used as an input to the classifier, $\text{Cls}$, as

$$\hat{y}_s = \text{Cls}(u_s).$$
The process described by Eqs (7) and (8) is repeated until \( s = S \) or \( y_s \) matches a predefined symbol, depending if the decoder is in optimization or inference process. The encoder, the decoder, and the classifier are jointly optimized to minimize the binary cross-entropy at each time-step and between the predicted, \( \hat{y}_s \), and ground truth, \( y_s = [y_{s,1}, \ldots, y_{s,D}] \), one-hot encoding of words.

3. EVALUATION

To evaluate our method, we employ a freely and well-curated audio captioning dataset, called Clotho \cite{audio-captioning}, and the baseline of the DCASE 2020 audio captioning task. For assessing the performance of our method, we use machine translation and captioning metrics, employed by most of the existing audio captioning work.

3.1. Dataset and data pre-processing

Clotho contains audio clips of CD quality (44.1 kHz sampling rate, 16-bit sample width), and 5 captions for each audio clip. The time duration of the audio clips ranges from 15 to 30 seconds, and the amount of words in each caption ranges from eight to 20 words. Clotho provides three splits for developing audio captioning methods, namely development, evaluation, and testing. The development and evaluation splits are freely available online\footnote{https://zenodo.org/record/3490684},\footnote{https://github.com/audio-captioning/clotho-dataset} while the testing split is withheld for scientific challenges. In this work, we employ the development and evaluation splits of Clotho, having 2893 and 1045 audio clips, yielding 14465 and 5225 captions, respectively.

We choose Clotho because it is built to offer audio content diversity, and extra care has been taken for eliminating spelling errors, named entities, and speech transcription in the captions. Additionally, Clotho is already employed at the DCASE 2020 audio captioning task\footnote{https://github.com/DK-Nguyen/audio-captioning-sub-sampling}.

We extract \( F = 64 \) log-scaled mel-band energies from each of the 4981 audio clips of Clotho, using an 1024-sample long window (approximately 23 ms) with 50% overlap, and the Hamming windowing function. This results in having sequences from \( T = 1292 \) to \( T = 2584 \) audio feature vectors, for audio clips of 15 and 30 seconds duration, respectively. We process the captions of Clotho, starting by appending (eos) to all captions, where (eos) is a special token that signifies the end of the sequence (i.e. the caption). Then, we identify the set of words in the captions, include token that signifies the end of the sequence (i.e. the caption). Then, \( S \) success yields a sequence of \( y \) seconds duration, respectively. We process the captions of Clotho, namely development, evaluation, and testing. The development and evaluation splits are freely available online\footnote{https://zenodo.org/record/3490684},\footnote{https://github.com/audio-captioning/clotho-dataset} while the testing split is withheld for scientific challenges. In this work, we employ the development and evaluation splits of Clotho, having 2893 and 1045 audio clips, yielding 14465 and 5225 captions, respectively.

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3.2. Hyper-parameters and training procedure

To optimize our method and fine tune its hyper-parameters, we employ the development split. By empirical observation on the values of the loss for the development split, we decided to round the loss value to three decimal digits and stop the training if the loss did not improve for 100 consecutive epochs. For the training of our method, we employed a batch size of 16 (mainly due to computational resources constraints). To apply a uniform \( T \) and \( S \) in a batch, we calculate the maximum \( T \) and \( S \) in the batch and we prepend vectors of \( \{0\}^T \) to each \( X \) and append the one-hot encoded vector of (eos) to every \( Y \), in order to make them have the \( T \) and \( S \) equal to the maximum \( T \) and \( S \) in the same batch. Additionally, we observed that there is a considerable imbalance at the frequency of appearance of the tokens at the captions. That is, some \( w_i \), for example “a” and “the”, appear quite frequently (e.g. over 4000 times) at the captions, but some appear quite fewer times, e.g. five. To overcome this imbalance, each token, \( w_i \), is inversely weighted by its frequency in the dataset, resulting in the following loss formulation

\[
\mathcal{L}(\hat{y}_s, y_s) = \Phi_s \mathcal{L}(\hat{y}_s, y_s),
\]

where \( \Phi_s \) is a weight for the loss calculation of the token represented by \( y_s \). But due to the quite large frequency of tokens like “a”, we observed that \( \Phi_s \) could get values as low as \( 1e-5 \), which when compared to a value of \( \Phi_s = 1 \) for the non-frequent tokens, has a great difference. This difference at the values of \( \Phi_s \) results in hampering significantly the learning of the frequent tokens and, in addition, will not ever contribute to the training of our method since we round \( \mathcal{L} \) to three decimal digits. Thus, we employed a clamping of \( \Phi_s \) as

\[
\Phi_s = \begin{cases} \min(f_w) & \text{if } \min(f_w) \geq \beta, \\ \beta & \text{otherwise,} \end{cases}
\]

where \( \beta \) is a hyper-parameter that we set to \( 5e - 1 \) by following the above described process, \( f_w \) is the frequency of the \( w_i \) token in the development split, \( \min(f_w) \) is the token that the \( y_s \) corresponds to, and \( \min(f_w) \) is the minimum frequency of all tokens in the Clotho dataset. We follow the baseline method of the DCASE 2020 audio captioning task, and we use \( L = 3 \), with \( \Xi = 256 \) and \( \Psi = 256 \), which are the same as in the baseline of DCASE 2020 audio captioning task. According to Clotho, \( D = 4366 \). We optimize the parameters of our method using \( \mathcal{L}' \) and the Adam optimizer\footnote{https://github.com/DK-Nguyen/audio-captioning-sub-sampling}, with a learning rate of \( 1e - 4 \) and the values for \( \beta_1 \) and \( \beta_2 \) that are reported to the corresponding paper\footnote{https://github.com/DK-Nguyen/audio-captioning-sub-sampling}, and we employ dropout with a probability of \( p = 0.25 \) between RNN\footnote{https://github.com/DK-Nguyen/audio-captioning-sub-sampling} and RNN\footnote{https://github.com/DK-Nguyen/audio-captioning-sub-sampling} and RNN\footnote{https://github.com/DK-Nguyen/audio-captioning-sub-sampling}.

We choose hyper-parameters that yielded the lowest loss value for the development split, following the above mentioned policy of stopping the training process and implementing a random search over the combinations of \( \Phi_s \) and learning rate of Adam. To evaluate the impact of the sub-sampling, we employ four different values for \( M \), namely 2, 4, 8, and 16. Finally, the total amount of parameters of our method is 4 573 711, and the code of our method is based on the PyTorch framework and is freely available online\footnote{https://github.com/DK-Nguyen/audio-captioning-sub-sampling}.

3.3. Evaluation and metrics

We assess the performance of our method by using the above mentioned processes and hyper-parameters, and employing the metrics used in the DCASE 2020 audio captioning task. Each metric is calculated using the the predicted sequence of words \( \hat{Y} \) for a \( X \), and all the ground truth sequences \( Y \) for the same \( X \). We compare the obtained values against the ones reported by the baseline method.
Table 1: Results for the baseline method, i.e. \( M = 1 \), and our proposed method with sub-sampling factor \( M = \{2, 4, 8, 16\} \).

| Metric      | \( M = 1 \) | \( M = 2 \) | \( M = 4 \) | \( M = 8 \) | \( M = 16 \) |
|-------------|-------------|-------------|-------------|-------------|-------------|
| BLEU        | 0.389       | 0.426       | 0.418       | 0.417       | 0.426       |
| BLEU_1      | 0.136       | 0.151       | 0.151       | 0.154       | 0.147       |
| BLEU_2      | 0.055       | 0.058       | 0.061       | 0.063       | 0.058       |
| BLEU_3      | 0.015       | 0.020       | 0.018       | 0.025       | 0.022       |
| ROUGE_{Lg}  | 0.262       | 0.274       | 0.275       | 0.274       | 0.274       |
| METEOR      | 0.084       | 0.092       | 0.091       | 0.089       | 0.090       |
| CIDEr       | 0.074       | 0.092       | 0.090       | 0.093       | 0.093       |
| SPICE       | 0.053       | 0.040       | 0.037       | 0.040       | 0.036       |
| SPIDEr      | 0.034       | 0.066       | 0.064       | 0.067       | 0.064       |

4. RESULTS AND DISCUSSION

In Table 1 are the values of the employed metrics for the evaluation split of Clotho. As can be seen from Table 1 using a sub-sampling factor \( M \geq 2 \) always improves the values of the metrics. This fact clearly indicates that our proposed method of sub-sampling benefits the performance of audio captioning methods. The maximum value of SPIDEr is obtained for \( M = 8 \), is 0.067, and can be mainly attributed to the better SPICE score than the value of \( M = 8 \) yields. Though, the values of the metrics for the different sub-sampling factors, do not exhibit some systematic behaviour. That is, increasing above 2, i.e. \( M > 2 \) does not result in increasing or decreasing the performance. This can be attributed to the fact that the employed method employs a fixed-length output from the encoder. Thus the increased impact from reducing more the length of the sequence, cannot be observed since the output of the encoder is always a fixed-length vector. This fact strongly indicates that the impact of the increased \( M \) might be more visible in an audio captioning method, that employs an alignment mechanism which uses the whole output sequence of the encoder, and not only a fixed-length vector (e.g. attention).

5. CONCLUSIONS AND FUTURE WORK

In Table 2 is the resulting reduction in the time needed for obtaining all the predicted outputs using the Clotho evaluation split, and the resulting length of the output sequence of the encoder compared to the input sequence \( X \). As can be observed from Table 2, the increase in \( M \) has also a clear impact at the time needed for obtaining the predicted captions. This is to be expected, since with temporal sub-sampling, the output of the encoder is 99.6% shorter compared to the length of the input audio.

In this paper we presented an approach for audio captioning that utilizes temporal sub-sampling, given the empirical observation that a word in a general audio caption refers to a sequence of audio samples. Our approach is focusing on methods that use a multi-layered and RNN-based encoder, utilizing a temporal sub-sampling of the output sequence of each RNN layer of the encoder. We evaluated our approach using the freely available audio captioning dataset, Clotho, using multiple factors of sub-sampling. The obtained results clearly indicate that temporal sub-sampling can benefit the audio captioning methods. We observed an increase at all metrics and with all sub-sampling factors greater than 2, compared to the case of not using sub-sampling (i.e. \( M = 1 \)). The maximum benefit was observed for \( M = 8 \), where an increase of 1.3 is observed for SPIDEr. From the variation of the values of the utilized metrics, according to the different sub-sampling factors, we hypothesize that the temporal sub-sampling might have a more pronounced effect when is employed in a method that uses an alignment mechanism like attention. Though, more research is needed for verifying or disproving that.
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