Data Quality In The Cultural Heritage Sector: From An Image Processing Perspective

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The ADOCHS Project



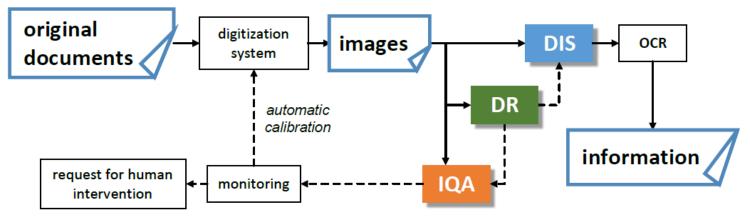




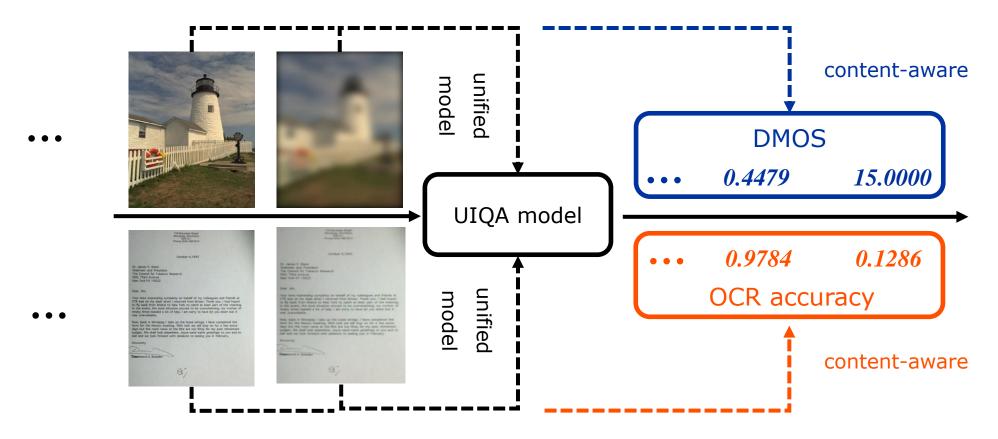
Images – Digitization in the Cultural Heritage Sector



- Digitization in the Cultural Heritage Sector
 - ☐ Google Books: over 40 million books
 - ☐ **Europeana Newspapers**: aggregating 18 million historic newspaper pages and converting 10 million newspaper pages to full text
 - ☐ Royal Library of Belgium (KBR): 4500 medieval codices and about one million prints and drawings
- Challenges and Opportunities
 - ☐ Image Quality Assessment (IQA)
 - ☐ Image Understanding
 - Document Image Segmentation (DIS)
 - Damage Recognition (DR)

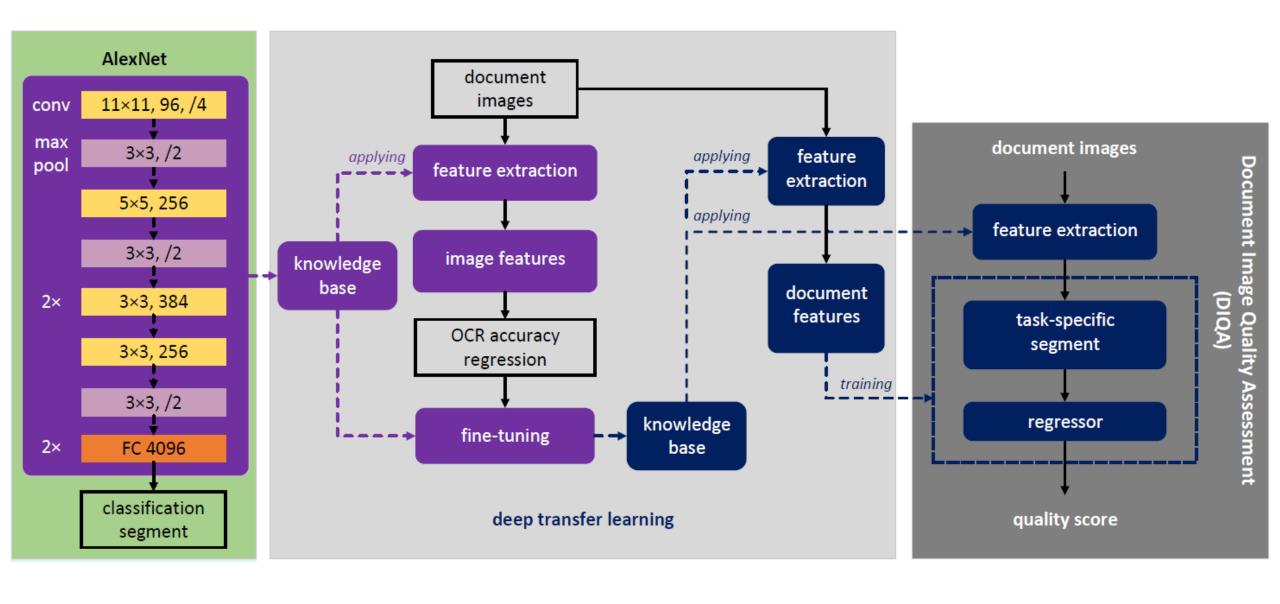


A Unified Approach to Image Quality Assessment



- A unified model to process natural and document images simultaneously
- Content-aware such that different types of quality information is provided according to different types of input images

Document Image Quality Assessment based on Transfer Learning



Document Image Quality Assessment based on Transfer Learning

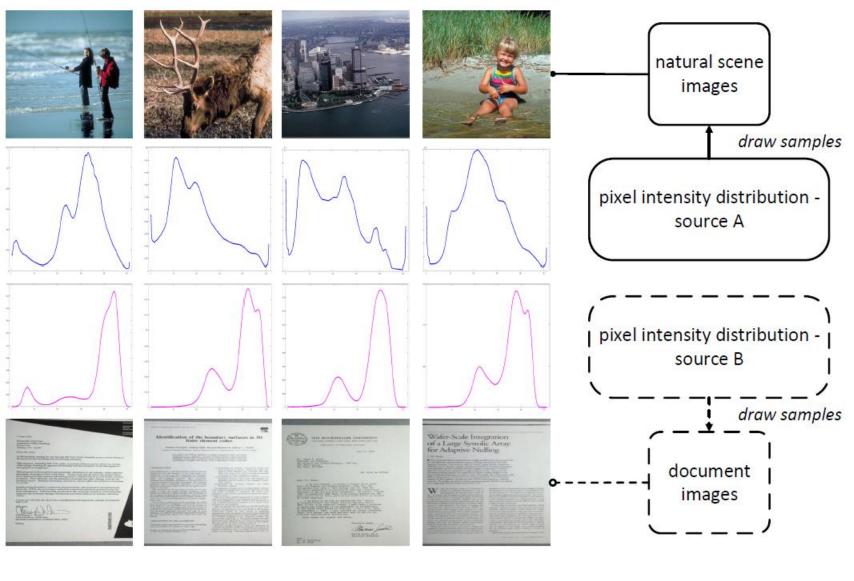
DIQA Model	PLCC	SRCC
CORNIA	0.937	0.862
CNN	0.950	0.898
LDA	-	0.913
HOS	0.960	0.909
Sparse Model	0.935	0.928
RNN	0.956	0.916
proposed method	0.965	0.931

DIQA Model	Document-wise		General	
DIQA Model	PLCC	SRCC	PLCC	SRCC
CORNIA	0.9747	0.9286	0.9370	0.8620
Focus	0.9378	0.9643	0.6467	-
MetricNR	0.9750	0.9107	0.8867	0.8207
CG-DIQA	0.9523	0.9429	0.9063	0.8565
proposed method	0.9763	0.9550	0.9651	0.9312

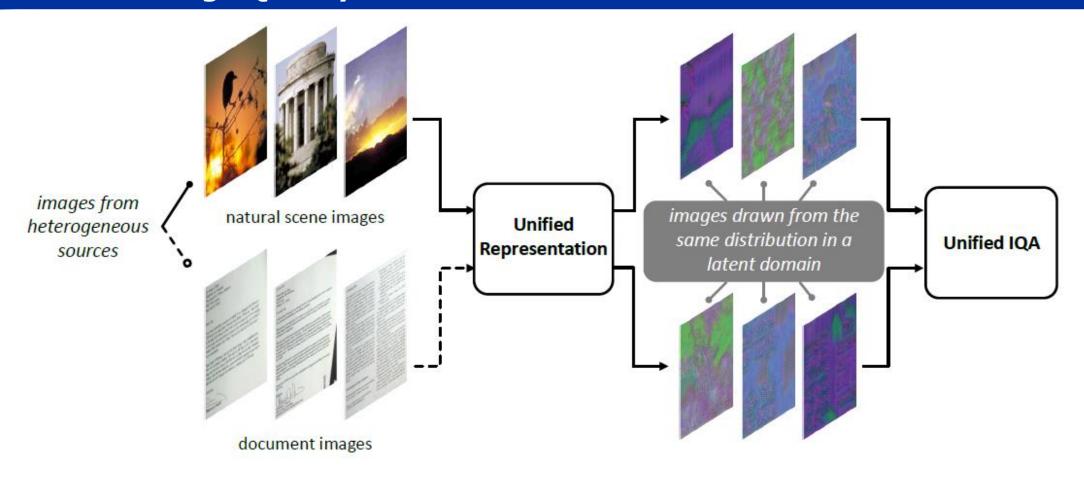
> Cross-Domain Homogeneity between Natural and Document Images

The knowledge learned on natural image processing can be effectively exploited for the OCR accuracy prediction of document images.

Unified Image Quality Assessment

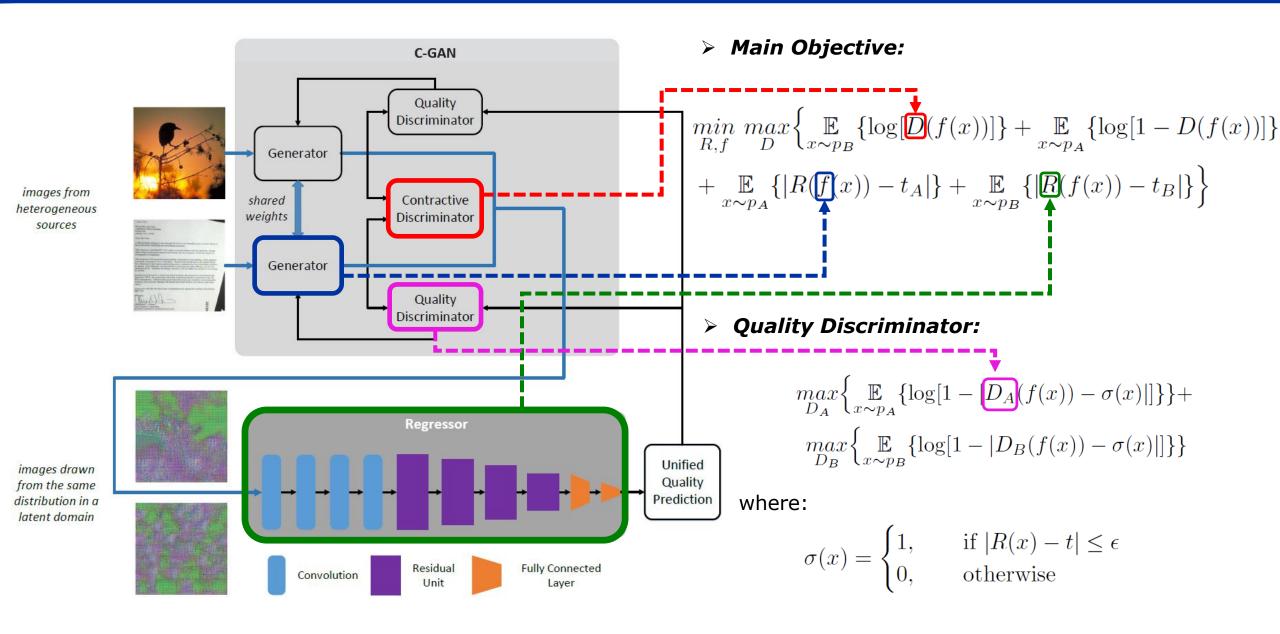


- Cross-Domain Homogeneity between Natural and Document Images
- Possible to process natural and document images simultaneously within one quality assessment model
- Balanced performance on these two types of images can be obtained with the UIQA model
- The process of learning a common representation is mixed with that of regressing the common representation towards respective quality scores difficult to investigate and develop

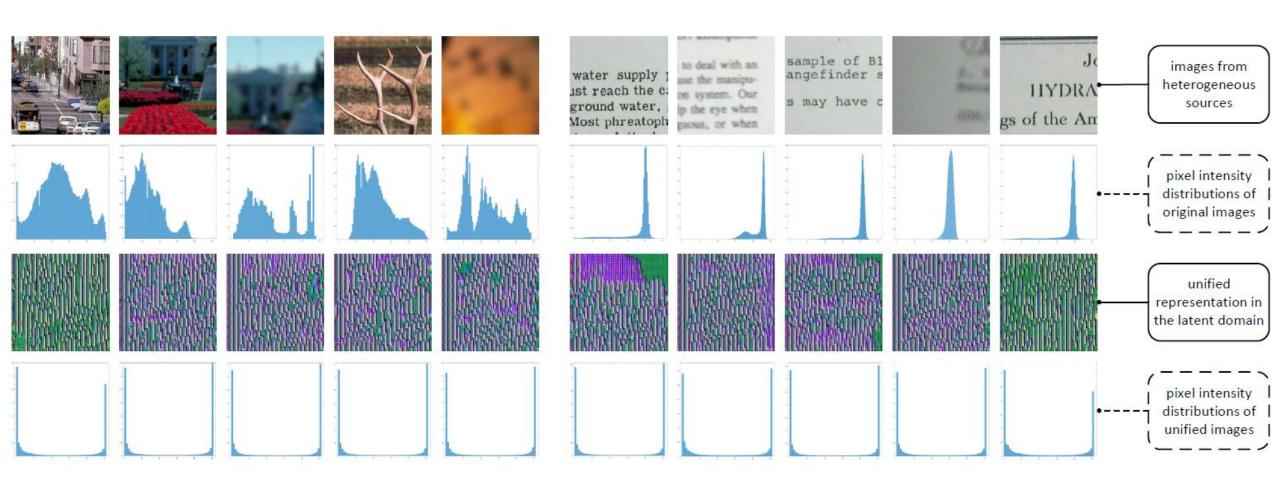


> Cross-Domain Homogeneity between Natural and Document Images

- Learning a common representation (i.e. a generalization) of natural and document images in a latent domain
- The process of generalization is separated from that of regression
- The quality assessor operates as if it is processing a single type of images



Qualitative evaluation: visualization of the operation of the C-GAN model



Unified Image Quality Assessment based on Transfer Learning

LIVE + SOC CSIQ + SOC



Comparing to content-specific IQA and DIQA models

IQA Models	CSIQ		SOC	
	PLCC	SRCC	PLCC	SRCC
BLIINDS2	-	0.880	N.A.	
DIQA	-	0.870		
CORNIA	-	0.854		
NRSL	-	0.896		
CNN	N.A.		0.950	0.898
CNN			0.926	0.857
RNN			0.956	0.916
LDA			-	0.913
Sparse Model			0.935	0.928
Proposed method	0.92	0.89	0.932	0.916

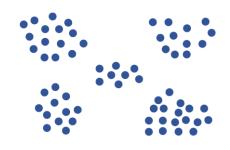
 Cross-dataset evaluation of the proposed UIQA model on the natural scene images

IQA Models	LIVE		
TQA Wodels	PLCC	SRCC	
BLIINDS2	-	0.915	
DIQA	-	0.962	
CORNIA	-	0.957	
NRSL	-	0.808	
Proposed method	0.91	0.952	

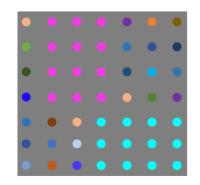
Gestalt Principles and Text Homogeneity



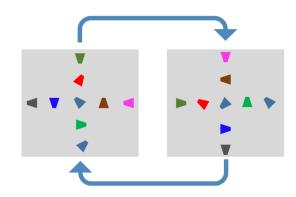
> Proximity



Similarity

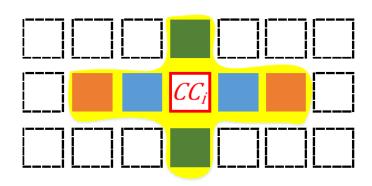


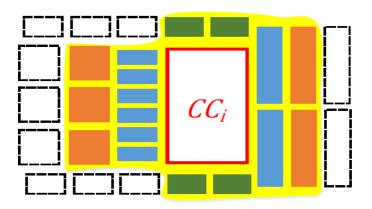
Symmetry



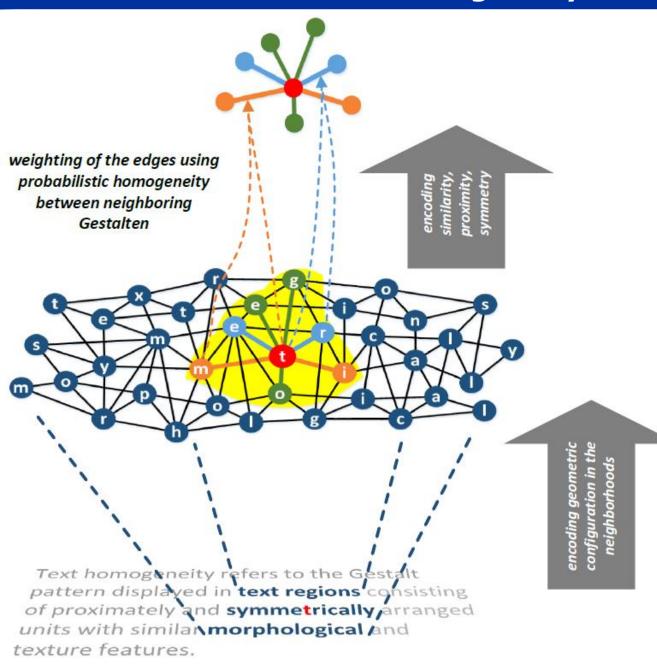
> Conceptualization

Text homogeneity is the homogeneous pattern displayed in text regions, which consists of **proximately** and **symmetrically** arranged units with **similar** *morphological* and *texture* features.





Probabilistic Local Text Homogeneity – A Neighborhood Graph



Description of local text homogeneity on G(V,E)

If we take a one-step walk from a Gestalt \mathcal{CC}_i by following an arbitrary (symmetry) direction, and arrives at another Gestalt, say \mathcal{CC}_j , the probability that \mathcal{CC}_j is located within a short (proximity) distance and resembles (similarity) \mathcal{CC}_i is higher when \mathcal{CC}_i is a text component (e.g. a letter from a paragraph).

• probabilistic weighting $w_{ij} = P(S_{ij} = s_{ij}^+)$

$$S_{ij} = \begin{cases} s_{ij}^+, & \text{if } CC_i \text{ and } CC_j \text{ are homogeneous,} \\ s_{ij}^-, & \text{if } CC_i \text{ and } CC_j \text{ are heterogeneous;} \end{cases}$$

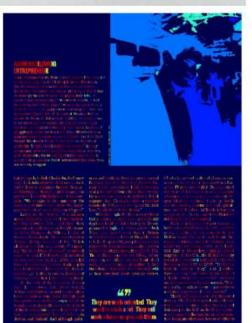
Probabilistic Local Text Homogeneity – Resultant Probability Map



Four Tech Waves To Watch









0.9

0.8

0.7

0.6

0.5

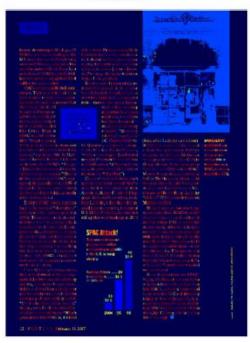
0.4

0.3

0.2

0.1

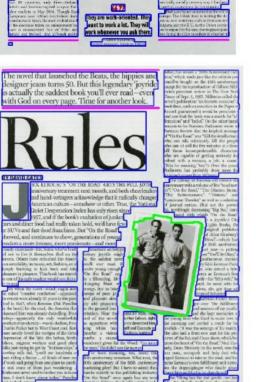


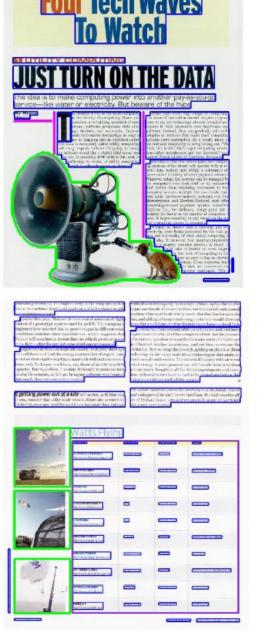


Document Segmentation with Probabilistic Homogeneity - Performances

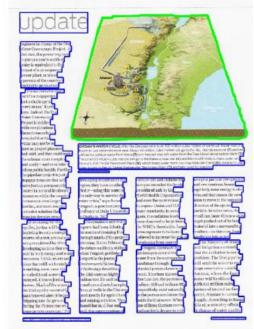


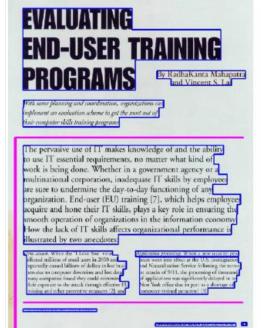








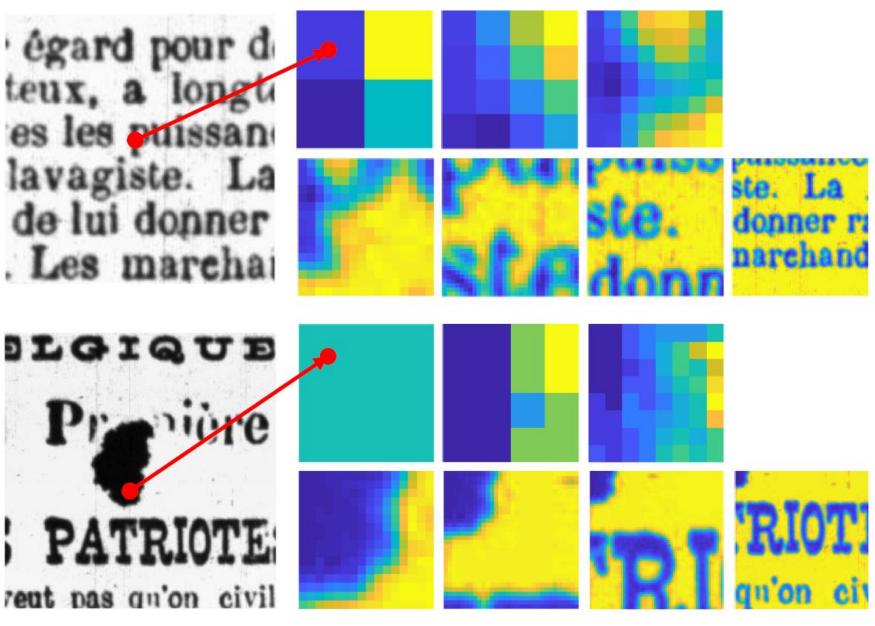




Document Segmentation with Probabilistic Homogeneity - Performances



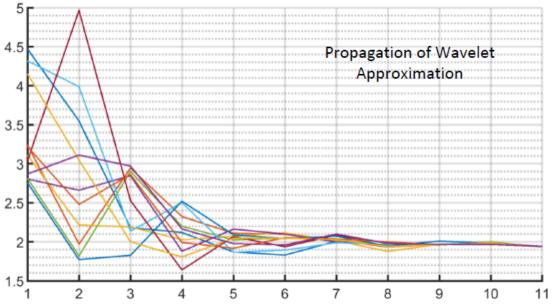
Propagation of Wavelet Approximation

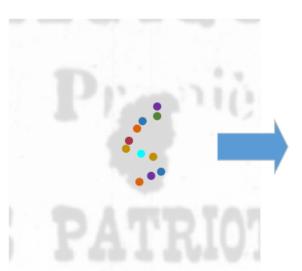


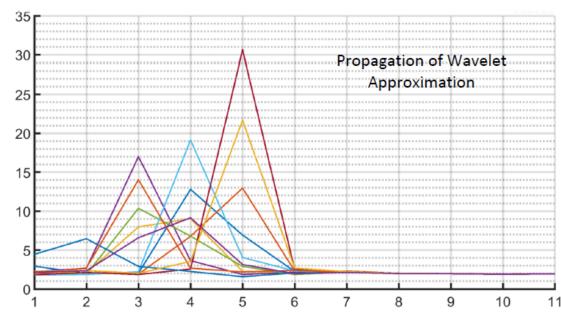
- > Text Homogeneity Revisit
- Text Homogeneity pattern
- Neighborhood transition

Propagation of Wavelet Approximation









> Wavelet Propagation

propagation of wavelet approximation

(PWA) and propagation of cone-of-influence wavelet approximation (PCWA).

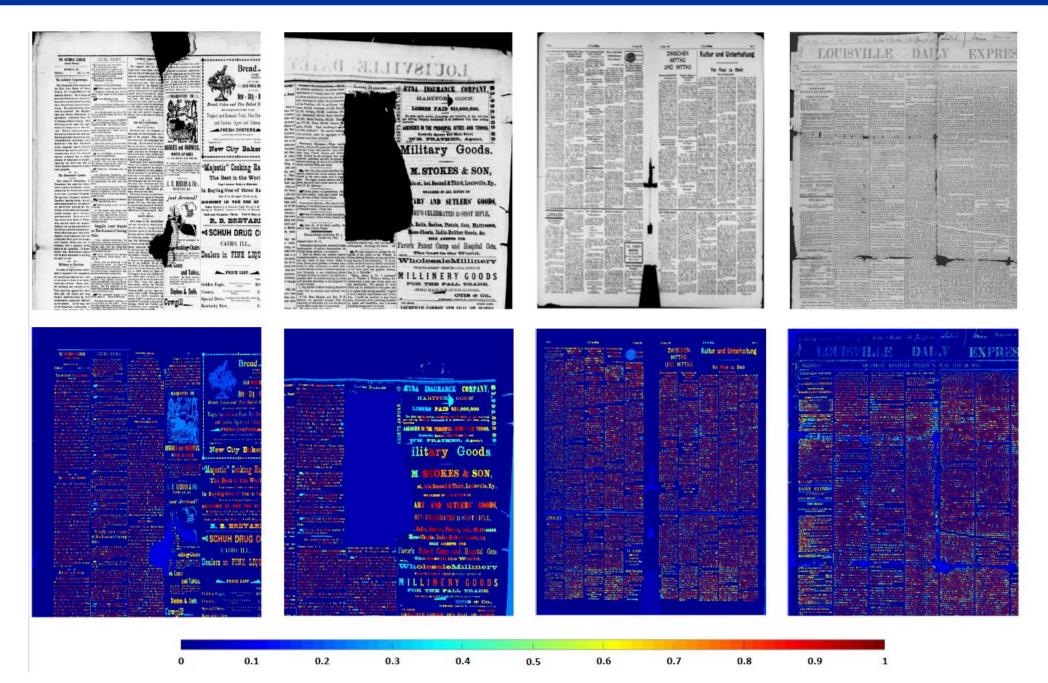
• PWA
$$\alpha_{n \to k, l} \triangleq \log_2 \left(\frac{1}{k - n} \sum_{j=n}^{k-1} \frac{|w_{\phi}^{j+1, l}|}{|w_{\phi}^{j, l}|} \right)$$

• PCWA

$$\beta_{n \to k, l} \triangleq \log_2 \left(\frac{1}{k - n} \sum_{j=n}^{k-1} \frac{|I_{j+1, l}|}{|I_{j, l}|} \right),$$

$$I_{j,l} \triangleq \sum_{m \in C(j,l)} |w_{\phi}^{j,m}|$$

Bayesian Distortion Recognition



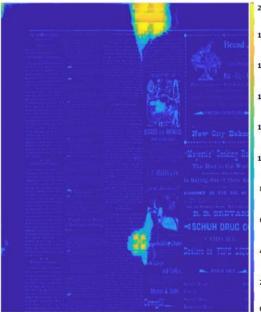
Bayesian Distortion Recognition

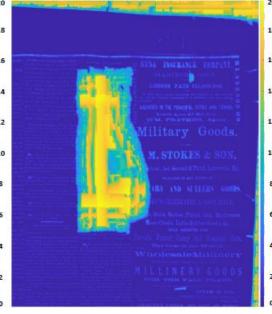


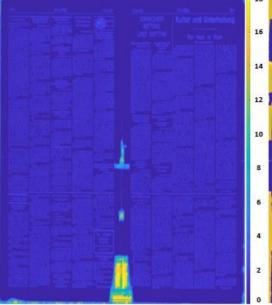


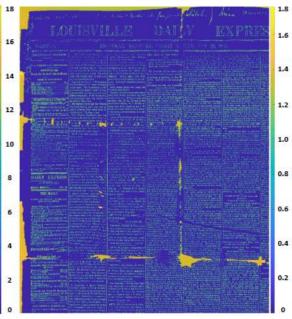




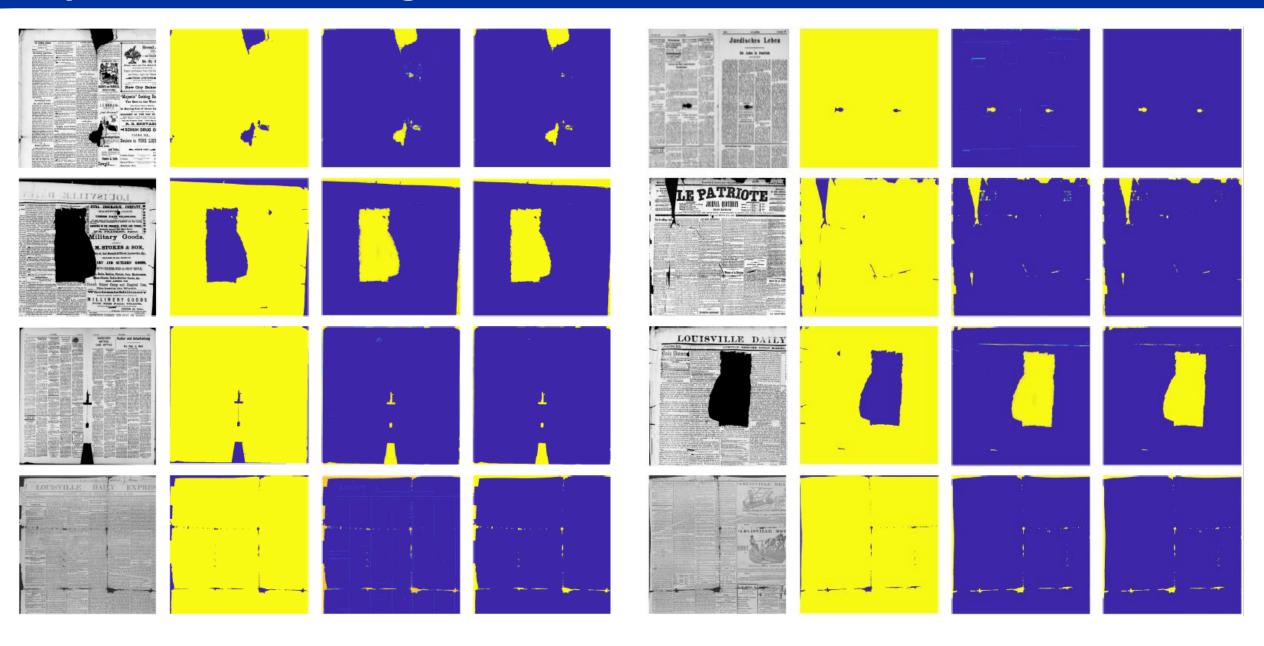








Bayesian Distortion Recognition



Conclusion



Thank you for your attention!

Q & A