Inkball Models for Character Localization and Out-of-Vocabulary Word Spotting



Review: Inkball Models

- Writing model = disks of ink in a particular configuration
- Any sample gives a model



- Flexible connections between adjacent disks
 - Gaussian distribution around offset point
 - Generative model: sampling gives new versions



Part-Structured Models

 Complex model is made of simple parts in a spatial relationship



- Proposed layout of parts is a *configuration*
- Likelihood of configuration has two factors:
 - Do observations support layout of parts? E_{ω}
 - Does layout of parts match expected offsets? E_{ξ}



$$E = E_{\xi} + \lambda E_{\omega}$$

Efficient Inference

• Part detectors do some localization



Eyes

Nose



• Offset detections and combine



position, can place

subordinate parts

Prior Work: ICDAR 2013

- Used inkball models for word spotting
- No training: each query word used as model
- Localizes target word on page of text

• A quick brown Fox jumps over the lazy dog. Jackdaws love my big sphinx of quartz. Pack my box with five dozen liquor jugs.

This Work: Two Goals

- Inkball models for character segmentation
 - Attribute individual pixels to characters
 - Known transcript only



- Word spotting with text queries
 - Use synthetic word models
 - Relies on character models developed above

Regiment - Regiment

Character Localization

- Maximal points of character model fit
 - Multiple scales
 - Any location

Barrel



- Energy minimization chooses best sequence for entire word at once
 - Expected (x,y) displacement
 - Scale consistency
 - Explanation of all ink pixels



Every Pixel Wants to be Happy

• Render each candidate fit against image

– E.g.: Possible 'r' candidates Barrel Barrel Barrel Barrel Barrel

• Pixels with exactly one explanation are best



Final Pixel Attribution

• Clean segmentation with some heuristics

- Fix attribution problems using nearest neighbor

- Untouched components are stray marks

an

Ø

Bulk Statistics



- Fit to large data set \rightarrow Useful statistics
 - Character separation for bigrams
 - 1D or 2D offsets (e.g., superscripts)
- Problem of sparse data (tz rarer than th)
 - Bin samples by bigram
 - Add mean offset to every bin
 - Median bin value = offset estimate
 - Robust; conservative



Synthetic Queries

- What do you need to build synthetic words?
 - Model of each character
 - Displacement data for character bigrams
- Search process:



Data Set Profile



- Chancery script
- 60 characters
- Binarized
- Not deslanted
- 4857 words



- Medieval German
- 94 characters (includes accented)
- Low-quality binarized
 & deslanted
- 23485 words

OOV Performance

• Precision around 50% on rare (OOV) words



Real vs. Synthetic

• Results for real query images vs. synthetic



Full Vocabulary Results

Results on all images (in & out of vocabulary)
 QBE only, Synthetic only, Hybrid QBE/Synthetic



Conclusion

- Inkball models allow synthetic query images
- Improvement possible with future work
 - Letter variants arms vs.
 - Better character joins
- Inkball models give algorithmic insight into handwritten forms
 - Locate letters and parts of letters
 - Attribute ink properly

and

Part-Structured Models

• Complex object made of simple parts in a spatial relationship



- Two factors give location likelihood:
 - Match of observations to part appearance E_{ω}
 - Proximity to offset locations of connected parts E_{ξ}



Tree structure on parts → efficient algorithm

What was the error?

- Error in ICDAR 2013 paper: bad interpolation
- Significant when few exemplars
- Example: 2 relevant words, ranked 1 & 3



Character Localization

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Orders



- Energy minimization chooses best sequence for entire word at once
 - Expected (x,y) displacement
 - Scale consistency
 - Explanation of all ink pixels

