Rescoring Sequence-to-Sequence Models for Text Line Recognition with CTC-Prefixes

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Abstract. In contrast to Connectionist Temporal Classification (CTC) approaches, Sequence-To-Sequence (S2S) models for Handwritten Text Recognition (HTR) suffer from errors such as skipped or repeated words which often occur at the end of a sequence. In this paper, to combine the best of both approaches, we propose to use the CTC-Prefix-Score during S2S decoding. Hereby, during beam search, paths that are invalid according to the CTC confidence matrix are penalised. Our network architecture is composed of a Convolutional Neural Network (CNN) as visual backbone, bidirectional Long-Short-Term-Memory-Cells (LSTMs) as encoder, and a decoder which is a Transformer with inserted mutual attention layers. The CTC confidences are computed on the encoder while the Transformer is only used for character-wise S2S decoding. We evaluate this setup on three HTR data sets: IAM, Rimes, and StAZH. On IAM, we achieve a competitive Character Error Rate (CER) of 2.95\% when pretraining our model on synthetic data and including a character-based language model for contemporary English. Compared to other state-of-the-art approaches, our model requires about 10-20 times less parameters. Access our shared implementations via this link to GitHub.

Keywords: Text Line Recognition, Handwritten Text Recognition, Document Analysis, Sequence-To-Sequence, CTC

1 Introduction

Optical Character Recognition (OCR), the transcription of digital images into machine-actionable text, is still a challenging problem even though there were great advancements in recent years. A typical OCR pipeline consists of two steps: text detection and text recognition. Currently, most text recognition systems act on lines of text, and thus convert a sequence of arbitrary length (here the width of the text line image) into another sequence of different (typically shorter) length. There are two established approaches to tackle this problem: S2S \cite{11} and CTC \cite{4}.
S2S approaches are a very generic approach as they do not constrain the lengths of the input or output sequence, nor their ordering\(^3\). A S2S system comprises two modules: the *encoder* encodes the line images into features. The *decoder*, starting from an Start-of-Sequence \((\langle \text{sos} \rangle)\)-token, decodes the encoded line character-(or token)-wise until an End-of-Sequence \((\langle \text{eos} \rangle)\)-token is emitted.

Since written visual and decoded characters are ordered in the task of Text Line Recognition (TLR), the CTC algorithm can be applied. Here, analogue to S2S, the line image is first encoded, then CTC decodes the complete sequence in one step: at each position of the encoded feature sequence, CTC predicts either the desired character or a special *blank* character, meaning there is no output. This results in a so-called *confidence matrix* that stores a probability distribution for each character plus the blank for each position in the line. Best path decoding determines the most likely characters, then repeated character predictions are fused and blanks are erased to obtain the final transcription.

S2S has some advantages which are eminent in better accuracies compared to CTC (see, e.g., [10] or [7]), but there are also fundamental problems when it comes to TLR (see, e.g., [14]): a crucial problem is that S2S approaches tend to predict \((\langle \text{eos} \rangle)\)-tokens prematurely or delayed which is why parts of the original sequence are cropped or repeated several times. Similarly, repetition or skipping of characters, digits, or whole words can also occur within the sequence. In TLR, this can result in severe in errors if, for example, repeating digits in a large number are “skipped”. The reason for this behaviour is that the mutual-attention modules are not always certain about the snippet that shall be decoded next. There are attempts to tackle this problem by modifying the attention. A comparison of six different attention versions, e.g., monotonic (force left to right transcription) or penalised (penalising features that were already attended to), was performed by [10] for HTR. In contrast, CTC approaches do not suffer from any of these problems by design. Hence, combining the best of both worlds is reasonable but non-trivial since CTC and S2S have very different concepts for decoding.

Watanabe et al. [12] proposed an algorithm to use CTC scores during decoding with a S2S approach. Their network architecture is constructed similar to S2S approaches using attention, however, a second CTC-based decoder is added to the shared encoder. Upon decoding, the CTC-Prefix-Score is computed to weigh the next character probabilities of the decoder. Since [12] only applied their approach to speech recognition, in this paper, we examine the applicability on TLR which, to the best of our knowledge, has not been performed, yet. Thereto, we setup a traditional CNN/LSTM encoder, and a Transformer-based decoder. Optionally, we add a character-based Language Model (LM).

We evaluate our models on two contemporary and one historic handwritten datasets each in a different language: IAM [8] for English, Rimes [1] for French, and StAZH (not published, yet) for historic Swiss-German.

To summarise, in this paper, we contribute the following:

\(^3\) Arbitrary ordering is required, e.g., for translation tasks.
– We propose a hybrid CTC/Transformer decoder architecture for TLR using both the CTC confidence matrix and S2S based on [12].
– Additionally, we apply pretraining on synthetic data and a LM to achieve state-of-the-art results on IAM.
– We share our Tensorflow-based implementation⁴ of the network architectures, the CTC-Prefix-Scorer, and our beam search.

The remainder of this paper is structured as follows: first, we discuss related work in the area of TLR and HTR. Next, we introduce our methodology and describe the computation of CTC-Prefix-Scores for joint CTC/Transformer-decoding. Afterwards, we present the three datasets and evaluate our methods. We conclude with a discussion of our results and future work.

2 Related Work

In recent years, TLR and HTR have been studied quite excessively. A thorough literature review of handwritten OCR is provided by Memon et al. [9].

Bluche et al. [2] proposed gated convolutional layers in a CNN/LSTM/CTC-based approach achieving a CER of 3.2% on IAM when using a LM with a limited vocabulary size of 50K words. In [10], Michael et al. compare different attention mechanisms in the decoder for S2S-based HTR. Their best model on IAM yielded a CER of 4.87% without the usage of external data or a LM.

Transformers for TLR were first introduced by Kang et al. [5]. They proposed a CNN/Transformer encoder and a Transformer decoder yielding a CER of 4.67% on IAM when pretraining their model on synthetic data, setting a new best value for open vocabulary HTR. This approach was extended by Wick et al. [14] who proposed a bidirectional decoding scheme: one Transformer reads the line forwards, another one backwards. The final results is obtained by voting.

Diaz et al. [3] compared different network architectures and decoding schemes for TLR. They varied Recurrent Neural Networks (RNNs), Gated Recurrent Convolution Layers, and self-attention layers for the encoder, and CTC or Transformer-based S2S for the decoder. Choosing a LM and a pretrained model on an internal real-world dataset, they reached a new state-of-the-art CER of 2.75% using CTC and self-attention on the IAM downstream task.

Li et al. [7] proposed a pure S2S-Transformer-based approach, i.e., they replaced every CNN from the network architecture. Their large model with 558 million parameters achieved a CER of 2.89% on IAM if pretrained on several millions of synthetic lines. A separate LM was not applied since the decoder was already capable to learn an intrinsic LM.

3 Data

To evaluate our proposed methods, we use three different datasets for HTR: IAM [8], StAZH, and Rimes [1]. Table 1 summarises the language, alphabet size |A|, and number of lines for training, validation, and testing.

⁴ https://github.com/Planet-AI-GmbH/tfaip-hybrid-ctc-s2s
Table 1. Overview of the three used datasets showing their language, alphabet size $|A|$, and the number of training, validation, and test lines.

| Dataset     | Language                | $|A|$ | # Train  | # Val   | # Test  |
|-------------|-------------------------|------|----------|---------|---------|
| IAM         | English (en)            | 79   | 6,161    | 966     | 2,915   |
| StAZH       | Swiss-German (de-ch)    | 109  | 12,628   | 1,624   | 1,650   |
| Rimes       | French (fr)             | 100  | 10,171   | 1,162   | 778     |

For the popular IAM-dataset we use Aachen’s partition\(^5\). StAZH is an internal dataset of the European Union’s Horizon 2020 READ project and thus not openly available, yet. The documents contain resolutions and enactments of the cabinet as well as the parliament of the canton of Zurich from 1803 to 1882. We included it for additional results on historical handwritings.

To train our English LM, we collected over 16 million text lines from news, webpages, and wikipedia. For the French LM, we used a wikipedia dump with about 30 million text lines. To train a Swiss-German LM only about 1 million text lines of contemporary Swiss-German language were collected.

4 Methods

In this section we present our proposed approach for line-based HTR. First, we describe preprocessing steps and our network architecture which comprises the CTC- and Transformer-based branches for decoding. Afterwards, we present the training of the model and how inference including the CTC-Prefix-Score and an optional LM is performed. Finally, we describe the training of the character-based LM and our line synthesiser for artificial lines used for pretraining the HTR models.

4.1 Preprocessing

To preprocess a line, we apply contrast normalisation without binarisation, normalisation of slant and height, then scale the line images to a fixed height of 64 pixels while maintaining their aspect ratio. To artificially increase the amount of training data, we augment the preprocessed images by applying minor disturbances to the statistics relevant for the normalisation algorithms. Furthermore, we combine dilation, erosion, and grid-like distortions\(^{15}\) to simulate naturally occurring variations in handwritten text line images. These methods are applied to the preprocessed images randomly each with an independent probability of 50%.

4.2 Network-Architecture

Similar to current approaches, we propose a network architecture that is comprised of three basic components (see Figure 1): a visual backbone that extracts

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\(^5\) https://github.com/jpuigcerver/Laia/tree/master/egs/iam
Fig. 1. Our proposed network architecture. The visual backbone is a CNN with a subsampling factor of 8, the encoder comprises three LSTM-layers, and the decoder is a Transformer build up by stacked self-attention, mutual-attention layers, and absolute positional encoding (PE).

high-level features with a limited receptive field, an encoder that can learn context, and a decoder that transcribes the features into characters. The backbone comprises three convolutional layers and two max-pooling layers which subsample the (rescaled) original line image with a dimension of $64 \times W \times 1$ to a feature map of $4 \times \frac{W}{8} \times 64$. The final output is height-concatenated to a dimension of $\frac{W}{8} \times 256$. The encoder consists of three stacked bidirectional LSTM-layers, each with 256 hidden nodes and a dropout rate of 0.5.

The Transformer decoder first applies a trainable embedding layer on the history of characters, and then adds sinusoidal absolute positional encoding to enable the attention modules to learn the order of characters. Note, that no additional positional encoding is applied to the outputs of the encoder since it is learned autonomously. Afterwards, to learn long range dependencies between the decoder features, a self-attention module, and to couple the textual with the visual features, a mutual-attention module are applied. Last, a Pointwise Feed-Forward (PFF) layer is applied. Two blocks each consisting of one self-attention, one mutual-attention, and one PFF are stacked to form the final output. Ultimately, a dense layer maps the features to the alphabet size $|A| + 1$ (including the (eos)-token).

Each Multi-Head-Attention (MHA) requires three inputs, a query $Q$, key $K$, and value $V$, whereby the output $Y$ is computed as

$$Y_i = \text{Softmax}\left(\frac{Q_i \cdot K_i'}{\sqrt{f}}\right) \cdot V',$$
where \( f \) is the number of features, \( i \) is the \( i \)-th entry of each matrix, and \( Q', K', V' \) are obtained by three independent linear transformations using the matrices \( W_Q, W_K, W_V \). Several so-called attention heads using different transformations are computed in parallel and concatenated afterwards. In a self-attention module, all inputs are identical: \( Q \equiv K \equiv V \).

The backbone and encoder form a sub-network that can be applied for HTR autonomously if decoded with CTC after appending an additional dense layer to map the encoder outputs to \(|A| + 1\) (including the blank token). These outputs, the CTC confidences, are later used during training and decoding (see next Sections).

### 4.3 Training

The total loss \( L_{\text{tot}} \) for training comprises two components: the CTC-loss \( L_{\text{CTC}} \) computed on the CTC confidences, and the character-wise Cross-Entropy-loss \( L_{\text{CE}} \) applied to the decoder outputs. Both losses are weighted by the factor \( \lambda_{\text{CTC}} \in [0, 1] \) which denotes the influence of \( L_{\text{CTC}} \):

\[
L_{\text{tot}} = \lambda_{\text{CTC}} \cdot L_{\text{CTC}} + (1 - \lambda_{\text{CTC}}) \cdot L_{\text{CE}}
\]

Throughout this paper, we set \( \lambda_{\text{CTC}} = 0.3 \) which is a compromise of having a greater influence of the decoder but also a non-negligible encoder contribution.

Teacher forcing is applied to speed-up training by presenting the Ground Truth (GT)-sequence, prefixed with a \( \langle \text{sos} \rangle \) token, to the decoder during training (see Figure 1). The characters in the “future” are masked so that the network has no access for predicting the “next” character. Note that we do not apply label smoothing.

Our setup computes the exponential mean average with a decay of 0.99 of all weights during training to obtain the final model weights for evaluation. We use an ADAM-optimiser with global gradient clipping of 5.0. The learning rate is increased linearly from 0.0 to a maximum of 0.001 after five epochs and then reduced by a factor \( \sqrt{5/i_{\text{epoch}}} \), where \( i_{\text{epoch}} \) is the current epoch. Training is finished if the model saturates on the validation dataset. The best model on the validation dataset is stored as final model.

### 4.4 Inference

During inference (see Figure 2), the decoder transcribes the input character by character starting with a \( \langle \text{sos} \rangle \) token using beam search with a beam width of \( n_{\text{beams}} \). The confidences for the next character are a combination of three parts that each contributes costs \( C \in \mathbb{R}^{(|A| + 1)} \) (alphabet size plus \( \langle \text{eos} \rangle \)), the negative logarithms of the confidences:

- The decoder directly outputs confidences for the next character \( C_{\text{CE}} \).
- Based on the CTC confidences which are computed by the additional dense layer after the encoder (orange), the CTC-Prefix-Score \( C_{\text{CTC}} \) of the next sequence is computed (see next Section).
Fig. 2. The decoding scheme using beam search. The character costs of the CTC-Prefix-Score, the S2S decoder, and LM are weighted ($\lambda_{\text{ctc}}, \lambda_{\text{lm}}$) and summed up to obtain the next best characters for decoding. The history of the decoded sequence (dashed arrows) is required in all three modules to predict the next character. For comparison, best path decoding can be applied directly on the CTC confidences.

- A LM which computes confidences for the next character $C_{\text{LM}}$ solely based on the previous sequence (see Section 4.5).

The total costs $C_{\text{tot}}$ are computed as

$$C_{\text{tot}} = \lambda_{\text{CTC}} \cdot C_{\text{CTC}} + (1 - \lambda_{\text{CTC}}) \cdot C_{\text{CE}} + \lambda_{\text{LM}} \cdot C_{\text{LM}}$$

where $\lambda_{\text{LM}} \in [0, 1]$ is the weight of the LM.

**CTC Prefix Score** The CTC-Prefix-Score decoding of Watanabe et al. [12] is an addition to the S2S decoding scheme by penalising paths in the beam search that contradict the CTC confidences. Here, we provide only a coarse description of their algorithm and refer to the original paper for the algorithms and the mathematical details. For a deeper description of the CTC algorithm we refer to the original paper of Graves et al. [4].

The forward variables of CTC allow to compute the probability of a sequence of characters by summing up the confidences of all possible paths that result in this sequence. The CTC-Prefix-Score is the total score of all paths that start with a given but end with an arbitrary sequence. Watanabe et al. propose to add this score to rescale each path during beam search decoding of S2S. If a path emits an (eos)-token the full CTC-score is used for rescaling. This overall setup prevents paths that prematurely end or skip characters since those receive a bad CTC-Prefix-Score. Unfortunately, the computation is slow since for each beam all possible path endings must be summed up for each decoding step.

**Beam Search** The applied beam search tracks the best $n_{\text{beams}}$ character sequences that have not yet finished, and all (or only the best) completed sequences, i.e., those that predicted an (eos)-token. By default, for each unfinished
sequence, $C_{\text{tot}}$ and its parts are computed. Hereby, as already stated, the computation of the CTC-Prefix-Score is costly if evaluated for every possible next character. To speed up the computation, we determine so-called “pre-beams” (see, e.g., the usage in [6]) which splits the computation of $C_{\text{tot}}$ in

$$C_{\text{pre}} = (1 - \lambda_{\text{CTC}}) \cdot C_{\text{CE}} + \lambda_{\text{LM}} \cdot C_{\text{LM}}$$

and

$$C_{\text{tot}} = \lambda_{\text{CTC}} \cdot C_{\text{CTC}} + C_{\text{pre}}.$$ 

After $C_{\text{pre}}$ is computed, the search space is narrowed by reducing the possible beams to a maximum of $1.5 \cdot n_{\text{beams}}$. Only the CTC-Prefix-Scores for the remaining characters $C_{\text{CE}} \in \mathbb{R}^{1.5 \cdot n_{\text{beams}} + 1}$ are evaluated. Then the actual $n_{\text{beams}}$ best beams are selected. This simplification (if $1.5 \cdot n_{\text{beams}} < |A|$) assumes that the best characters of the decoder are similar to those of the encoder and will lead to only minor differences in the result. To the best of our knowledge, there is no open-source Tensorflow implementation for beam search supporting pre-beams which is why we share our code on GitHub.

### 4.5 Language Model

Our character-based LM is a traditional Transformer (equivalent to the decoder of Figure 1 without mutual-attention) which stacks six self-attention and subsequent PFF layers with 512 output nodes, and 2,048 nodes in the first PFF dense layer. We use 8 attention heads and do not apply dropout. The embedding layer has a dimension of 128. The training hyper-parameters are identical to the ones of training the HTR model.

Text samples are transformed and augmented by applying random transformations on the text:

1. The text is randomly cropped (start and end) to a length between 768 and 1,024 characters.
2. If the first character is upper case, its case is switched with a probability of 0.5, while if it is lower, it is switched with a probability of 0.1.
3. The IAM dataset does not follow traditional spacing rules, e.g., by inserting spaces before punctuation. Therefore, we add an additional rule for IAM only that randomly inserts spaces before, after, or on both sides of $;,-;:‘”‘?!\{\}[]$ with a probability of 0.1. This results in a LM that will have uncertainty on the exact location of spaces and special characters, but high ones on characters.

### 4.6 Synthetic Line Generation

Synthetic handwritten lines are used to pre-train the visual features and also to train the “intrinsic” LM of the decoder. To render synthetic lines (see Figure 3 for some examples), we collected several cursive computer fonts. The sentences are generated analogously to the cropping rules used for the LM (see Section 4.5).
Drinking and driving absolutely not be tolerated by anyone.

To cook, bring a large pot of water to a boil

were 1,472 households with 92.0% of housing units

Fig. 3. Three synthetically rendered lines based on the English text corpus.

Table 2. Top-1 and top-10 accuracies of the trained LMs for correctly predicting the next character on the listed dataset. The model was trained on an additional corpus for the respective language.

| Dataset Language | Top-1 | Top-10 |
|------------------|-------|--------|
| IAM en           | 58.1% | 90.4%  |
| StAZH de-ch      | 52.5% | 87.3%  |
| Rimes fr         | 58.5% | 92.8%  |

Data augmentation during preprocessing (see Section 4.1) then varies the renderings with clean synthetic computer fonts to make the network more robust against real-world data.

5 Results

In this section, we present our evaluation results. The network architecture and decoding are implemented in the open-source framework tfaip \[13\] which is based on Tensorflow. The encoder plus backbone, decoder, and LM comprise 3.2, 1.6, and 19.0 million parameters, respectively. The combined model has about 24 million parameters in total.

First, we show the accuracies of our trained LMs and the performances of the pretrained models applied to the three datasets. Then, we measure the CERs when training on real data, optionally starting from the pretrained models. Next, the LM is added and $n_{beams}$ is varied. We conclude our experiments with an ablation study and a comparison to related work.

5.1 Language Models

Table 2 shows the top-1 and top-10 accuracies, to correctly predict the next character, of the three LMs. The accuracies are stated for the validation datasets of IAM, StAZH, and Rimes, including the augmentations applied in Section 4.5. The independent training data was chosen from the respective datasets (see Section 3).

All LMs yield a top-1 accuracy of over 50% and a top-10 accuracy of about 90%. Note that, as expected, the LM for StAZH is the worst because the data
Table 3. CER given in percent of the models pretrained on artificial lines synthesised for the respective language. We list the CER for using solely the encoder with CTC best path decoding and our proposed CTC/Transformer combination.

| Dataset | CTC Val. | CTC Test | CTC/Trafo Val. | CTC/Trafo Test |
|---------|----------|----------|----------------|----------------|
| IAM     | 17.4     | 19.5     | 15.3           | 17.3           |
| StAZH   | 64.7     | 65.1     | 64.6           | 64.3           |
| Rimes   | 24.3     | 25.1     | 22.4           | 23.0           |

Table 4. Influence of using pretrained models. The CER is given in percent. We list the CER for using solely the encoder with CTC best path decoding and our proposed CTC/Transformer combination.

|            | Validation | Test |
|------------|------------|------|
|            | CTC        | CTC/Tr | CTC    | CTC/Tr |
| IAM        | No         | 3.63   | 3.38   | 5.47   | 5.10   |
| IAM        | Yes        | 3.17   | 2.60   | 4.99   | 3.96   |
| StAZH      | No         | 3.22   | 2.93   | 3.05   | 2.81   |
| StAZH      | Yes        | 3.17   | 2.64   | 3.06   | 2.66   |
| Rimes      | No         | 4.84   | 4.47   | 4.31   | 3.88   |
| Rimes      | Yes        | 4.87   | 4.14   | 4.25   | 3.49   |

of the training corpus is contemporary Swiss-German (de-ch) while StAZH comprises historic documents where spellings are different. Since the French (fr) corpus is larger than the English (en) one, the accuracy is higher. Other reasons for the lower accuracy on English are the different whitespace rules and the additional augmentation to map this.

5.2 Pretraining on Synthetic Data

Table 3 lists the CERs for the pretrained models which are trained exclusively on synthetic data generated for each of the three languages. Naturally, since only synthetic data was used, the models perform very poorly on real world data, especially on StAZH which is the most difficult dataset. Combining CTC and the Transformer for decoding yields slightly better results than the standalone encoder with CTC which is explained by the fact that the decoder learned an intrinsic LM.

5.3 Training on Real Data

Table 4 shows the CER when training on the actual real-world data, optionally using the pretrained model from Section 5.2. On both the validation and test sets of the respective datasets, the CER shrinks when using the pretrained model
Table 5. The upper half shows the influence of using an additional LM during decoding by varying its weight $\lambda_{lm}$. The bottom half investigates the influence of varying the number of beams $n_{beams}$ during beam search decoding. All CERs and WERs are given in percent.

| LM    | CER [%] | WER [%] |
|-------|--------|---------|
|       | 0      | 0.1     | 0.5     | 1     | 0      | 0.1     | 0.5     | 1     |
| IAM   | 3.96   | 3.69    | 3.19    | 3.64  | 12.20  | 11.12   | 9.17    | 10.34 |
| StAZH | 2.66   | 2.66    | 2.79    | 3.81  | 11.87  | 11.75   | 12.48   | 16.72 |
| Rimes | 3.49   | 3.40    | 3.39    | 3.57  | 9.03   | 8.65    | 8.28    | 8.49  |

| Beams | 1  | 5  | 10 | 20 | 1  | 5  | 10 | 20 |
|-------|----|----|----|----|----|----|----|----|
| IAM   | 5.81| 3.19| 3.17| 3.13| 14.09| 9.17| 9.00| 8.93|
| StAZH | 4.37| 2.79| 2.79| 2.79| 15.54| 12.48| 12.48| 12.50|
| Rimes | 4.10| 3.39| 3.19| 3.19| 9.19 | 8.28 | 7.61 | 7.61 |

and CTC/Transformer for decoding. However, the benefit is clearly higher for the IAM dataset. If only using CTC for decoding, pretraining has a smaller impact, and even leads to slightly worse results for StAZH on the test set and for Rimes on the validation set. Since the CTC branch only includes visual information, we explain this by the handwritten computer fonts which are more similar to IAM but differ considerably from the writings in the other two datasets. This however shows that the pretrained decoder actually learned an intrinsic LM because using the pretrained model always shows an improved CER when using CTC/Tr.

5.4 Enabling the Language Model

Even though the decoder of the HTR model is already capable to learn a LM as shown in the previous section, we examine if an additional specialised and larger LM (see Section 4.5) further improves the results. The upper half of Table 5 summarises the results by setting $\lambda_{lm}$ to 0, 0.1, 0.5, and 1 ($n_{beams} = 5$). $\lambda_{lm} = 0$ corresponds to using no LM and thus to the values of Table 4 (last column). Here, we only show the results when combining all three decoding paths (CTC/Tr/LM), see Figure 2).

On IAM, the LM with $\lambda_{lm} = 0.5$ yields clearly improved results (CER = 3.2%) which further reduces the CER by 20% (relative). This shows that the intrinsic LM of our HTR model is not yet powerful enough to “fully” learn the English language.

In contrast, using the LM trained on a contemporary Swiss-German corpus does not further improve the results on the historic StAZH dataset, instead the results worsen. The reason is that the historic and contemporary writings are too different and therefore induce errors instead of correcting misspellings.

Similar to IAM, the French LM fits well. However, since the French alphabet size is larger than the English one, a higher beam count is required to obtain the best results as shown in the next Section.
5.5 Varying the Beam Count

The bottom half of Table 5 lists the CERs and WERs when varying \( n_{\text{beams}} \) if using a LM with \( \lambda_{\text{LM}} = 0.5 \). Setting \( n_{\text{beams}} = 1 \) corresponds to best path decoding. The results show that increasing \( n_{\text{beams}} \) from one to five has the highest impact on the results. On IAM, further increases only led to small improvements. More beams on StAZH had no impact because the LM does not fit well. Setting \( n_{\text{beams}} = 10 \) further reduced the error rates on Rimes which we explain by the bigger alphabet size due to characters with diacritics such as “é, è, ê, è”.

5.6 Ablation Study

Furthermore, we performed an ablation study to measure the impact of pretraining, the inclusion of a LM, and the decoder. We chose IAM, set \( \lambda_{\text{LM}} = 0.5 \) (if a LM is used), and \( n_{\text{beams}} = 5 \). The results of the CERs and WERs are listed in Table 6 (upper half).

As expected, the CER always benefits from starting with a model pretrained on synthetic data. In experiments A and B we only use the encoder combined with CTC-best-path-decoding which therefore primarily shows the influence of pretraining on the visual backbone and the BiLSTM-encoder: using pretraining improves the CER by about 9%, relatively. The Transformer decoder benefits by a larger margin (see, e.g., G and I where the CER is reduced by about 23%). The reason is that the Transformer can learn an intrinsic LM in addition to the improved visual features from the encoder.

Comparison of C-F to G-J, respectively, shows the impact of the CTC-Prefix-Score during decoding which always leads to improved results, independent of using pretraining or a LM. Furthermore, it is astonishing that combining a LM with a non-pretrained model results in very bad CERs (D). Visual inspection of the transcribed lines shows that there are many lines that are too short, i.e., words were skipped inbetween but mainly at the end. Here, the CTC-Prefix-Score (H) has a high impact since it penalises beams that do not cover all characters that are detected by the encoder.

Our best model (without additional training data, K) is obtained by combining all proposed improvements (pretraining on synthetic data, a LM, and adding the CTC-Prefix-Score) and a bigger beam width of \( n_{\text{beams}} = 20 \), resulting in a CER of 3.13% and a WER of 8.94%.

The last column of Table 6 lists the number of lines that can be processed per second, using a batch size of 1 and CPU decoding only. The numbers show that using S2S instead of CTC results in a slowdown of about 5-6. The combination of S2S with the CTC-Prefix-Score further reduces the speed by a factor of about 3. Adding a LM reduces the decoding speed by another factor of about 2. Thus, with \( n_{\text{beams}} = 5 \), this results in a speed reduction of about 26.

Increasing \( n_{\text{beams}} \) by a factor of 4 does reduce the decoding speed by another factor of 2 (only). The dependency for low beam counts is non-linear since all beams can be processed in parallel.
Table 6. Ablation study and comparison with related work. All CERs and WERs are given in percent. Transformers (Tr) in the encoder are comprised of stacked self-attention layers, Transformers in the decoder consist of mixed self- and mutual-attention layers. Our decoding is performed with 5 beams, exclusions with 20 beams are marked. “+ Data” denotes whether during training additional synthetic (syn) or real data is used, or if the IAM validation set is included (val). The LM column lists if a LM (trained on external corpora) with open vocabulary (Open) or with a limited vocabulary size (50K works) was used during inference. The number of parameters (#P) are given in millions. The last column lists the number of samples that can be processed per second using a batch size of 1 and a CPU only.

| Authors | Enc. | Dec. | + Data | LM | CER  | WER  | #P  | #/s |
|---------|------|------|--------|----|------|------|-----|-----|
| A Ours  | LSTM | CTC  | No     | No | 5.47 | 17.93| 3.2 | 10.77|
| B Ours  | LSTM | CTC  | Syn    | No | 4.99 | 16.85| 3.2 | 11.57|
| C Ours  | LSTM | Trafo| No     | No | 5.61 | 16.24| 4.8 | 1.90 |
| D Ours  | LSTM | Trafo| No     | Open| 14.38| 18.25| 24  | 0.50 |
| E Ours  | LSTM | Trafo| Syn    | No | 4.15 | 12.22| 4.8 | 2.50 |
| F Ours  | LSTM | Trafo| Syn    | Open| 6.46 | 13.38| 24  | 0.86 |
| G Ours  | LSTM | CTC/Tr| No  | No | 5.09 | 15.88| 4.8 | 0.69 |
| H Ours  | LSTM | CTC/Tr| No  | Open| 4.33 | 12.69| 24  | 0.37 |
| I Ours  | LSTM | CTC/Tr| Syn | No | 3.96 | 12.20| 4.8 | 0.70 |
| J Ours  | LSTM | CTC/Tr| Syn | Open| 3.20 | 9.19 | 24  | 0.40 |
| K Ours (20) | LSTM | CTC/Tr| Syn/Val| Open| 3.13 | 8.94 | 24  | 0.18 |
| L Ours  | LSTM | CTC/Tr| Syn/Val| Open| 3.01 | 8.81 | 24  | 0.42 |
| M Ours (20) | LSTM | CTC/Tr| Syn/Val| Open| 2.95 | 8.66 | 24  | 0.18 |
| N Bluche [2] | LSTM | CTC  | No  | 50K | 3.2  | -    | 0.75 | -   |
| O Michael [10] | LSTM | S2S  | Val | No  | 4.87 | -    | -    | -   |
| P Kang [5] | Tr   | Tr   | Syn  | No  | 4.67 | 15.45| -   | -   |
| Q Wick [14] | Tr   | Bi-Tr| No   | No  | 5.67 | -    | -    | -   |
| R Diaz [8] | Tr   | CTC  | Syn/Real | Open| 2.75 | -    | ≈12  | -   |
| S Li [7]   | Tr   | Tr   | Syn  | No  | 3.42 | -    | 334  | -   |
| T Li [7]   | Tr   | Tr   | Syn  | No  | 2.89 | -    | 558  | -   |

5.7 Comparison with the State of the Art

Table 6 also includes performances of previous publications. Our best model yields a competitive CER of 3.13% which outperforms most previous models that, similar to our approach, do not include additional real-world data for training (N-Q). We even outperform N who use, in contrast to our open vocabulary LM, a LM with a limited vocabulary size of 50,000 words. Comparing P to E, which are comparable setups, in terms of including synthetic data and only using the Transformer for decoding, shows that our overall method is superior. The reasons might be our preprocessing or the different network architecture. Q can be compared to C since both use the same preprocessing pipeline but a different network architecture which explains the similar results.
Setup R which achieves the current best value with a CER of 2.75% also includes a large amount of additional real-world data which is why a direct comparison must be considered as biased. Nevertheless, this verifies our observations that including additional data (here the validation set of IAM) further improves the results up to a CER of 3.01% and 2.95%, for \( n_{\text{beams}} = 5 \) or 20 (L and M), respectively.

The large model of the recent publication of Li et al. [7] (T) also outperforms our best model, while their base model (S) is significantly worse even though this model is already significantly larger (334M vs 24M parameters). We expect that the increased model size in cooperation with a improved text synthesising method, as used by [7], explains their further improvements.

6 Future Work

In this paper, we proposed the combination of a CNN/LSTM-encoder and Transformer-decoder network for TLR. To solve intrinsic problems of the S2S-approach, we added the CTC-Prefix-Score [12] which was, to the best of our knowledge, not yet applied in the context of TLR. Furthermore, we added a separately trained Transformer as a LM. On the well-established IAM-dataset, we achieved a competitive CER of 2.95% significantly outperforming a current state-of-the-art model with ten times more parameters [7]. Our approach is outperformed solely by a significantly larger model ([7], 20 times more parameters), or by including an additional dataset with other real-world handwritten data [3].

A crucial disadvantage of our approach compared to CTC-based ones is the very slow decoding time. In practice, this must outweigh the gain in performance for the actual use-case. Even though we already incorporated some methods to speed up decoding, e.g., by reducing the search space of the CTC-Prefix-Score, other possibilities must be explored. A straightforward approach is to use tokens instead of single characters. Since a token comprises several characters, and can thus form syllables or even complete words, the number of iterated decoding steps is massively reduced. For TLR, this approach has already proven to be successful by [7].

References

1. Augustin, E., Carré, M., Grosicki, E., Brodin, J.M., Geoffrois, E., Prêteux, F.: Rimes evaluation campaign for handwritten mail processing. In: International Workshop on Frontiers in Handwriting Recognition (IWFHR’06). pp. 231–235 (2006)
2. Bluche, T., Messina, R.: Gated convolutional recurrent neural networks for multilingual handwriting recognition. In: 2017 14th IAPR international conference on document analysis and recognition (ICDAR). vol. 1, pp. 646–651. IEEE (2017)
3. Diaz, D.H., Qin, S., Ingle, R., Fujii, Y., Bissacco, A.: Rethinking text line recognition models. arXiv preprint arXiv:2104.07787 (2021)
4. Graves, A., Fernández, S., Gomez, F., Schmidhuber, J.: Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks. In: Proceedings of the 23rd international conference on Machine learning. pp. 369–376. ACM (2006)
5. Kang, L., Riba, P., Rusiñol, M., Fornés, A., Villegas, M.: Pay attention to what you read: Non-recurrent handwritten text-line recognition. arXiv preprint arXiv:2005.13044 (2020)
6. Li, C., Shi, J., Zhang, W., Subramanian, A.S., Chang, X., Kamo, N., Hira, M., Hayashi, T., Boeddeker, C., Chen, Z., Watanabe, S.: ESPnet-SE: End-to-end speech enhancement and separation toolkit designed for ASR integration. In: Proceedings of IEEE Spoken Language Technology Workshop (SLT). pp. 785–792. IEEE (2021)
7. Li, M., Lv, T., Cui, L., Lu, Y., Florencio, D., Zhang, C., Li, Z., Wei, F.: Trocr: Transformer-based optical character recognition with pre-trained models. arXiv preprint arXiv:2109.10282 (2021)
8. Martí, U.V., Bunke, H.: The iam-database: an english sentence database for offline handwriting recognition. International Journal on Document Analysis and Recognition 5(1), 39–46 (Nov 2002)
9. Memon, J., Sami, M., Khan, R.A., Uddin, M.: Handwritten optical character recognition (ocr): A comprehensive systematic literature review (slr). IEEE Access 8, 142642–142668 (2020)
10. Michael, J., Labahn, R., Grüning, T., Zöllner, J.: Evaluating sequence-to-sequence models for handwritten text recognition. In: 2019 International Conference on Document Analysis and Recognition (ICDAR). pp. 1286–1293. IEEE (2019)
11. Sutskever, I., Vinyals, O., Le, Q.V.: Sequence to sequence learning with neural networks. In: Advances in neural information processing systems. pp. 3104–3112 (2014)
12. Watanabe, S., Hori, T., Kim, S., Hershey, J.R., Hayashi, T.: Hybrid ctc/attention architecture for end-to-end speech recognition. IEEE Journal of Selected Topics in Signal Processing 11(8), 1240–1253 (2017)
13. Wick, C., Kühn, B., Leifert, G., Sperfeld, K., Strauß, T., Zöllner, J., Grüning, T.: tfaip—a generic and powerful research framework for deep learning based on tensorflow. Journal of Open Source Software 6(62), 3297 (2021)
14. Wick, C., Zöllner, J., Grüning, T.: Transformer for handwritten text recognition using bidirectional post-decoding. In: International Conference on Document Analysis and Recognition. pp. 112–126. Springer (2021)
15. Wigington, C., Stewart, S., Davis, B., Barrett, B., Price, B., Cohen, S.: Data augmentation for recognition of handwritten words and lines using a cnn-lstm network. In: ICDAR. pp. 639–645 (11 2017)