Context	Studied architectures	Experiments	Conclusion	References
ŀ	Have convolutions alre for unconstrained	eady made ro handwriting	ecurrence obs recognition ?	olete
	Denis Coquenet, Yann So	oullard, Clémen Paquet	t Chatelain, Thie	rry

LITIS Laboratory - EA 4108 Normandie University - University of Rouen, France

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Sequence alignment

Connectionist Temporal Classification (CTC)

Focus on optical model only without language model nor lexicon constraints

Recurrent models

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

Non-recurrent models

- Fully Convolutional Networks (FCN) [Ptucha2018]
- FCN with gating mechanism [Yousef2018; Ingle2019]

Do we really need recurrence for handwritten text recognition ?



Our baseline model - CNN+BLSTM



Features

- From [Soullard2019] (state-of-the-art results)
- Recurrent model
- 8 convolutions
- 2.5 million of parameters

n : number of characters in the alphabet

Experiments

Our Gated-CNN - overview



Features

- Based on baseline model
- Non-recurrent model
- 21 convolutions
- 6.9 million of parameters
- Shared weight layers
- Depthwise Separable Convolutions
- Residual connections

Our G-CNN - gates

Gating mechanism



Cont	ext Studied architectures	Experiments	Conclusion	References
RII	MES dataset			
	Dataset characteristics			
	 +1,300 writers 			

- French writings
- 12,723 pages segmented into lines

RIMES dataset split

Training	Validation	Test	Alphabet
9,947	1,333	778	100

Example

First experiment : Raw comparison

Architecture	CER(%)	CER (%)	Training	Parameters (M)
Architecture	validation	test	time	r arameters (m)
CNN+BLSTM	6.98	6.88	1d22h59	4.1
CNN+Dense only	17.73	19.03	1h10	1.5
G-CNN	9.92	10.03	10h00	6.9

• BLSTM layers responsible for a large amount of parameters (2.6 M)

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- BLSTM layers responsible for a large amount of parameters (2.6 M)
- BLSTM layers increase performance dramatically (-12.15 in test)
- G-CNN : more parameters but training time shorter (parallel computing)

Second experiment - Robustness against complexified data

Modified version of RIMES dataset

Lined paper background addition

Examples



• Similar behavior - CER increased by 2.39 for the CNN+BLSTM and 2.52 for the G-CNN

Third experiment - Impact of data augmentation

7-time augmented training set

- Raw
- contrast alteration
- sign flipping
- long/short scaling
- width/height dilation
- \bullet CER decreased by 1.3 for the G-CNN and 0.94 for the CNN+BLSTM

Context	Studied architectures	Experiments	Conclusion	References
Conclusi	ion			
CNIN	DICTM			

- Better performance
- Longer training time

G-CNN

- Deeper networks, bigger receptive fields
- Architecture and tuning complex
- Gating mechanism almost enables to reach the same performance

Future works: exploring other alternatives

- Toward an even lighter network with FCN
- Attention models [Michael2019]

Context	Studied architectures	Experiments	Conclusion	References
References	5			
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