The UOB-Télécom ParisTech Arabic handwriting recognition and translation systems for the OpenHaRT 2013 competition

Olivier Morillot^a, Cristina Oprean^a, Laurence Likforman-Sulem^a, Chafic Mokbel^b, Edgard Chammas^b and Emmanuèle Grosicki^c

> ^aTélécom ParisTech and CNRS LTCI, Paris, France ^bUniversity of Balamand, Tripoli, Lebanon ^cDGA, Paris, France

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NIST Open Handwriting Recognition and Translation Evaluation & Workshop (OpenHaRT 2013)

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OpenHaRT 2013 competition

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Outline

- 1 Working team and submitted systems
- 2 Preprocessing and feature extraction
- 3 Recognition task (DIR)
 - BLSTM system
 - HMM system
 - Language modeling
 - Performances
- 4 Translation tasks (DTT & DIT)
 - Framework
 - Performances
- 5 Conclusion

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Two research groups

- Télécom ParisTech (Institut Mines-Télécom): Laurence Likforman-Sulem, Cristina Oprean, Olivier Morillot and Emmanuèle Grosicki
- University of Balamand: Chafic Mokbel and Edgar Chammas

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Submitted systems

Document Image Recognition (DIR): 4 systems submitted

- 1 BLSTM recognizer (primary: p-blstm)
- ▶ 3 HMM recognizers (contrastive: c-baseline, c-contextualhmm, c-hmm)
- Document Text Translation (DTT):
 - 2 systems using MOSES toolkit (constrained: p-baseline_1, unconstrained: p-baseline_2)
- Document Image Translation (DIT):
 - ▶ 1 system using HMMs and MOSES toolkit (p-baseline_1)

Text line approach

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Segmentation-free text-line approach



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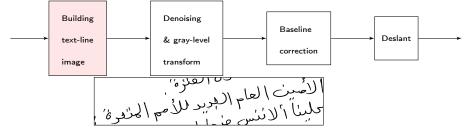
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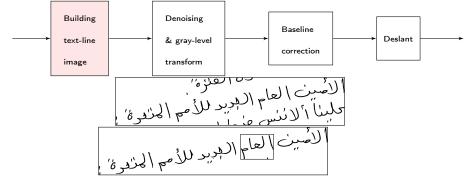


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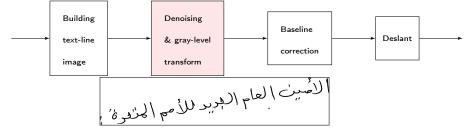


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Segmentation-free text-line approach



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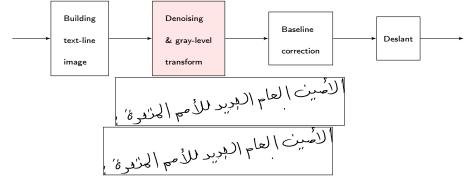
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Segmentation-free text-line approach

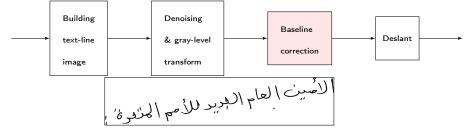


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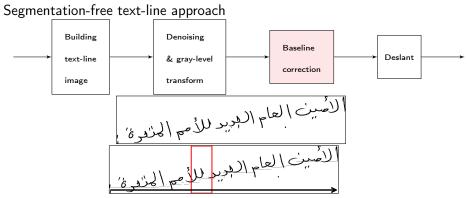


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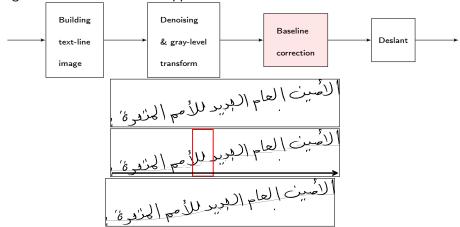


[Morillot et al., A new baseline correction algorithm for text-line recognition with bidirectional recurrent neural networks, Journal of Electronic Imaging, 2013]

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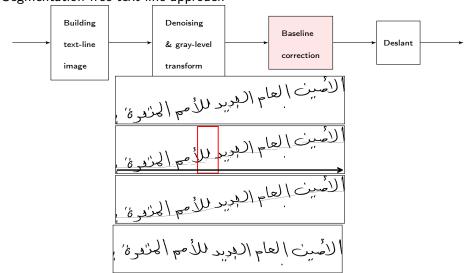
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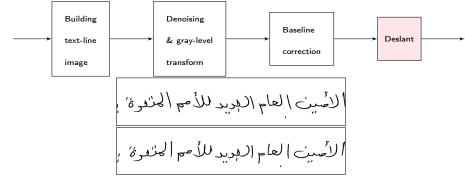


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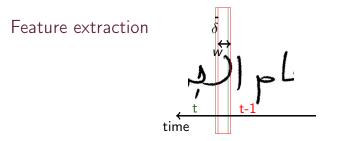


Figure : Overlapping sliding window extraction

- Extraction window width w = 9, shift $\delta = 2$
- 37 features: statistical and geometrical

[Al-Hajj-Mohamad et al., 2009, Oprean et al., 2013]

- 2 features representing background/foreground transitions,
- ▶ 12 features: concavity configurations,
- 3 features: gravity center position,
- ▶ 3 features: density of pixels, above and below the baselines,
- ▶ 8 directional features: histogram of gradients for 8 orientations.

Derivative features -> 74 features

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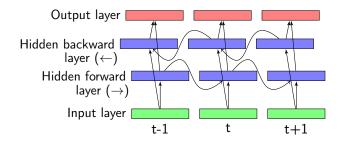
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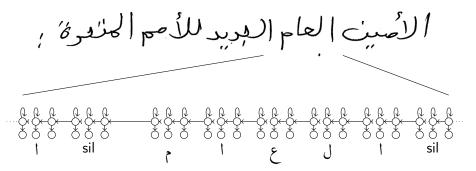
BLSTM system

Bidirectional recurrent network:



- LSTM blocks [Hochreiter and Schmidhuber, 1997]
- ▶ 1 Hidden layer for each direction: 100 blocks per layer
- BLSTM implementation introduced in the works of [Graves et al., 2009]

HMM system



- Bakis topology: no transition from a state to a previous state
- Context-dependent and context-independant modeling of characters
- 5 states for small size letters and punctuations
- 8 states were used for larger letters
- Observation probability density function: mixture of 32 Gaussians
- HTK library

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Language modeling

- Bigram model with back-off strategy
- Based on training database text-lines' transcriptions
- ► SRILM library

DIR experimental conditions

System id	Method	Training data	Dic/LM size
p-blstm	BLSTM	11%	22,000 words
c-hmm	НММ	11%	30,000 words
c-contextualhmm	contextual HMM	11%	30,000 words
c-baseline	contextual HMM	all words and	33,000 words
		3.5% of line images	

11% of training data: mix between different document categories (AAW, AHR, arb, $\ldots)$

DIR results

0.8 0.6 Accuracy (1-WER) 0.4 0.2 UOB-TelecomParisTech (p-blstm 1_20130430) [0.520663] UOB-TelecomParisTech (c-baseline 1-20130430) [0.252403] UOB-TelecomParisTech (c-hmm_1_20130490) [0 214040] UOB-TelecomParisTech (c-contextualhmm_1_20130430) [0.065131] 0 0 20 40 80 100 60 Documents (in %)

2013 / DIR / LINE / CONSTRAINED / ALL / 1-WER

Figure : UOB-TelecomParisTech DIR results

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Machine translation: framework

- f word string in the foreign language (here Arabic)
- e word string in the native language (here English)
- e* set of word strings in the native language
- Goal: Find the most probable native language sentence e provided the observed foreign sentence f
- $\blacktriangleright \ \widetilde{e} = \arg \max_{e \in e^*} P(e|f) = \arg \max_{e \in e^*} P(f|e)P(e)$
- P(e) usually known as the statistical language model in the native language.
- Defining P(f|e) not straight-forward

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Machine translation: our systems

- Systems built with MOSES toolkit
- Constrained systems using training data provided by the NIST:
 - DTT system trained on actual transcriptions of sentences
 - DIT system trained on actual transcriptions of sentences
- Unconstrained DTT system based on a previous model:
 - Trained on LDC "Arabic News Translation Text Part 1" database (LDC 2004T17)
 - 440,000 arabic words (vocabulary: 25,000 words)
 - Newspaper articles: AFP, Xinhua and An Nahar

DTT & DIT experimental conditions

System id	Training data	Dic/LM size
DTT p-baseline-1	100%	50,000
DIT p-baseline-1	100%	50,000

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DTT results

0.8 0.6 Accuracy (1-TER) 0.4 0.2 UOB-TelecomParisTech (p-baseline_1_20130514) [0.213126] 0 0 20 40 80 100 60 Documents (in %)

2013 / DTT / LINE / CONSTRAINED / ALL / 1-TER

Figure : UOB-TelecomParisTech DTT results

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DIT results

0.8 0.6 Accuracy (1-TER) 0.4 0.2 UOB-TelecomParisTech (p-baseline_1_20130430) [0.081458] 0 0 20 40 80 100 60 Documents (in %)

2013 / DIT / LINE / CONSTRAINED / ALL / 1-TER

Figure : UOB-TelecomParisTech DIT results

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Conclusion

- Best recognition result with BLSTM: 1 WER = 52%
- Only 11% of the available data used for training (16,000 out of 145,000 text-lines)
- Text-line approach
- Perspectives
 - Use a larger part of training data
 - Combine recognizers
 - Using the recognizer's outputs for DIT training
 - Factored language models to improve translation

Thank you !

Image: A matrix

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