Recurrence-free unconstrained handwritten text recognition using gated fully convolutional network

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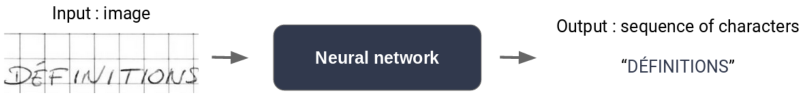
Deep learning handwriting recognition system



Constraints

- Images (input) of variable size
- Sequence of characters (output) of variable length

Sequence alignment

Connectionist Temporal Classification (CTC) [Graves2006]

State of the art

Recurrent models (recurrent layers)

- Multi-Dimensional Long-Short Term Memory (MDLSTM) [Pham2014; Voigtlaender2016]
- Convolutional Neural Network + Bidirectional Long-Short Term Memory (CNN+BLSTM) [Puigcerver2017]

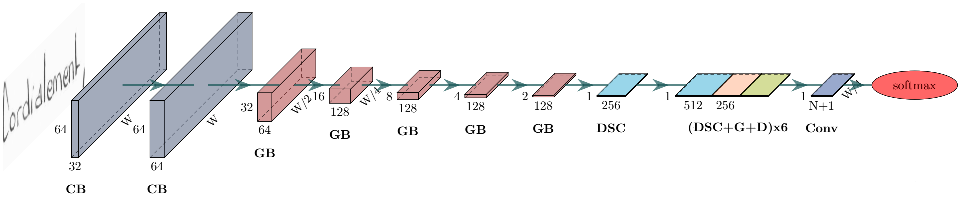
Non-recurrent models

- Convolutional Neural Networks (CNN) [Ptucha2018]
- Gated Fully Convolutional Network (GFCN) [Yousef2018; Ingle2019]

Attention models (recurrent process)

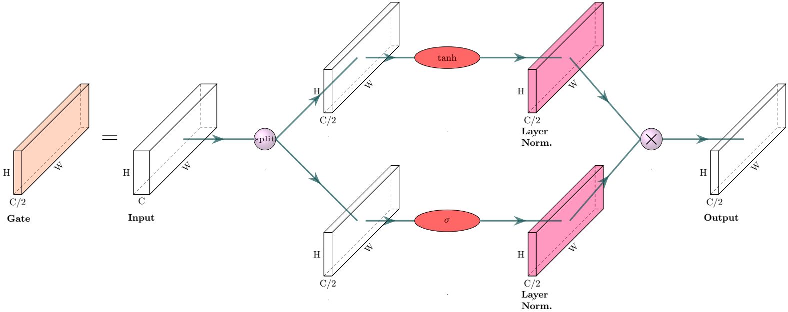
- Encoder-decoder architecture with soft attention [Chowdhury2018; Michael2019]

Our GFCN model



- G (Gate)
- DSC (Depthwise Separable Convolution)
- CB (Convolution Block) = Conv + Conv + Instance Norm. + Dropout
- GB (Gate Block) = DSC + DSC + Instance Norm. (+ MaxPooling) + Gate + Dropout
- (H, W, C) = (Height, Width, Feature maps)
- N = charset size (+ 1 for the CTC blank)

Gate


H
C/2
W
Gate
=
H
C
W
Input
split
H
C/2
W
H
C/2
W
tanh
σ
H
C/2
W
Layer
Norm.
H
C/2
W
Layer
Norm.
H
C/2
W
Output

Details

Architecture

- Deep: 22 convolutional layers
- Parameters: 1.4 M
- Receptive field: (196, 240)
- Input: Fixed-height image (64px) preserving the original width

Hyperparameters

- Framework: Pytorch
- Optimizer: Adam(0.0001)
- loss: CTC

Datasets

- grayscaled line text images (300dpi)

Dataset characteristics

Dataset	Training	Validation	Test	Alphabet	Language
RIMES	9,947	1,333	778	100	French
IAM	6,482	976	2,915	79	English

Example

[RIMES]

[IAM]

Normalization techniques - visualisation

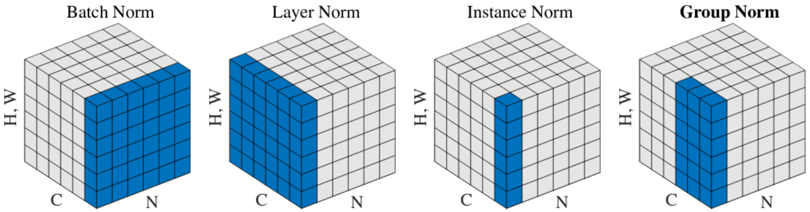


Image from [Wu2018]

- N: Mini-batch size
- H: Height
- W: Width
- C: Feature maps

Normalization techniques - results

Normalization	CER (%) 50 epochs	CER (%) 100 epochs	CER (%) 150 epochs	CER (%) 200 epochs	Time (/epoch)
Instance	6.87	**5.03**	**4.47**	**4.28**	**8.5 min**
Layer	**6.75**	5.04	**4.47**	**4.28**	15 min
Group (32)	7.10	5.30	4.86	4.32	8.75 min
Batch	9.6	5.7	5.4	4.8	**8.5 min**

Table: Effect of type of normalization for our GFCN with the RIMES dataset (for a mini-batch size of 2). CER is computed on the valid set.

Impact of ending blocks

Number of ending blocks (DSC+G+D)	CER (%) 100 epochs	CER (%) 200 epochs	Parameters	Receptive Field (h, w)
6 (baseline)	6.82	**5.80**	1,375,792	(196, 240)
5	**6.69**	5.97	1,241,904	(196, 212)
4	8.14	7.48	1,108,016	(196, 184)
3	6.93	6.23	974,128	(196, 156)
2	7.35	6.63	840,240	(196, 128)
1	8.30	7.83	706,352	(196, 100)

Table: Impact of the receptive field on the IAM dataset. CER is computed over the valid set.

IAM

Architecture	CER (%) validation	WER (%) validation	CER (%) test	WER (%) test	Parameters
2D-LSTM [Moysset2019]	5.41	20.15	8.88	29.15	0.8 M
2D-LSTM-X2 [Moysset2019]	5.40	20.40	8.86	29.31	3.3 M
CNN + 1D-LSTM [Puigcerver2017]	5.1		8.2		9.6 M
CNN + 1D-LSTM [Moysset2019]	**4.62**	17.31	**7.73**	25.22	9.6 M
Ours	5.23	21.12	7.99	28.61	1.4 M

Table: Comparative results on the IAM dataset without LM, lexicon nor data augmentation.

RIMES

Architecture	CER (%) validation	WER (%) validation	CER (%) test	WER (%) test	Parameters
2D-LSTM [Moysset2019]	3.32	13.24	4.94	16.03	0.8 M
2D-LSTM-X2 [Moysset2019]	3.14	12.48	4.80	16.42	3.3 M
CNN + 1D-LSTM [Moysset2019]	**2.9**	11.68	4.39	14.05	9.6 M
CNN + 1D-LSTM [Puigcerver2017]	3.0		**3.3**		9.6 M
Ours	3.82	15.60	4.35	18.01	1.4 M

Table: Comparative results on the RIMES dataset without LM, lexicon, nor data augmentation.

Conclusion

Our model

- A recurrent-less fully convolutional network
- Deep, with a large receptive field
- Competitive results on both RIMES and IAM datasets

Future works

Improving the performances

- Implement a data augmentation strategy

Toward paragraph-level text recognition

- Seq2Seq model with attention [Bluche2016; Bluche2017]

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Standard Convolution

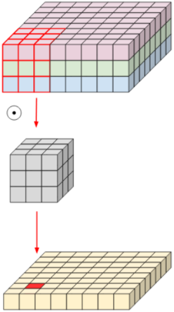
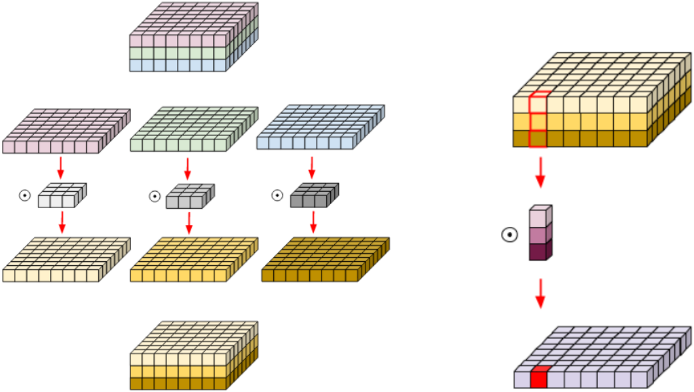


Image from
https://eli.thegreenplace.net/2018/depthwise-separable-convolutions-for-machine-learning/

Depthwise Separable Convolution



(a) Depthwise convolution (b) Pointwise convolution

Image from
https://eli.thegreenplace.net/2018/depthwise-separable-convolutions-for-machine-learning/

CTC

Image from `https://distill.pub/2017/ctc/`