The LITIS arabic handwriting recognition system

Lattice-based Combination Framework for HMM-based Handwriting Recognition Systems

Kamel Ait Mohand and Thierry Paquet
LITIS laboratory, University of Rouen

OpenHaRT workshop
August 23, 2013

Summary

Summary

OpenHaRT

- LITIS laboratory, Rouen, France
- DIR task, OpenHaRT 2013 competition
- Constrained and LINE segmentation condition
- Two systems submitted :
  - baseline system based on Hidden Markov Models
  - combination of the outputs of several systems (Primary)

Summary

Pre-processing

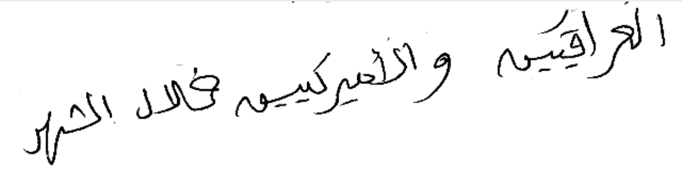
- First : extract line images (coordinates from MADCAT segmentation files)
- process line : image –> set of feature vectors
- Pre-processing chain :
  - image quality enhancement :
    - Wiener and bilateral filtering
    - contrast enhancement
    - mathematical morphology operations (noise removal)
  - adaptive binarization (Sauvola algorithm)
  - “normalize” style of writing :
    - deskew
    - deslant
    - Size normalization

Line deskew

Principle

- Correction of the line slope (*deskew*)
  - skewed line image
  - find extrema points
  - estimate line slope
  - slope correction (rotate line in the opposite direction)

Illustration

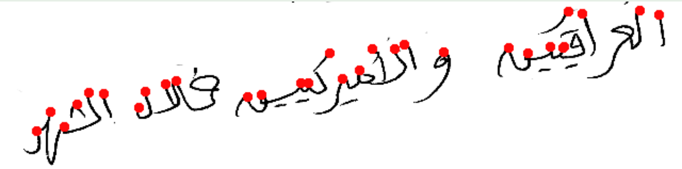


Line deskew

Principle

- Correction of the line slope (*deskew*)
  - skewed line image
  - find extrema points
  - estimate line slope
  - slope correction (rotate line in the opposite direction)

Illustration



Line deskew

Principle

- Correction of the line slope (*deskew*)
  - skewed line image
  - find extrema points
  - estimate line slope
  - slope correction (rotate line in the opposite direction)

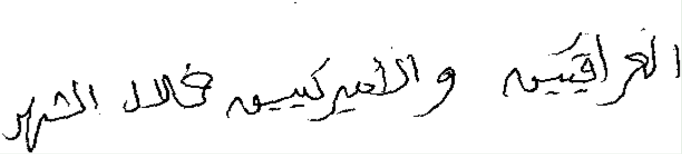
Illustration

Line deskew

Principle

- Correction of the line slope (*deskew*)
  - skewed line image
  - find extrema points
  - estimate line slope
  - slope correction (rotate line in the opposite direction)

Illustration

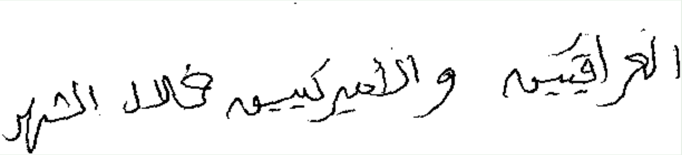


Line deslant

Principle

- Estimate the average slope angle of the characters :
  - histogram of the directions of Freeman contour
- Slope correction by a linear transformation :
  - shift each foreground pixel depending on its position

Illustration

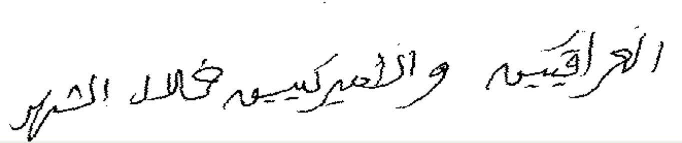


Line deslant

Principle

- Estimate the average slope angle of the characters :
  - histogram of the directions of Freeman contour
- Slope correction by a linear transformation :
  - shift each foreground pixel depending on its position

Illustration

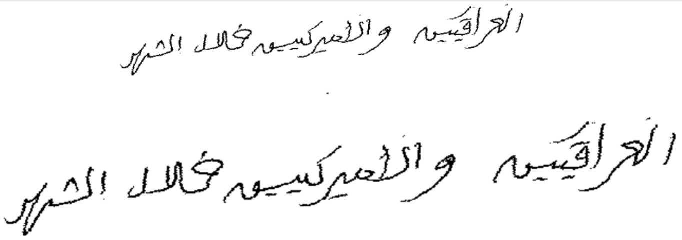


Size normalization

Principle

- Normalization of the line height
- Interpolation (Sinc kernel, “Lanczos”)
- Standard value of 48 pixels
- Purpose : homogeneity of lines content

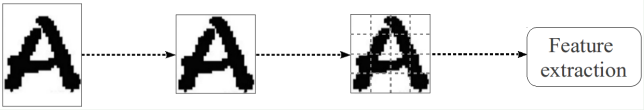
Illustration



Feature extraction

Procedure

- Sliding window approach (no explicit segmentation)
- For each window position :
  - 128 features histogram of gradient orientation
    - 4×4 grid
    - 8 discrete values for the gradient orientation
    - total : 128 features
  - 5 features for position and size of the connected components
  - Finally : 133 features
  - Good performance on latin script (arabic ?)

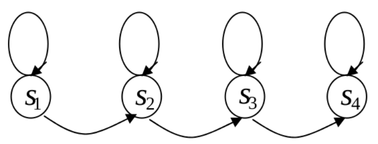


Summary

Character modelisation

- Primarily designed for latin script (no adaptation for arabic)
- One character = one Hidden Markov Model (HMM)
  - left-right continuous
  - mixtures of Gaussians data modelisation
- 144 characters :
  - contextual Arabic letters
  - digits
  - punctuations
  - inter-word space

left-right HMM



Training the models

Hidden Markov Models

- Hidden Markov Model :
  - a set of N states
  - a mixture of G gaussians for each states
  - parameters : transition prob., Gaussians μ and Σ
- Train HMMs :
  - find the best structure (define G and N)
    - heuristic method of Zimmermann and Bunke
  - estimate the parameters values
    - Baum-Welch algorithm
- Optimal values :
  - number of states : from 8 to 24
  - $G = 20$
  - 20 Baum-Welch iterations

Recognition phase

- Process the image (pre-processing, feature extraction)
- Recognition engine :
  - set of HMM models
  - arabic lexicon (64.000 words)
  - n-gram language model estimated on a 10,000,000 words corpus
- decoding with a two-pass forward-backward search
  - 1st pass : frame-synchronous beam search algorithm (2-gram)
  - 2nd pass : stack decoding search (3-gram)
- running time : less than 2 minutes on an average for one document

Baseline system results

- Origin of errors :
  - insufficient discriminating capabilities of mixtures of Gaussians
  - language modelisation problem :
    - bad lexicon (31.1% OOV)
    - small words concatenation (caused by the language model)
  - Rule-lines (ex.) : 14,30% vs. 27.71% WRR
  - Overlapping lines (ex.)
  - word segmentation errors (line-level recognition)

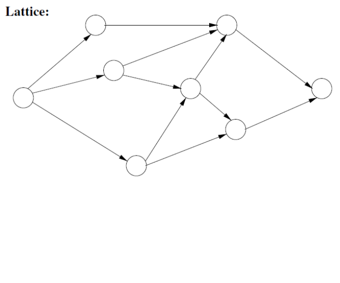
	NEWSWIRE	WEB	ALL
1-WER	0.2354	0.2467	0.2409

Summary

Word lattices and confusion networks

Word lattice

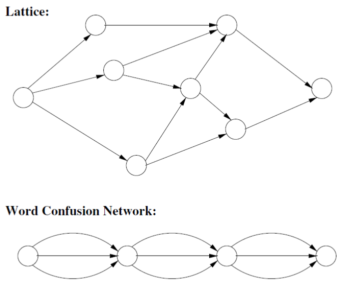
- Structured representation of N-best recognition hypotheses
- Each word (node) has :
  - word confidence score
  - time boundaries



Word lattices and confusion networks

Confusion network (CN)

- Weighted directed graph, compact representation of lattices
  - competing hypotheses organized in different sets (nodes)
  - words in sets are sorted by their scores
  - each set can also contain one empty word (ϵ)
- Decoding : select first word (highest probability) in each set



Systems combination

Principle

- Principle : combine outputs of several recognition engines
- Procedure :
  - take into account the N-best sequences of each system
  - extract lattices of each system and merge them
  - convert obtained lattice to a confusion network
- Advantage of converting a lattice to a CN :
  - create new paths with words from different engines
  - reinforce “good” word hypotheses
- Still under development...

Combination procedure

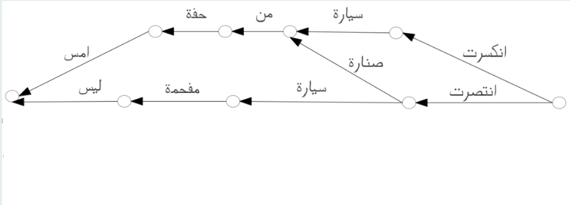
Successive operations

- run the recognition for several recognition systems
- output a word lattice for each system
- vertically concatenate lattices (merge their start and end nodes)
- weight the scores of each hypothesis (different weights for each system)

Combination procedure

Successive operations

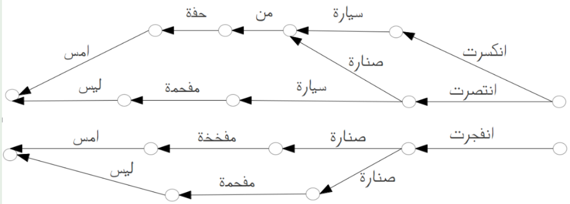
- run the recognition for several recognition systems
- output a word lattice for each system
- vertically concatenate lattices (merge their start and end nodes)
- weight the scores of each hypothesis (different weights for each system)



Combination procedure

Successive operations

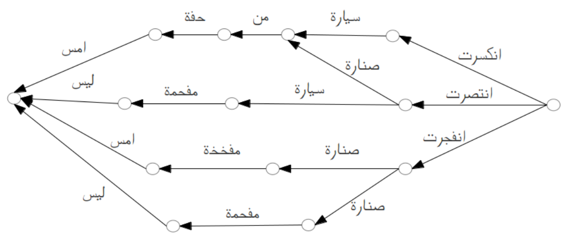
- run the recognition for several recognition systems
- output a word lattice for each system
- vertically concatenate lattices (merge their start and end nodes)
- weight the scores of each hypothesis (different weights for each system)



Combination procedure

Successive operations

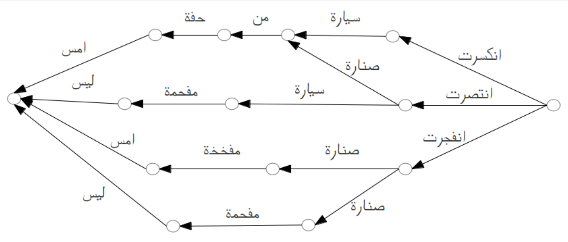
- run the recognition for several recognition systems
- output a word lattice for each system
- vertically concatenate lattices (merge their start and end nodes)
- weight the scores of each hypothesis (different weights for each system)



Combination procedure

Successive operations

- run the recognition for several recognition systems
- output a word lattice for each system
- vertically concatenate lattices (merge their start and end nodes)
- weight the scores of each hypothesis (different weights for each system)

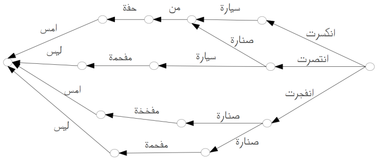


Combination procedure

Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



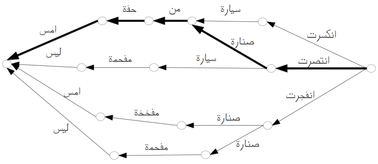
Confusion network

Combination procedure

Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



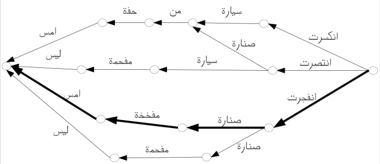
Confusion network

Combination procedure

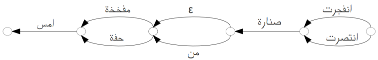
Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



Confusion network

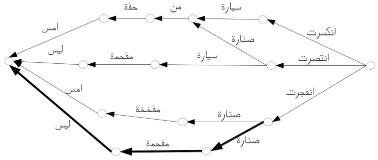


Combination procedure

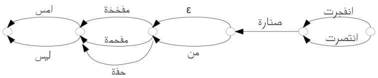
Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



Confusion network

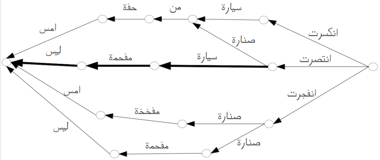


Combination procedure

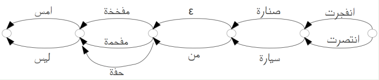
Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



Confusion network

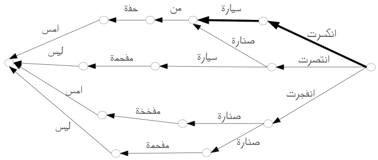


Combination procedure

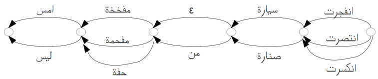
Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



Confusion network

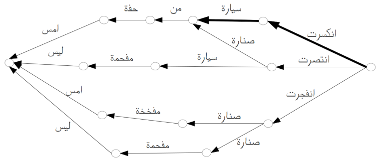


Combination procedure

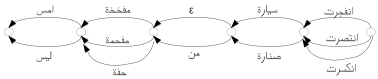
Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



Confusion network

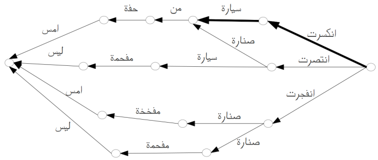


Combination procedure

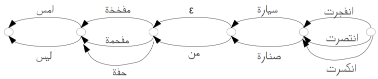
Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



Confusion network

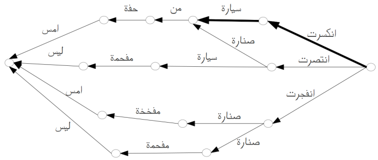


Combination procedure

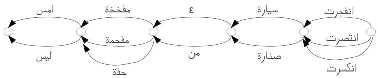
Conversion of combination lattice to a CN

- initialize with highest-probability path
- align remaining partial lattice paths to the CN
- rescore the words hypothesis (LM)
- decode the CN to get best path

Lattice



Confusion network



Combined systems

- Several different systems
- Outputs must be "complementary" : different classifiers or different feature extractors
- Lack of time : same classifier (HMM), same feature extractor
- Lack of time : different line sizes (normalization step)
  - 3 different image resolution values
  - get different HMM alignments on feature frames (different outputs)
- Long running time (N-best list extraction is time-consuming)

Combination results

- Low Recognition rate results (less than baseline)
- Errors due to :
  - Same problems than of baseline system
  - Better results if N is high. But we only used $N = 3$
  - outputs of combined systems are too close

Results

	NEWSWIRE	WEB	ALL
Baseline	0.2354	0.2467	0.2409
Combination	0.2189	0.2295	0.2241

Summary

Conclusion

- Arabic handwriting recognition engine based on Hidden Markov Models
  - low accuracy on evaluation dataset
  - several improvements needed (language modeling, discriminative classifier, line-removal)
- Combination framework of systems outputs that uses word lattices
  - unfinished (lack of time...)
  - running time optimisation
  - develop complementary systems for a successful combination

Thank you for your attention