



Technical Presentations

- └ Page Segmentation (and rule line separation)
- └ Page Layout Similarity
- └ Document ID/Script ID

This afternoon

- Signature Detection
- Logo Detection and Recognition
- Stamp Detection
- Font OCR



October 24, 2007

Document Image Retrieval Using Signatures and Logos



- **Motivation**
- Our Tasks
- Signature Detection Using Multi-scale Structural Saliency (CVPR 2007)
- Signature Matching for Document Image Retrieval
- Unconstrained Logo Detection in Document Images (ICDAR 2007)
- Software releases

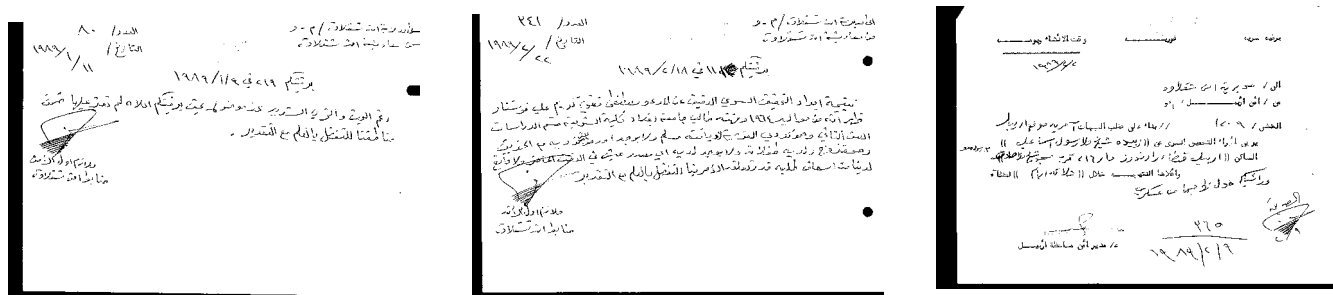


Problem Statement

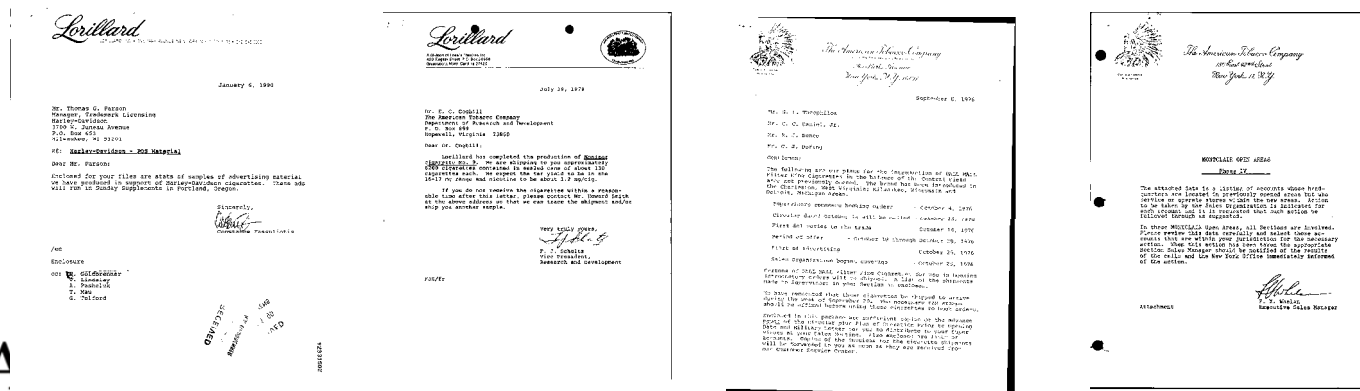


Given a large heterogeneous document image database, we are facing a few very challenging problems

- How can we retrieve documents authored or approved by a specific individual in unconstrained settings?



- How can we retrieve documents originating from an organization?



Motivation



- Signatures and logos provide exciting new dimensions for document image mining
- Solution to these problems are also important in document analysis systems in a range of application domains
 - Signature verification and identification
 - Business process automation

Roadmap



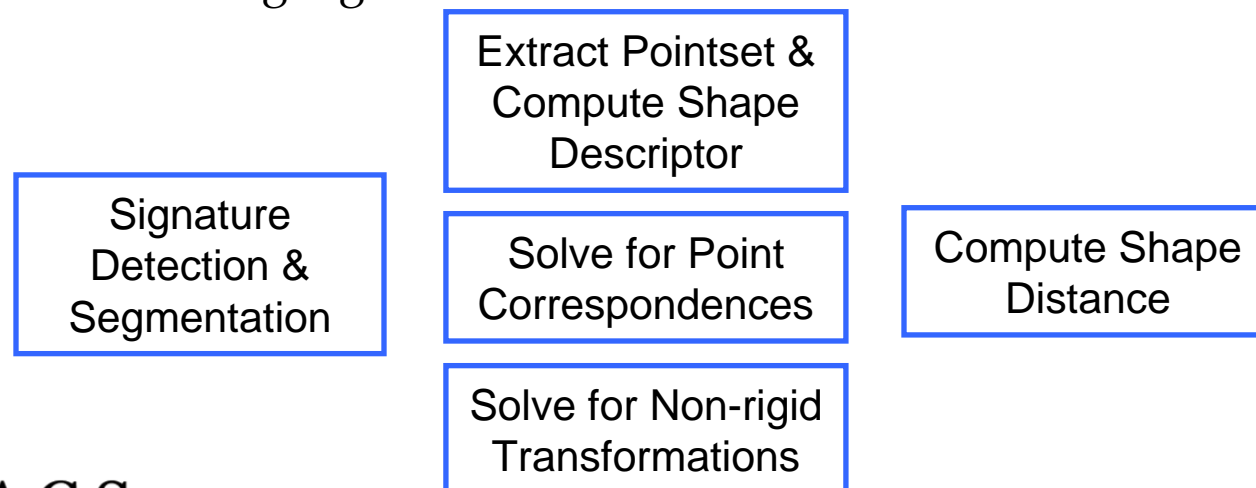
- Motivation
- **Our Tasks**
- Signature Detection Using Multi-scale Structural Saliency (CVPR 2007)
- Signature Matching for Document Image Retrieval
- Unconstrained Logo Detection in Document Images (ICDAR 2007)
- Software releases





Our Tasks

- Two problems are of fundamental interest to general content-based image retrieval
 - Detection and segmentation
 - Matching
 - Representation
 - Similarity measures
 - Matching algorithms



Roadmap



- Motivation
- Our Tasks
- **Signature Detection Using Multi-scale Structural Saliency (CVPR 2007)**
- Signature Matching for Document Image Retrieval
- Unconstrained Logo Detection in Document Images (ICDAR 2007)
- Software releases

Challenges

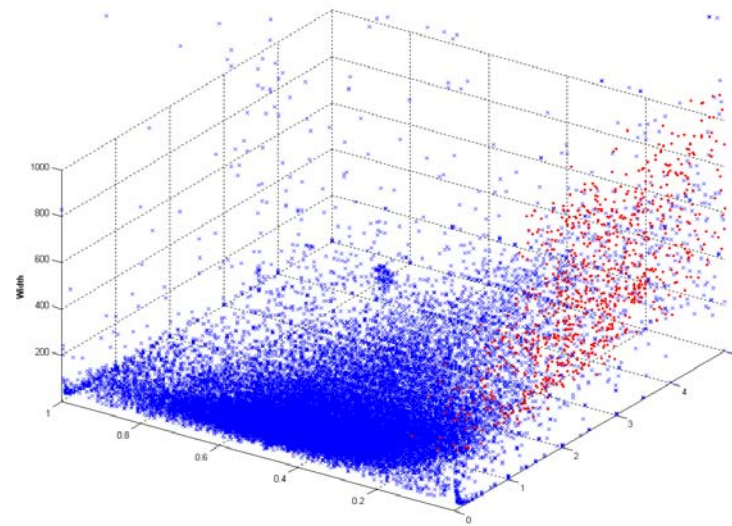
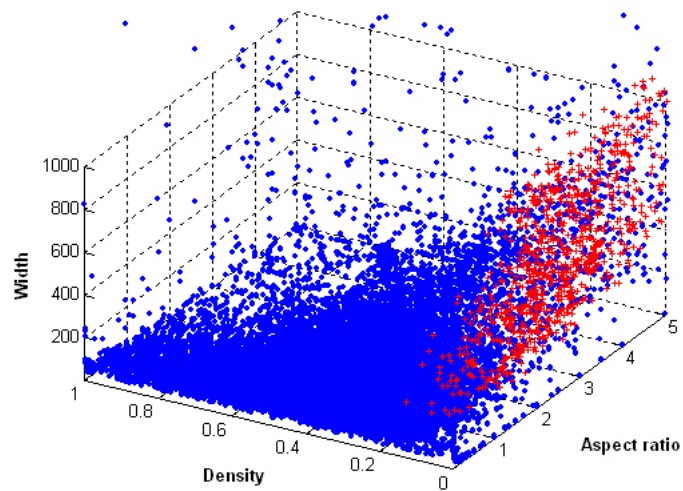


- Detecting free-form objects in cluttered backgrounds is a challenging problem in computer vision
- 2D nature of off-line signatures
 - Difficult to recover tempo order of unconstrained off-line handwriting [1]
- Large intra-class variations of signature
 - Intersession variability
 - Larger variations than other forms of handwriting
- Computation complexity



Intersession variability shown by Sabourin *et al.* [6]

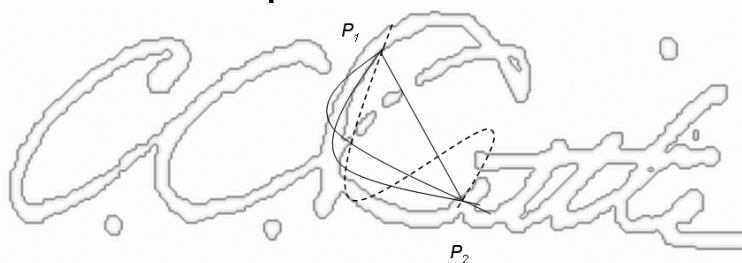
Intra-class Variations of Signatures



Overview of our approach



- We treat a signature as a global symbol. Rather than focusing on local features that typically have large variations, our approach aims to capture the structural saliency of a signature by searching over multiple scales
- We consider identifying salient structure and grouping its parts in two separate steps
- Two keys questions we addressed are:
 - How to effectively model off-line signature production under reasonable assumptions without its temporal information
 - What to effectively measure the structural saliency of signatures under such production model



Signature production model

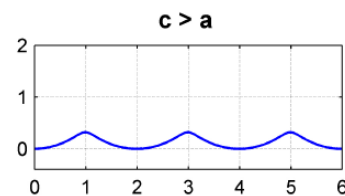


- We assume that
 - The pen moves in a cycloid fashion with reference to a sequence of shifting virtual baselines.
 - Local baseline changes as the pen moves its position with respect to the document.
 - Within a local curve segment, we consider that the baseline remains unchanged.
 - The locus of the pen maintains a proportional distance from the local center point (*focus*) to the local baseline (*directrix*).
- Oscillation theory of handwriting (Hollerbach, 1978)

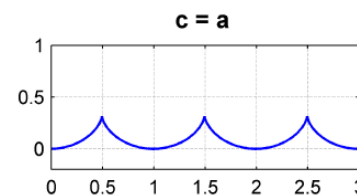
$$v_x = a (\sin(\omega_x(t - t_0) + \phi_x) + c)$$

$$v_y = b (\sin(\omega_y(t - t_0) + \phi_y))$$

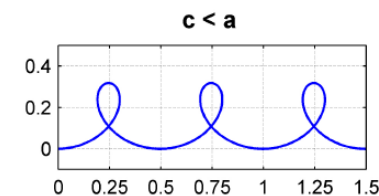
$$\text{Let } a = b, \omega_x = \omega_y \text{ and } \phi_x - \phi_y = \pi/2.$$



Curtate cycloid



Cycloid



Prolate cycloid



Signature production model

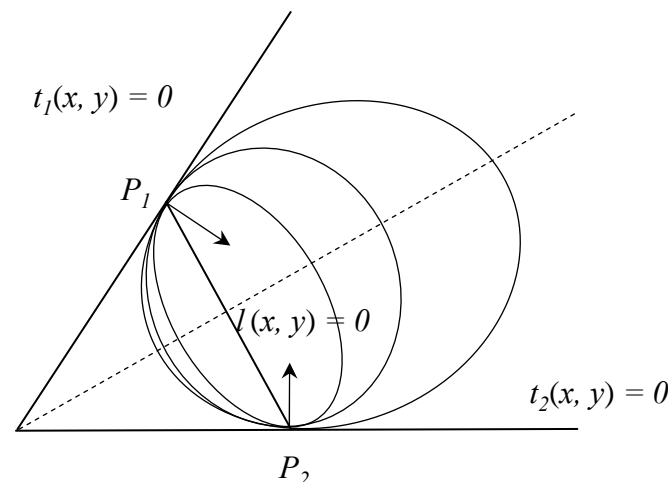


- This is equivalent to viewing signatures as piece-wise concatenations of small elliptic segments.
- The model imposes one additional constraint that limits the group of feasible second-order curves to smoother ellipses.

Measure of saliency for signatures



- How to measure the global saliency of a signature in the form of dynamic curvature without recovering its temporal order.

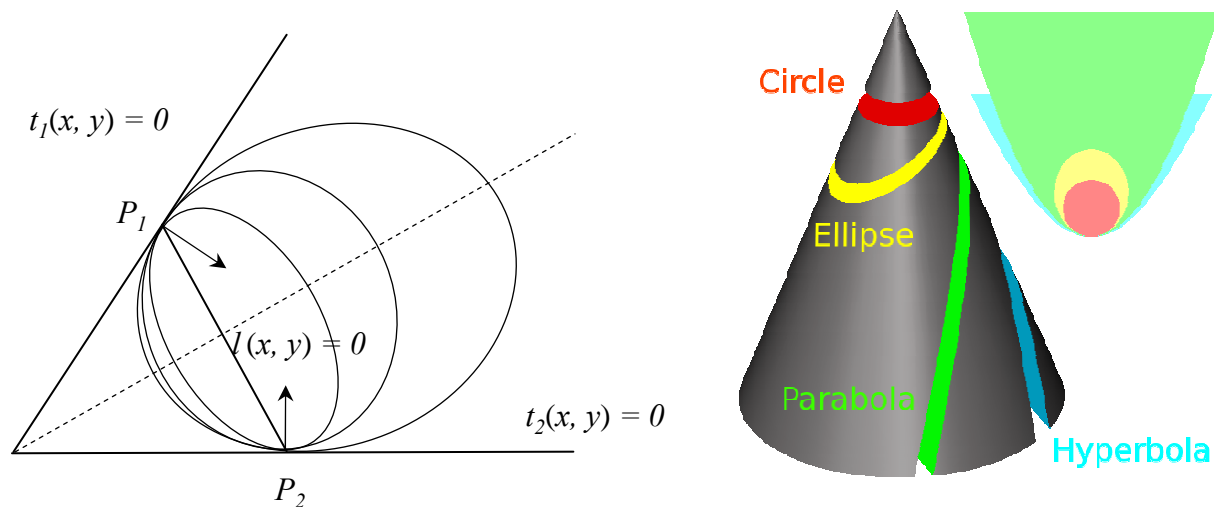


- Knowing two points P_1 and P_2 and their gradient directions, we know a family of second-order curves that pass both points

$$\begin{aligned} f(x, y) &\equiv l^2(x, y) - \lambda t_1(x, y)t_2(x, y) = 0 \\ &= ax^2 + 2hxy + by^2 + 2gx + 2fy + c = 0 \end{aligned} \quad (1)$$

Measure of saliency for signatures

- In the Cartesian coordinate system, the family of a quadratic equation in two variables is always a conic section



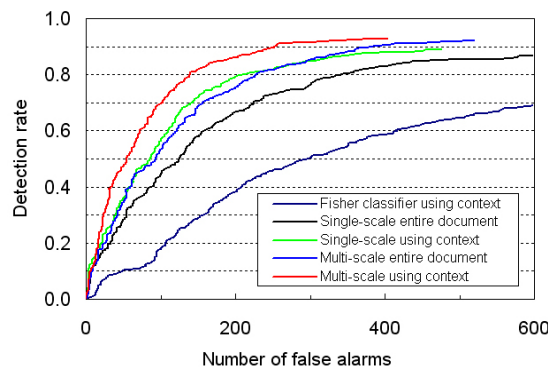
- For two points on a signature, i.e. for a set of $\{(x_1, y_1), (x_2, y_2), (p_1, q_1), (p_2, q_2)\}$, the range of λ value that corresponds to ellipses

$$0 < \lambda < \frac{4[p_1(x_2 - x_1) + q_1(y_2 - y_1)][p_2(x_1 - x_2) + q_2(y_1 - y_2)]}{(p_1q_2 - p_2q_1)^2}$$

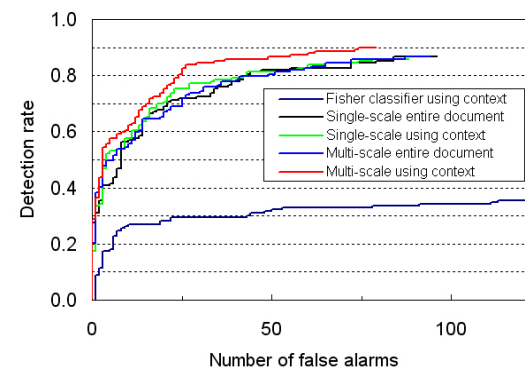


Evaluation

- We used two large collections of real world documents – Tobacco-800 and University of Maryland Arabic datasets.
- Using document context, our multi-scale signature detector achieves 92.8% and 86.6% detection rates for the Tobacco-800 and Maryland Arabic datasets, at 0.3 false-positives per image.



(a)



(b)

ROC curves for (a) Tobacco-800 dataset and (b) Maryland Arabic dataset.

Evaluation



Examples of detected signatures from Tobacco-800 and their saliency maps.



Evaluation

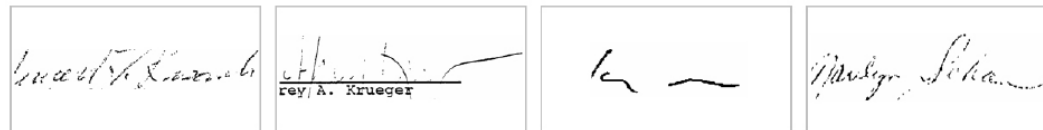


Examples of detected signatures from Maryland Arabic dataset and their saliency maps.

Evaluation



(a)



(b)

Examples of (a) falsely alarms (b) missed signatures

Roadmap



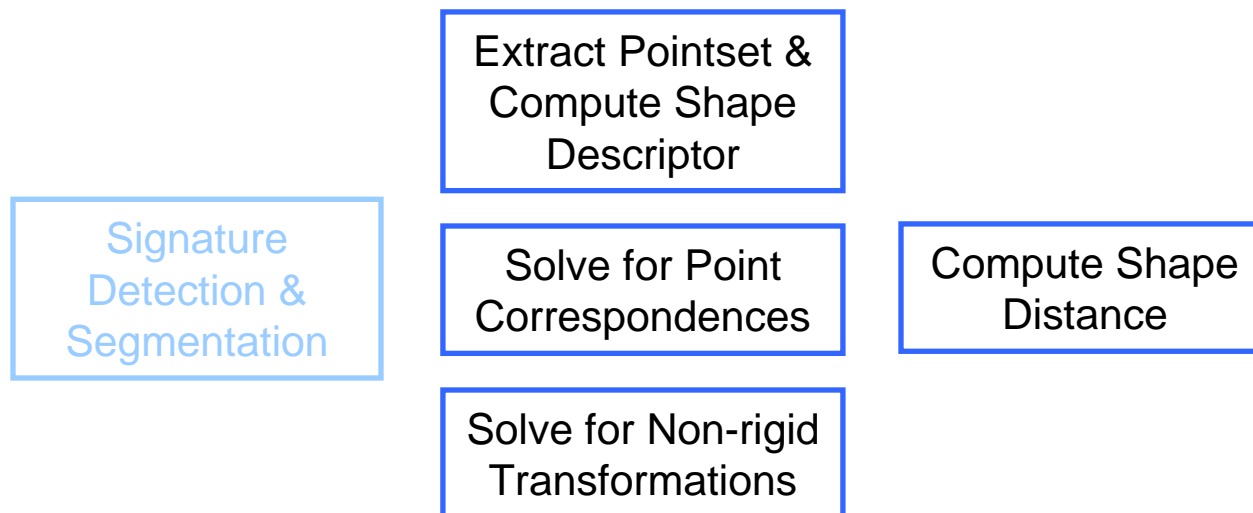
- Motivation
- Our Tasks
- Signature Detection Using Multi-scale Structural Saliency (CVPR 2007)
- **Signature Matching for Document Image Retrieval**
- Unconstrained Logo Detection in Document Images (ICDAR 2007)
- Software releases



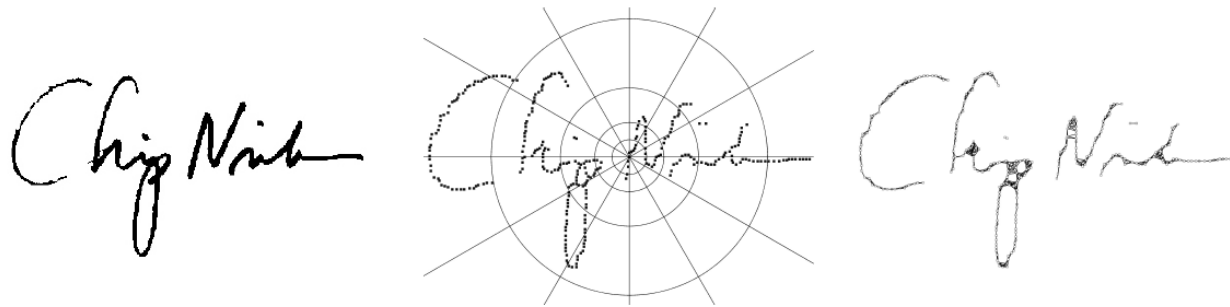
Overview of our approach



- We treat a signature as a shape
- Employ shape matching techniques for signature recognition
 - Shape representations
 - Shape matching algorithms
 - Measure of dissimilarities for shapes (shape distance)



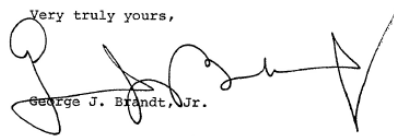
Shape representation



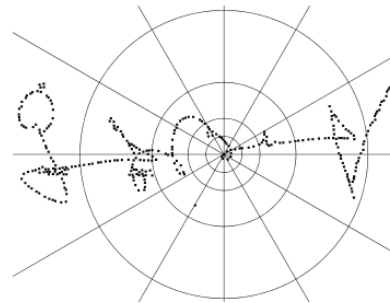
(a)

(b)

(c)



(d)



(e)



(f)

Shape contexts [Belongie *et al.*, 2002] and local-neighborhood-graph [Zheng and Doermann, 2006] constructed from detected and segmented signatures.

Shape matching



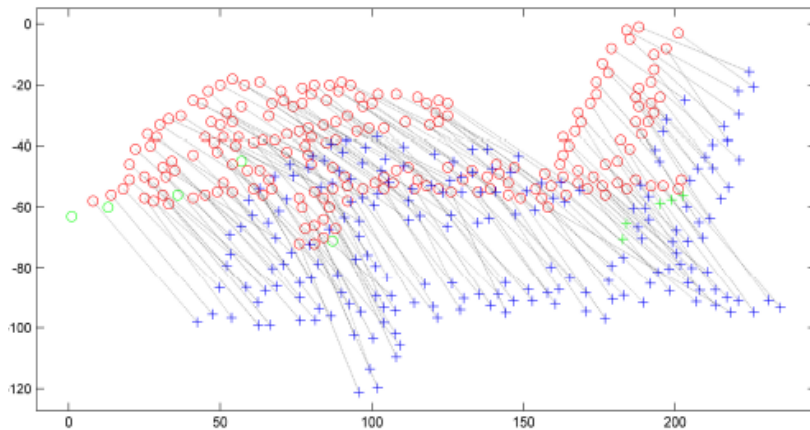
(a)

(b)

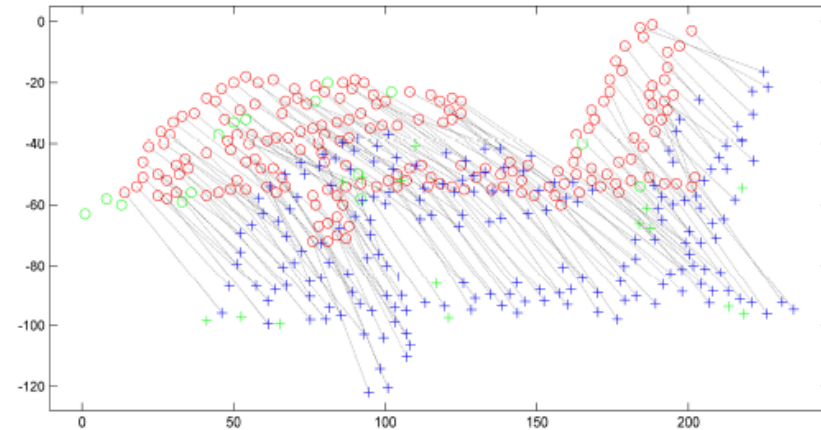


(d)

(e)



(g)

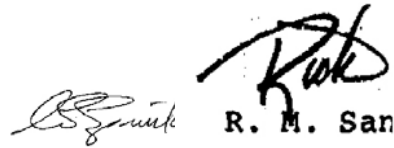


(h)

Illustration of signature matching using shape contexts and local-neighborhood-graph



Shape matching



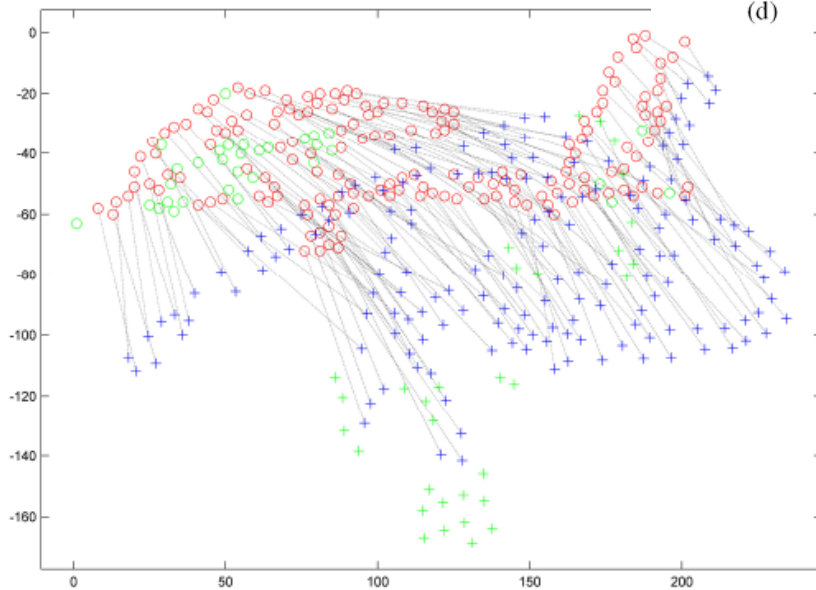
(a)

(c)

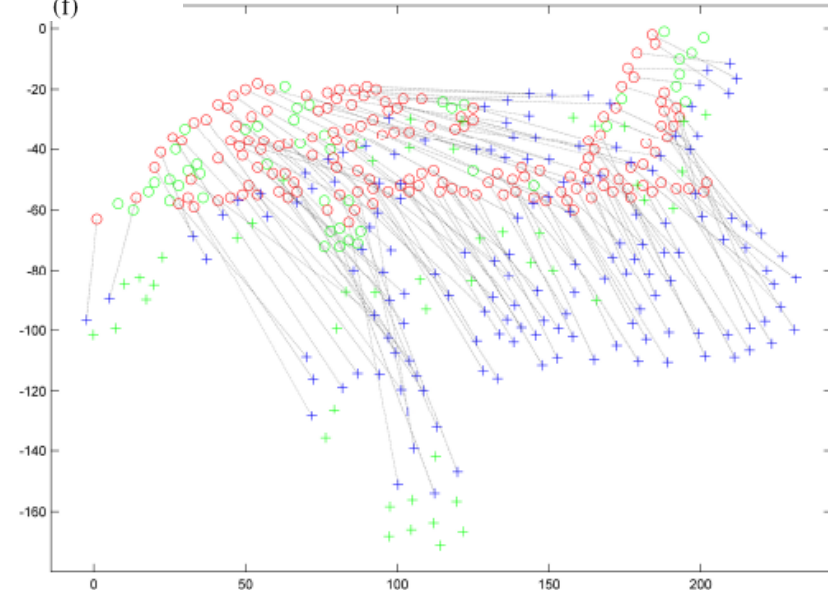


(d)

(f)



(i)



(j)



Illustration of signature matching using shape contexts and local-neighborhood-graph

University of Maryland Institute for Advanced Computer Studies

October 24, 2007

Shape matching evaluation



A query with eight relevant signature instances

Sincerely,
Hallie S. Jessup
Hallie S. Jessup

Top eight retrieved in the ranked list

<p>Sincerely, <i>Hallie S. Jessup</i> Hallie S. Jessup (1)</p>	<p>Sincerely, <i>Hallie S. Jessup</i> Hallie S. Jessup (2)</p>	<p>sincerely, <i>Hallie S. Jessup</i> Hallie S. Jessup (3)</p>	<p><i>Hallie S. Jessup</i> Hallie S. Jessup (4)</p>
<p><i>Hallie S. Jessup</i> Hallie S. Jessup (5)</p>	<p><i>William Squires</i> William Squires (6)</p>	<p><i>Hallie S. Jessup</i> Hallie S. Jessup Research Administrator (7)</p>	<p><i>Hallie S. Jessup</i> Hallie S. Jessup (8)</p>

Relevant instance outside the top eight in the ranked list

Hallie S. Jessup
Hallie S. Jessup
(10)

A signature query example. Among the total of eight relevant signature instances, seven appear in the top eight of the 460-element ranked list, giving an average precision of 94.2%, and an R-Precision of 87.5%. The irrelevant signature that is ranked among the top eight is highlighted with a blue bounding box.

Signature matching results



Table 1: Signature retrieval result using different similarity measures.

Similarity measures	Mean average precision	Mean R-precision
D_{sc}	66.9%	62.8%
D_{af}	61.3%	57.0%
D_{be}	59.8%	55.6%
D_{re}	52.5%	48.3%
$\frac{D_{sc} + D_{be}}{D_{sc} + D_{af} + D_{sc} + D_{re}}$	78.7%	74.3%
	84.5%	80.8%

Table 2: Signature retrieval result using multiple instances of signatures from the same person in each query.

Number of instances	Mean average precision	Mean R-precision
One	84.5%	80.8%
Two	88.6%	85.2%
Three	91.3%	88.1%

Current work



- Create groundtruth on Arabic documents for evaluation
- Preliminary results are very promising on Arabic datasets



References



1. S. Loncaric, "A survey of shape analysis techniques," *Pattern Recognition*, vol. 31, no. 8, pp. 983-1001, 1998.
2. R.C. Velkamp and M. Hagedoorn, "State of the art in shape matching," Utrecht University, Netherlands, Tech. Rep. UU-CS-1999-27, 1999.
3. H. Chui and A. Rangarajan, "A new point matching algorithm for non-rigid registration," *Computer Vision and Image Understanding*, vol. 89, nos. 2-3, pp. 114-141, 2003.
4. S. Belongie, J. Malik, and J. Puzicha, "Shape matching and object recognition using shape contexts," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 24, no. 4, pp. 509-522, 2002.
5. Y. Zheng and D. Doermann, "Robust point matching for non-rigid shapes: a relaxation labeling based approach," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 28, no. 4, pp. 643-649, April 2006.
6. C.R. Dyer and A. Rosenfeld, "Thinning algorithms for gray-scale pictures," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 1, no. 1, pp. 88-89, 1979.
7. T.Y. Zhang and C.Y. Suen, "A fast parallel algorithm for thinning digital patterns," *Communications of the ACM*, vol. 27, no. 3, pp. 236-239, 1984.

Roadmap



- Motivation
- Our Tasks
- Signature Detection Using Multi-scale Structural Saliency (CVPR 2007)
- Signature Matching for Document Image Retrieval
- **Unconstrained Logo Detection in Document Images (ICDAR 2007)**
- Software releases



Motivation



■ Logo Detection and Recognition

- enables identification of the source of documents from a given organization
- Most studies assume good logo detection and segmentation is available

■ Challenges

- Detection is required for any prior to extraction
- Extraction is required for any shape based matching/recognition process

Challenges



- Extremely large intra-class variations among logos
- Continuum between graphics, logos and text



Challenges



- Diverse document layouts, scanning qualities, and image degradations on real document datasets





Related work - Detection

Most work is focused on recognition. Related detection has taken a zone classification approach

- *S. Seiden, M. Dillencourt, S. Irani, R. Borrey, and T. Murphy. Logo detection in document images. ICISSST, pages 446–449, 1997.*
 - Applies XY Cuts, Uses Rule based Zone classification
- *T. Pham. Unconstrained logo detection in document images. Pattern Recognition, 36(12):3023–3025, 2003.*
 - Computes the spatial density on regions using fixed-width window, Experiments used synthetic images created by embedding logos from UMD logo database on blank pages



Claim #1

- Documents exist where *spatial* segmentation of Logos, Signatures and Stamps is not an option!

Thanks,

D. A. Beatty
D. A. Beatty

Sincerely,
Thomas A. Vollmuth
Thomas A. Vollmuth, Ph.D.
Toxicologist, Life Sciences

B&W

Lorillard
LORILLARD, INC. Research

NOV 10 1976
W. F. Gannon

B&W

W. F. Gannon
W. F. Gannon

J. B. Boder
J. B. Boder

RECEIVED
NOV 8 1976
W. F. GANNON

VENI-VIDI-VICI

RECEIVED
NOV 8 1976
W. F. GANNON

QC PME
J. B. Boder
J. B. Boder

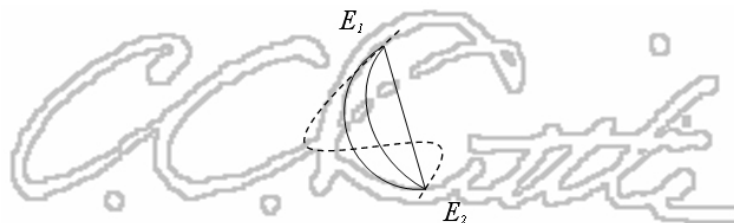
100337245





Claim #2

- Considering the more general problem of Detection (as opposed to segmentation->classification) allows us to integrate identification and extraction, and possibly recognition
- The concept has successfully been applied to:
 - Guangyu Zhu, Yefeng Zheng, David Doermann and Stefan Jaeger. *Multi-scale Structural Saliency for Signature Detection*. (CVPR 2007).
 - Guangyu Zhu, Stefan Jaeger and David Doermann. *A Robust Stamp Detection Framework on Degraded Documents*. SPIE 2006.



Our Challenge



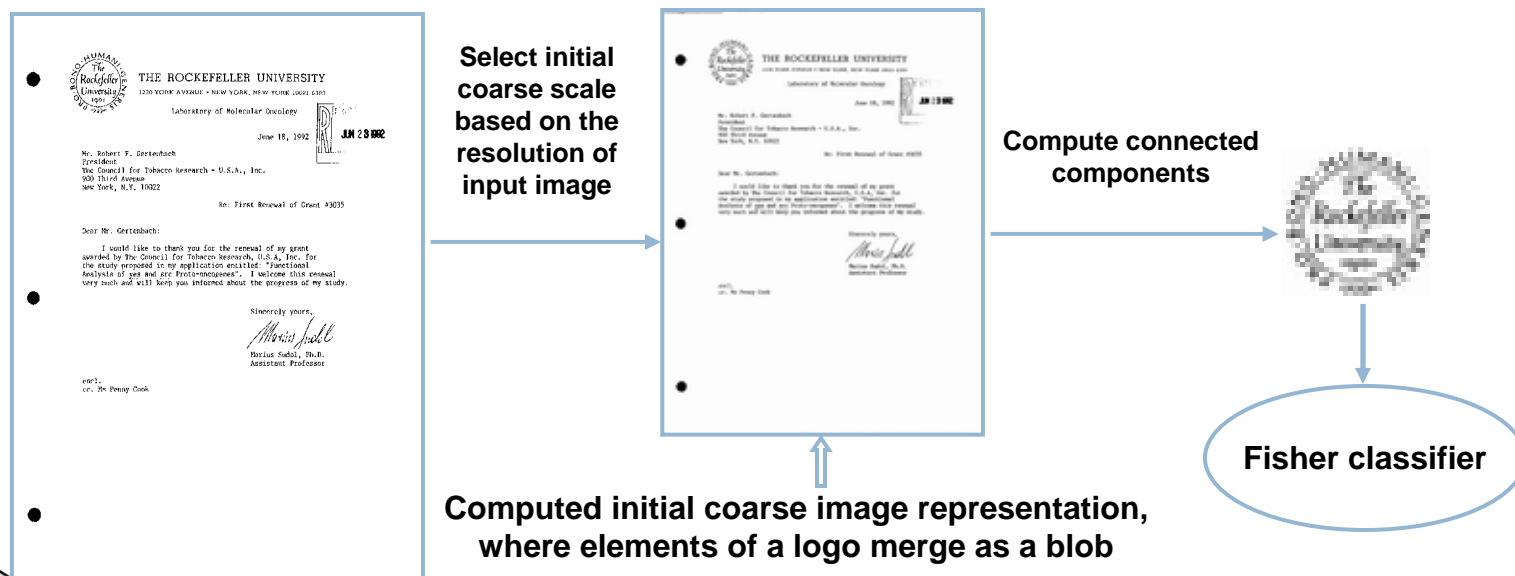
In the context of document image retrieval,

- ❑ provide complete formulation of logo detection and extraction
- ❑ provide evaluation metrics that quantitatively measure the quality of detected and extracted logos
- ❑ Testing on large, live document collections

Our approach



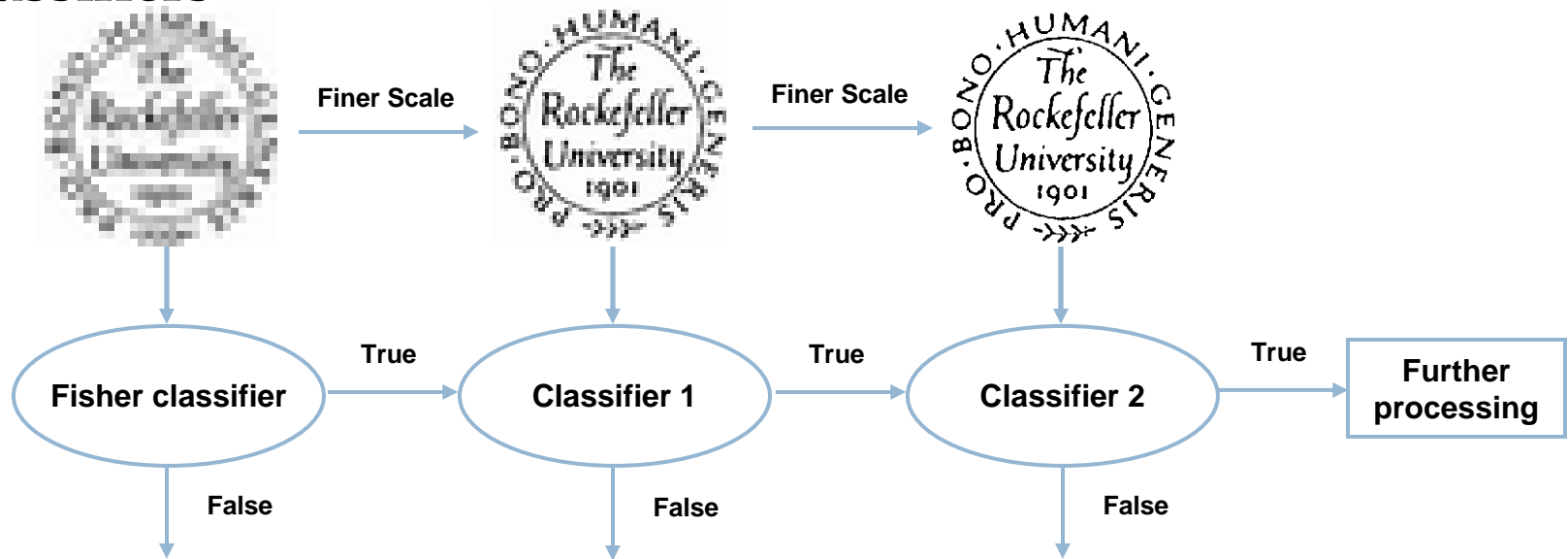
- A joint formulation for logo detection and extraction using a boosting strategy across multiple image scales
- At an initial coarse scale, a trained Fisher classifier performs an initial classification using features from document context and connected components



Multiscale Detection



- Each logo candidate region is further classified at successively finer image scales by a cascade of simple classifiers

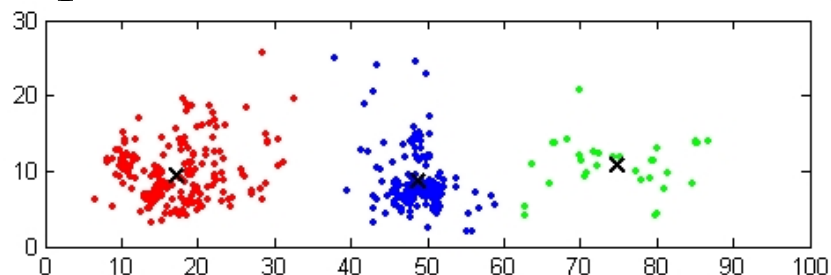


- The overall classifier is a strong learner, even if each individual classifier is in fact a weak learner



Feature selection and extraction

- How can we explore document context for logo detection?



Clustering result of logo positions using k -means ($k = 3$)

- We define context distance as

$$D_c(P) = \min_{i \in \{1, 2, \dots, k\}} (|p_x - c_x^i| + \lambda |p_y - c_y^i|)$$

- We select a compact list of features for classification

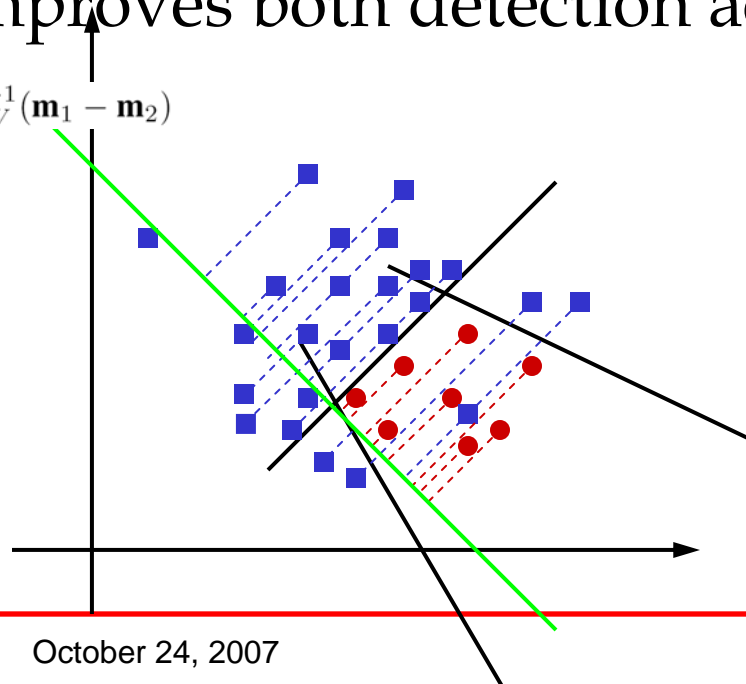
Context Distance	Area	Symmetry
Spatial Density	Aspect Ratio	Text Uniformity



Intuition

- Logos and non-logos are not linearly separable given the large variations involved
- Given the feature set, we can use Fisher linear discriminant analysis to get the best subspace for raw classification
- Boosting further improves both detection accuracy and precision

$$w_o = S_W^{-1}(m_1 - m_2)$$



Evaluation



- We use tobacco-800, a large public dataset that consists of 1290 real-world documents (full dataset 49 million pages)
- Use accuracy and precision as evaluation metrics

$$\text{Accuracy} = \frac{\# \text{ of correctly detected logos}}{\# \text{ of logos in groundtruth}}$$

$$\text{Precision} = \frac{\# \text{ of correctly detected logos}}{\# \text{ of detected logos}}$$

- Detection is at least $> 75\%$ and $< 125\%$ pixel are overlap

(detection
2006)

Summary of logo detection performance on the Tobacco-800 dataset

AMI

	Accuracy	Precision
Improved spatial density [9]	39.3%	32.1%
Fisher classifier only, <i>i.e.</i> , $ S = 1$	59.2%	41.7%
Multi-scale approach with $ S = 2$	57.0%	68.1%
Multi-scale approach with $ S = 3$	84.2%	73.5%



Evaluation



Examples of correctly detected logos from Tobacco-800

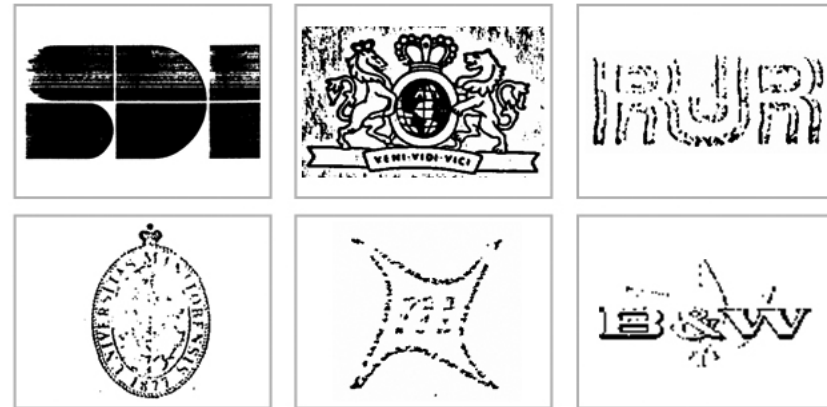
Evaluation



(a) Over/under-segmented logos



(b) Non logos



Examples of missed logos

Examples of incorrectly detected logos

Summary



- Proposed a multi-scale approach to logo detection and extraction approach (priori to retrieval)
- The cascade of classifiers at multiple scales is very effective in pruning the data points along the optimal projection direction given by the Fisher classifier
- Fisher linear discriminant analysis and boosting across image scales provide basis for good generalization
- Achieve overall 84.2% accuracy and 73.5% precision

Roadmap

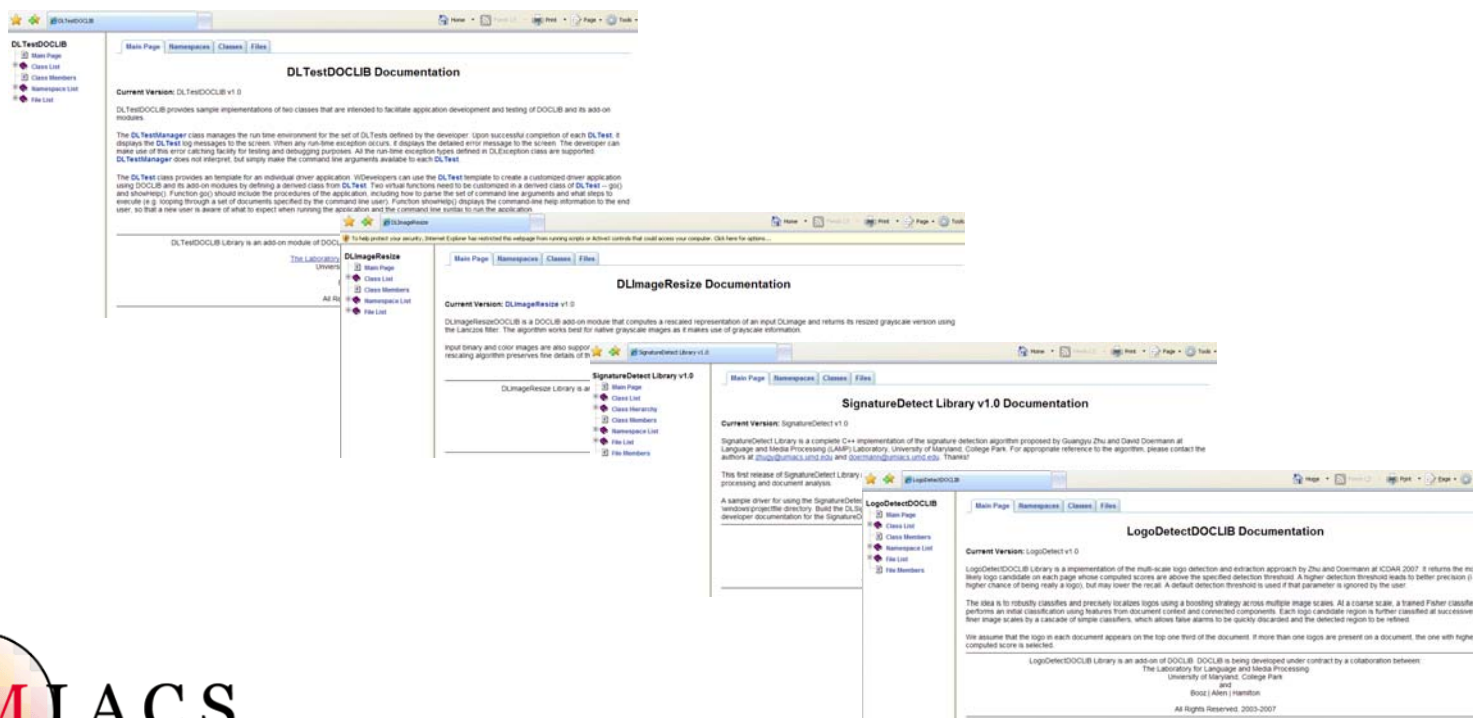


- Motivation
- Our Tasks
- Signature Detection Using Multi-scale Structural Saliency (CVPR 2007)
- Signature Matching for Document Image Retrieval
- Unconstrained Logo Detection in Document Images (ICDAR 2007)
- **Software releases**



Software releases

- Signature detection and logo detection code are released as Doclib add-on modules
- Production test on 32,000+ documents
- Signature matching and logo matching expected



Challenges in stamp detection

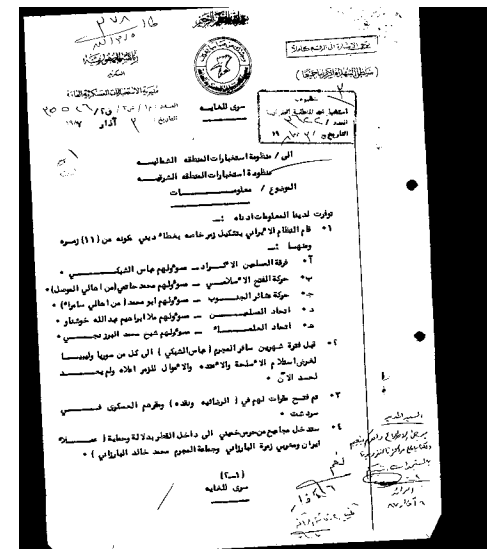
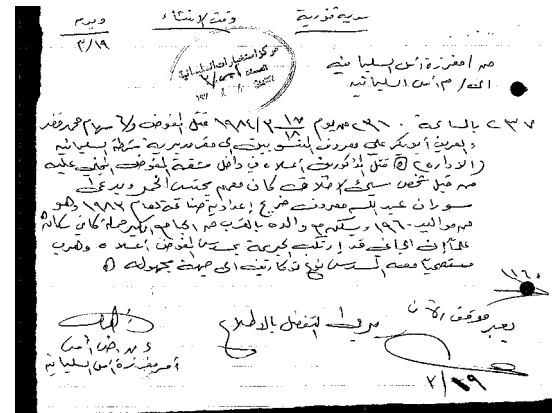


- Unique characteristics of stamps
 - ❑ Unstable and unpredictable patterns in documents
 - ❑ Outliers and occlusions are typical
 - ❑ Much lower spatial density compared to logo
 - ❑ Stamp instances appear as weaker regions within a full spectrum of background – text, figures, tables, watermark
 - ❑ Not generally valid to assume its location within the source

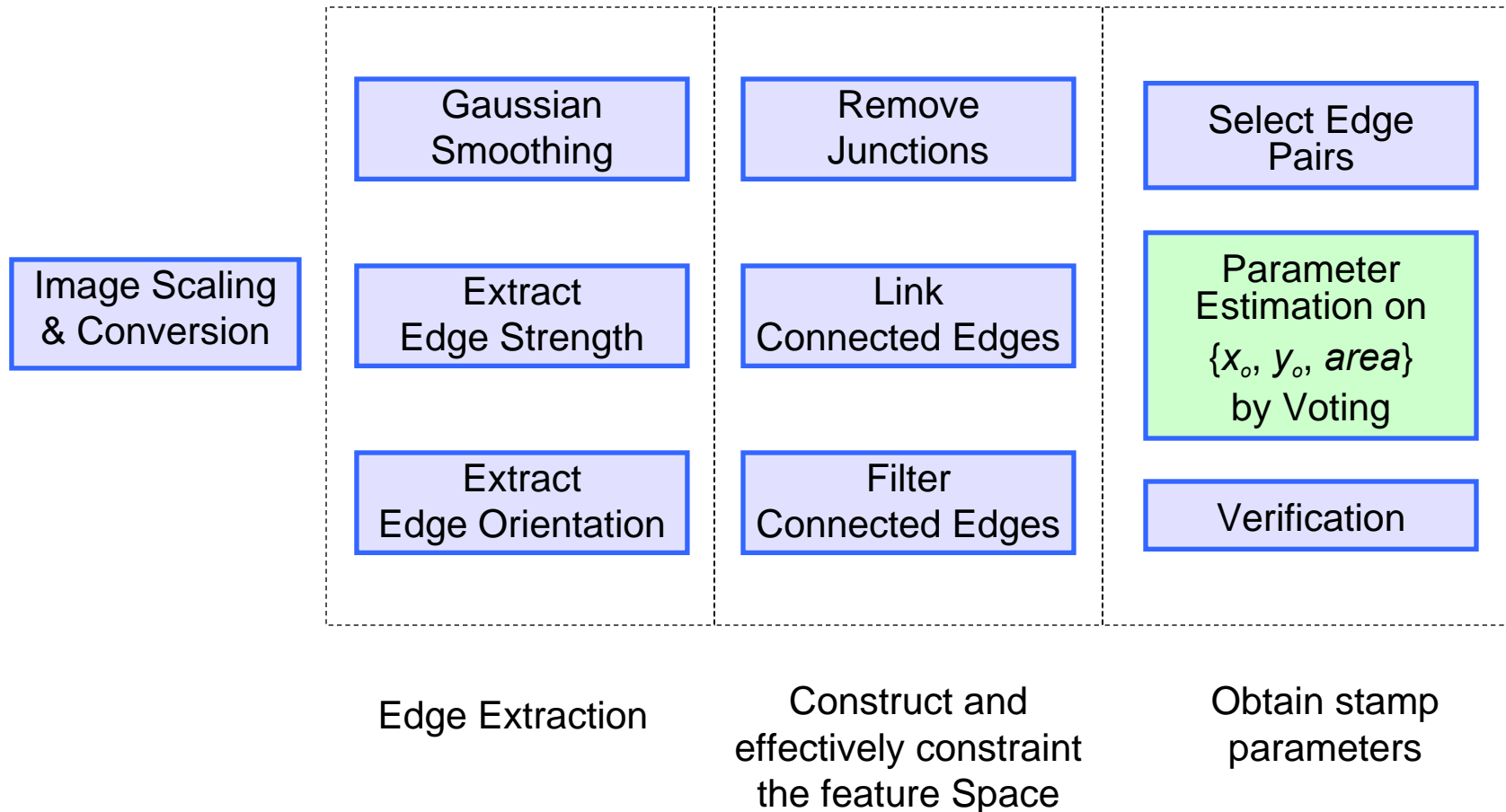


Motivations

- Treat stamps as regions with analytic shaped contours in noisy documents
 - All the stamps in our Arabic document databases are either elliptic or rectangular objects
 - Consider circular stamps as a special case of elliptic stamps.
- Our proposed stamp detection framework is based on recognizing strongly connected edge patterns
- Adopt the Hough transform voting scheme through efficient rectangle and ellipse parameterizations



Our stamp detection approach



Traditional ellipse detection techniques

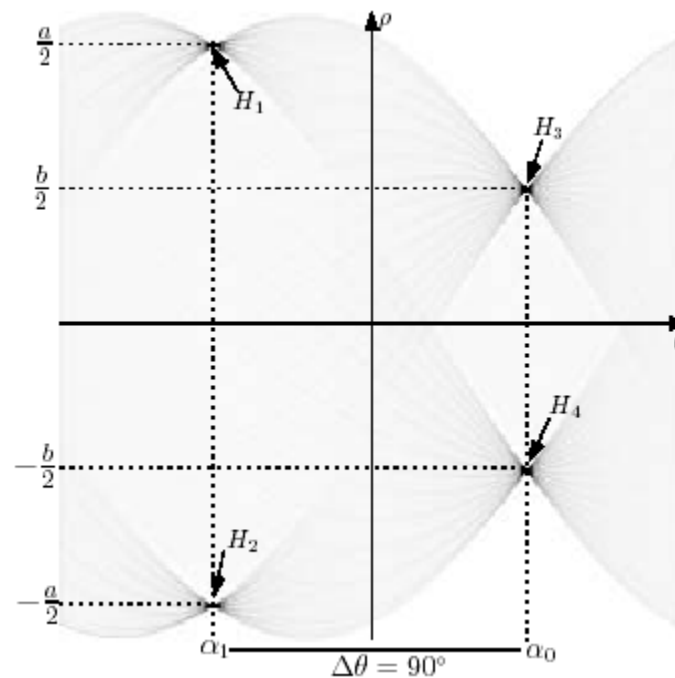
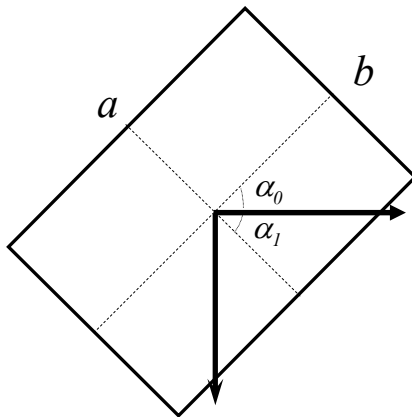


- Approaches based on Hough transform (HT) and its variants [2-6], RANSAC [7], and fuzzy logic [8-9] generally need to map sets of feature points to a parameter space
 - Obtaining the five parameters $\{x_o, y_o, a, b, \theta\}$ of an ellipse is computationally demanding
 - This parameterization is also inefficient as in many real problems, we only need to know a subset of these five parameters – e.g. $\{x_o, y_o, area\}$
- Other approaches including least-square fitting [10] and genetic algorithm [11] require pre-processing and are not robust against outliers/occlusions and noise

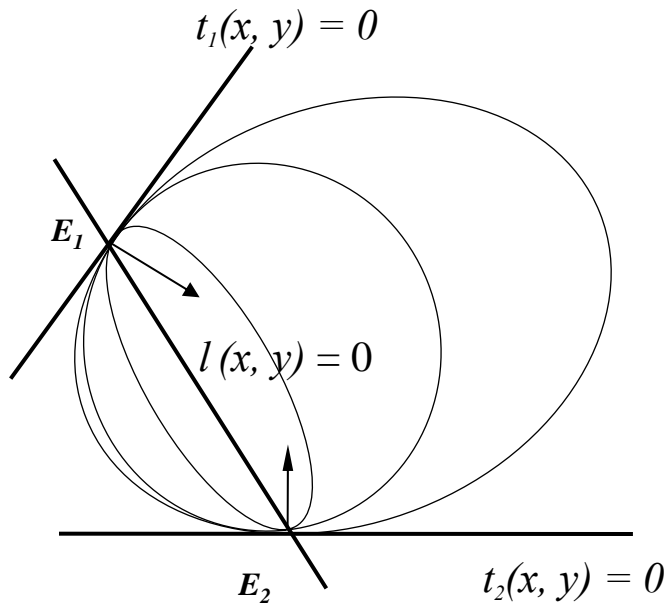
Traditional rectangle detection techniques



- Existing approaches focus heavily on finding line primitives and symmetric peak patterns in the Hough transform parameter space [15-18]



Ellipse detection method using pairs of edges



Tangent line passing E_1 :

$$t_1(x, y) \equiv p_1(x - x_1) + q_1(y - y_1) = 0$$

Tangent line passing E_2 :

$$t_2(x, y) \equiv p_2(x - x_2) + q_2(y - y_2) = 0$$

Line E_1E_2 :

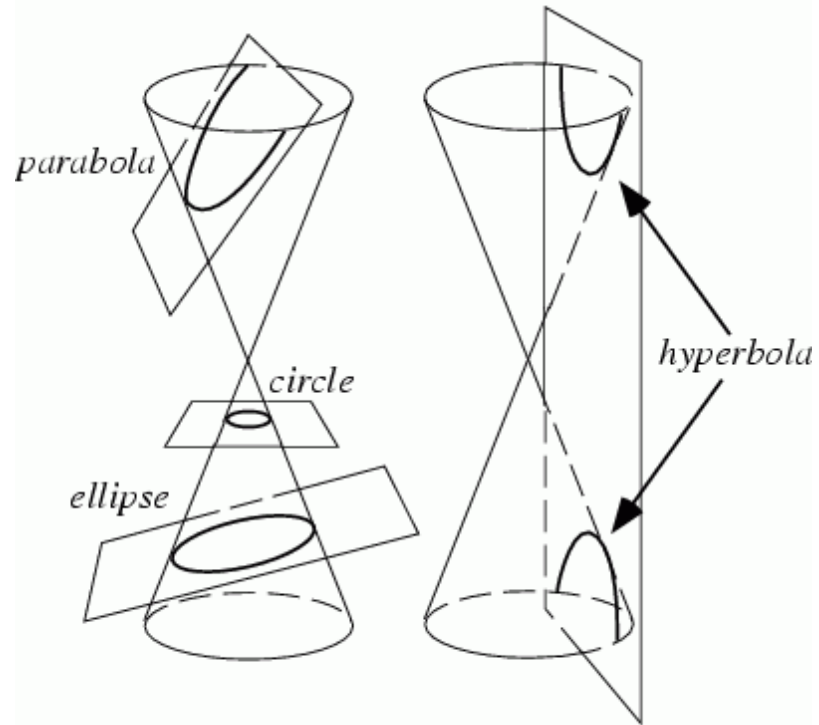
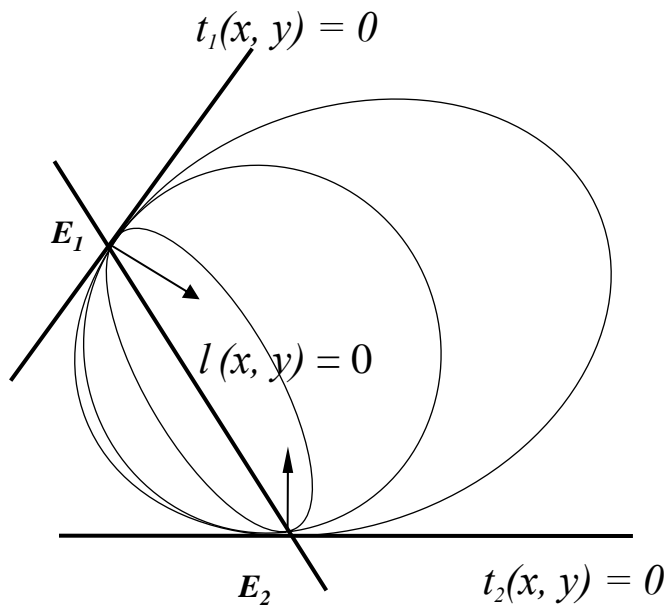
$$l(x, y) \equiv (y_1 - y_2)x + (x_2 - x_1)y +$$

$$x_1y_2 - x_2y_1 = 0$$

Define a quadratic function $f(x, y)$ as

$$f(x, y) \equiv l^2(x, y) - \lambda t_1(x, y)t_2(x, y) = 0 \quad (1)$$

Ellipse detection method using pairs of edges



The quadratic function $f(x, y)$ represents the family of 2nd-order curves that pass points E_1 and E_2 and tangent to lines $t_1(x, y)$ and $t_2(x, y)$.

Ellipse detection method using pairs of edges



- We can rewrite the quadratic function $f(x, y)$ in the canonical form of (2)

$$\begin{aligned} f(x, y) &\equiv l^2(x, y) - \lambda t_1(x, y)t_2(x, y) = 0 \\ &= ax^2 + 2hxy + by^2 + 2gx + 2fy + c = 0 \end{aligned} \quad (2)$$

- For any two connected edges, i.e. for a given set of $\{(x_1, y_1), (x_2, y_2), (p_1, q_1), (p_2, q_2)\}$, parameters a, b, c, f, g, h in equation (2) above can be simply mapped as first-order linear functions in λ .

Ellipse detection method using pairs of edges



$$a(\lambda) = (y_1 - y_2)^2 - \lambda p_1 p_2$$

$$b(\lambda) = (x_2 - x_1)^2 - \lambda q_1 q_2$$

$$c(\lambda) = (x_1 y_2 - x_2 y_1)^2 - \lambda (p_1 x_1 + q_1 y_1)(p_2 x_2 + q_2 y_2)$$

$$f(\lambda) = (x_1 y_2 - x_2 y_1)(x_2 - x_1) + \lambda [q_1 (p_2 x_2 + q_2 y_2) + q_2 (p_1 x_1 + q_1 y_1)]/2$$

$$g(\lambda) = (x_1 y_2 - x_2 y_1)(y_1 - y_2) + \lambda [p_1 (p_2 x_2 + q_2 y_2) + p_2 (p_1 x_1 + q_1 y_1)]/2$$

$$h(\lambda) = (y_1 - y_2)(x_2 - x_1) - \lambda (p_1 q_2 + p_2 q_1)/2$$

- For a given pair of edges with their respective gradient directions, the ellipse is uniquely parameterized by only one parameter λ .

Ellipse detection method using pairs of edges



- The center of the ellipse is given by:

$$x_o(\lambda) = \frac{h(\lambda)f(\lambda) - b(\lambda)g(\lambda)}{a(\lambda)b(\lambda) - h^2(\lambda)}$$

$$y_o(\lambda) = \frac{h(\lambda)g(\lambda) - a(\lambda)f(\lambda)}{a(\lambda)b(\lambda) - h^2(\lambda)}$$

- The area of the ellipse can be derived as [12]:

$$Area(\lambda) = \frac{\pi |d(\lambda)|}{\sqrt{a(\lambda)b(\lambda) - h^2(\lambda)}}$$

where

$$d(\lambda) = \frac{a(\lambda)f^2(\lambda) + b(\lambda)g^2(\lambda) - 2f(\lambda)g(\lambda)h(\lambda)}{a(\lambda)b(\lambda) - h^2(\lambda)} - c(\lambda)$$



Reduce search space for parameter λ

- The set of distinct value λ can also be effectively bounded by considering its range that corresponds to ellipses in the quadratic function $f(x, y)$.
- The range of meaningful λ value that corresponds to ellipses is given by [13]

$$0 < \lambda < \frac{4[p_1(x_2 - x_1) + q_1(y_2 - y_1)][p_2(x_1 - x_2) + q_2(y_1 - y_2)]}{(p_1q_2 - p_2q_1)^2}$$



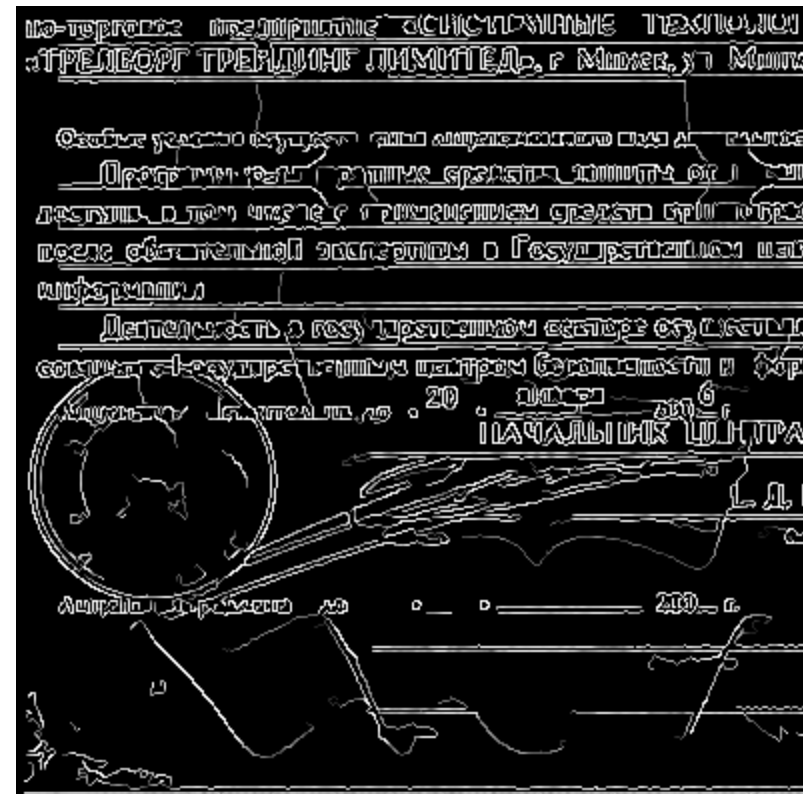
Computational complexity

- Let D be the number of distinct values in one dimensional parameter space and E the number of selected edge points
- Classic Hough transform based ellipse detection [14] runs in $O(ED^3)$, using orientation information of single edge points
- Our approach exploits the first-order derivative (gradient) of a pair of edges, which reduces the running time from $O(ED^3)$ to $O(E^2D)$
- Since we consider only those edge pairs that are from the same connected component of finite bounded length, further reducing the computation from $O(E^2D)$ to $O(ED)$

Demo

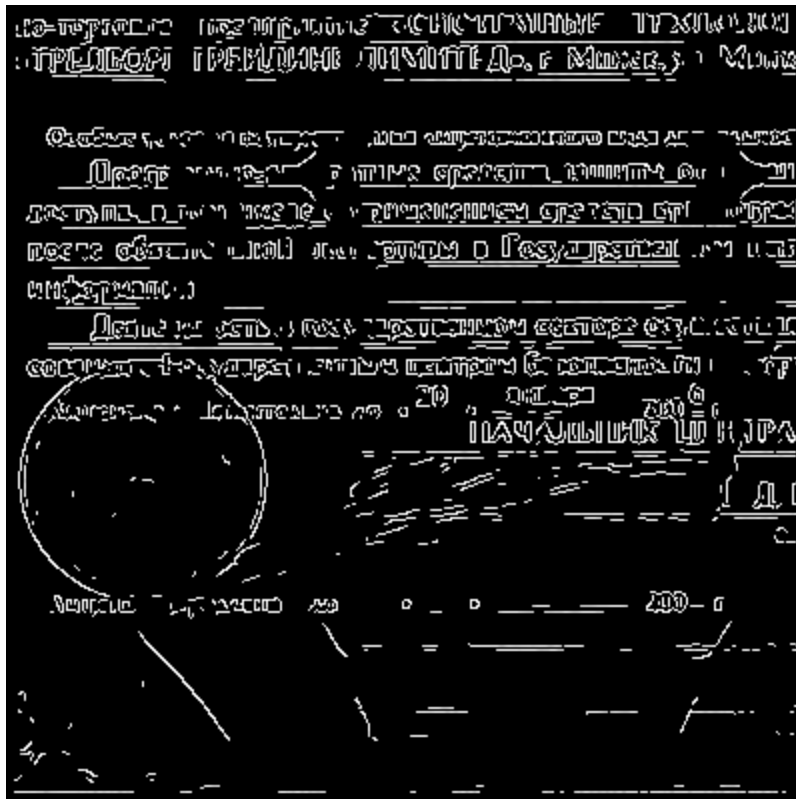


Region of a sample image

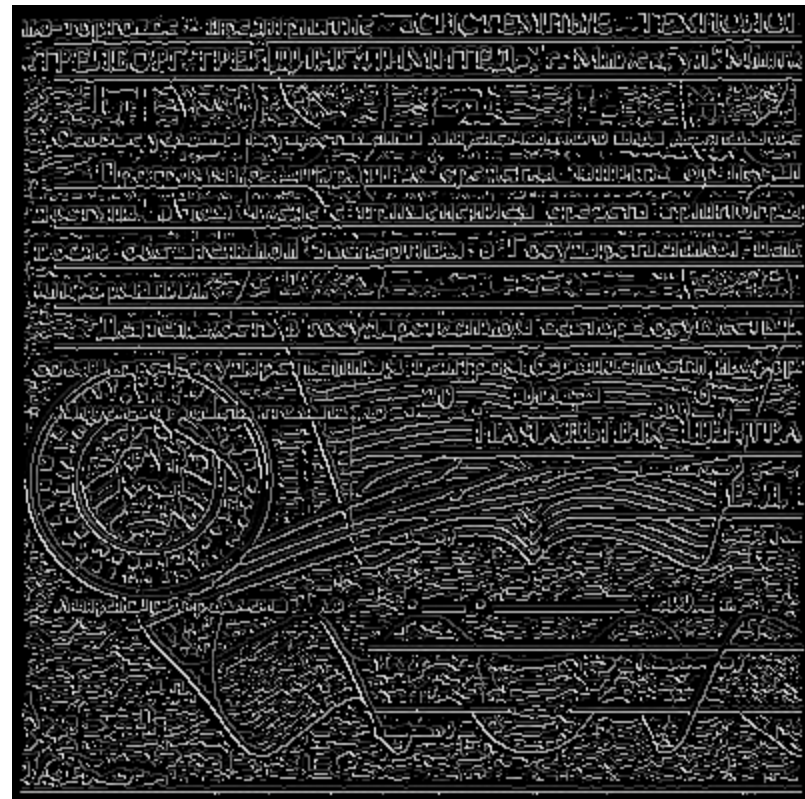


Strength of edge gradient

Demo



Strong edges



Orientation of edge gradient

Demo




Top 10 candidates in the 3-D parameter space in ellipse center and area, i.e. $(x_c, y_c, area)$

- (68, 238, 11313), score = [5485509]
- (56, 202, 6464), score = [501958]
- (52, 226, 8080), score = [431456]
- (72, 206, 8080), score = [352608]
- (84, 266, 6464), score = [278291]
- (84, 210, 6464), score = [260775]
- (44, 222, 8080), score = [247448]
- (28, 270, 3232), score = [241991]
- (40, 202, 4848), score = [224263]
- (76, 230, 9696), score = [215384]

Demo



 **Jakarta International School**

March 11, 2003

Letter of Recommendation for Gustavo Helman

The Middle School of Jakarta International School currently serves the needs of 580 students from over fifty-five nationalities. It is a demanding work environment in which administration, faculty, students, and parents possess high expectations. In my capacity as the Middle School Principal, I supervised Gustavo Helman during the past eighteen months.

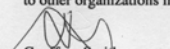
Gustavo possesses excellent teaching strategies balanced with strong knowledge of curriculum. Gustavo is a proven teacher of Modern Languages. During his time at JIS, Gustavo taught Spanish and one section of Japanese this year. Gustavo is well schooled in the proficiency-based approach to teaching modern languages. He is a very intelligent and a deep thinker relative to the art and science of teaching.


His style with students is warm and friendly, and he possesses high expectations in class. The atmosphere in his classroom is positive. He has involved students in a variety of valuable projects and assignments. I appreciate his approach to the teaching of Spanish and believe the classroom environment he creates is very conducive for learning.

Over the past several years, the Middle School Modern Languages department has actively revised curriculum. They have worked to articulate their curriculum in a set of unit planners with clearly described outcomes, skills, assessments, and activities. Gustavo has contributed strongly to this process. His technological skills combined with his strong organizational skills and knowledge of teaching has assisted colleagues in this area. His work ethic is strong and he presents himself professionally.

Gustavo pursues professional development opportunities. He is in the process of earning a doctorate, no small feat while teaching full time. In addition, he actively involves himself on the academic side of the profession. He presented a workshop at last year's EARCOS Teachers Conference and he is scheduled to present again, later this month, at the next ETC in Bangkok. He must be commended for his eagerness to pursue professional development opportunities.

Gustavo is departing Jakarta International School after two years for personal reasons. He has proven to be a solid contributor to our school and I have no doubt that he will positively contribute to other organizations in the future.


Geoffrey Sujih
Middle School Principal
Jakarta International School



P O Box 1078 JKS Jakarta 12010 Indonesia Telephone: (62-21) 769-2555 Fax: (62-21) 759-08843 <http://www.jisedu.org>



软件企业认定证书

经审核， 深圳市南凌科技发展有限公司 符合《鼓励软件产业和集成电路产业发展的若干政策》和《软件企业认定标准及管理办法》(试行)的有关规定， 认定为软件企业， 特发此证。

证书编号： 深R-2003-0274 发证机关： 深圳市信息化办公室
二〇〇三年 十一月 二十五日
2003 11 25



October 24, 2007

Demo



Do you have handwritten notes ?

... and don't need them anymore?

Well, bring them to us – we pay for it!

The Language and Media Processing Laboratory (LAMP) is collecting handwritten notes or annotations from classes, lectures, conferences, workshops, etc. for research in document image analysis. We are searching for notes written in the following scripts:

Arabic, Armenian, Burmese, Chinese, Cyrillic, Devanagari, Ethiopic, Greek, Hebrew, Japanese, Korean, and Thai.

Your notes may contain diagrams, tables, equations, and figures. Printed documents with a significant amount of handwritten annotations are also useful for us. However, the documents should not contain any personal information or names of individuals.

Since we have different needs for each script and also upper limits as to how many pages a writer can provide, you may contact us or send us some samples in advance to see if your data meets our requirements. If it does, you will receive \$5.00 for every 10 pages you provide by simply handing over your notes and allowing us to use them for our research. We would also pay the shipping charges for sending handwritten notes to us from friends in your home country.



Contact:

Dr. Stefan Jaeger, Dr. David Doermann
Laboratory for Language and Media Processing (LAMP)
3453 A.V. Williams Building, University of Maryland, College Park
Phone: 301-405-0125 or 1767
Email: {jaeger, doermann}@umiacs.umd.edu

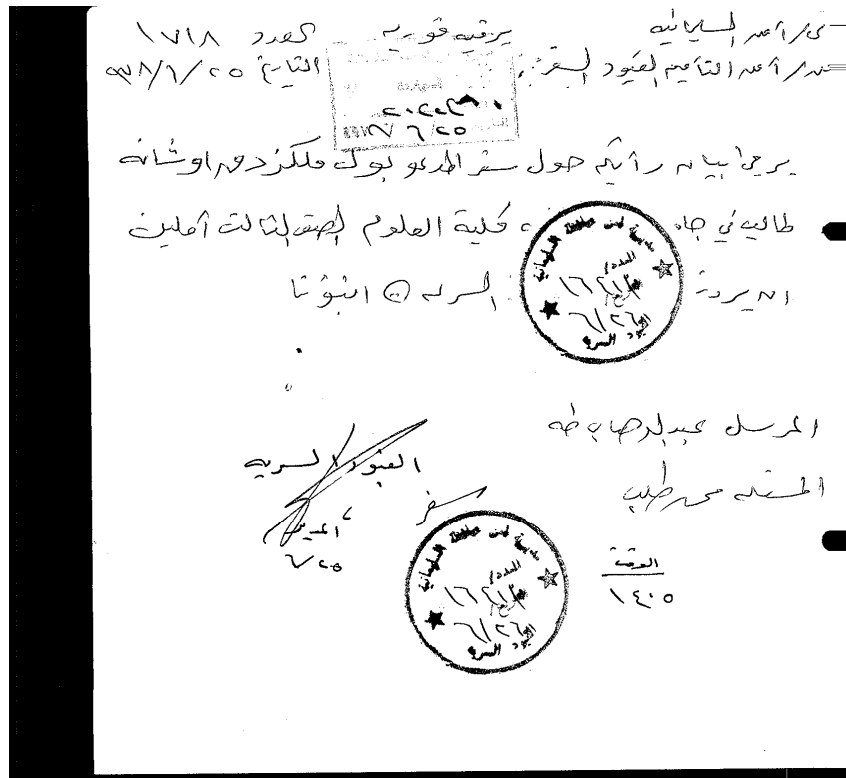


October 24, 2007

Demo



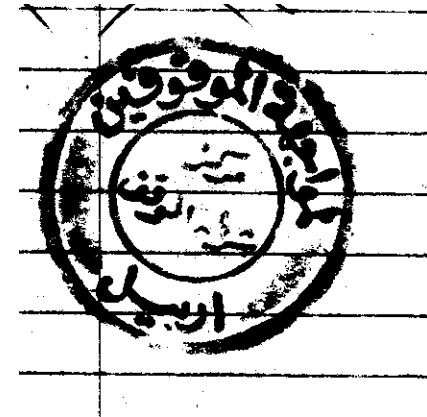
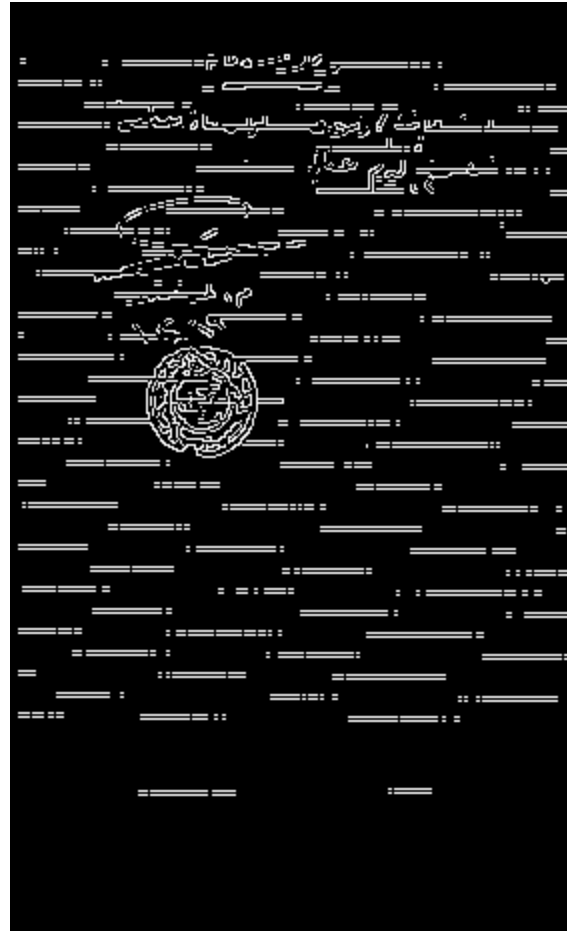
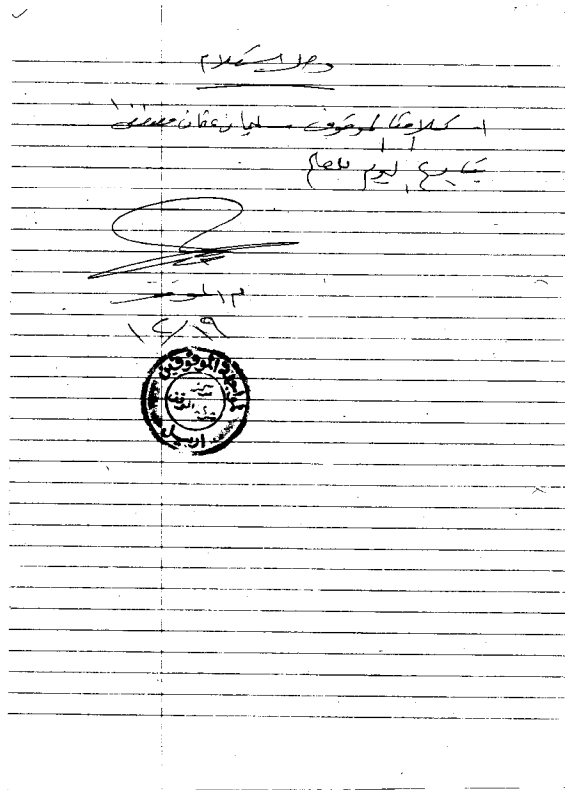
Capability to detect multiple stamp instances



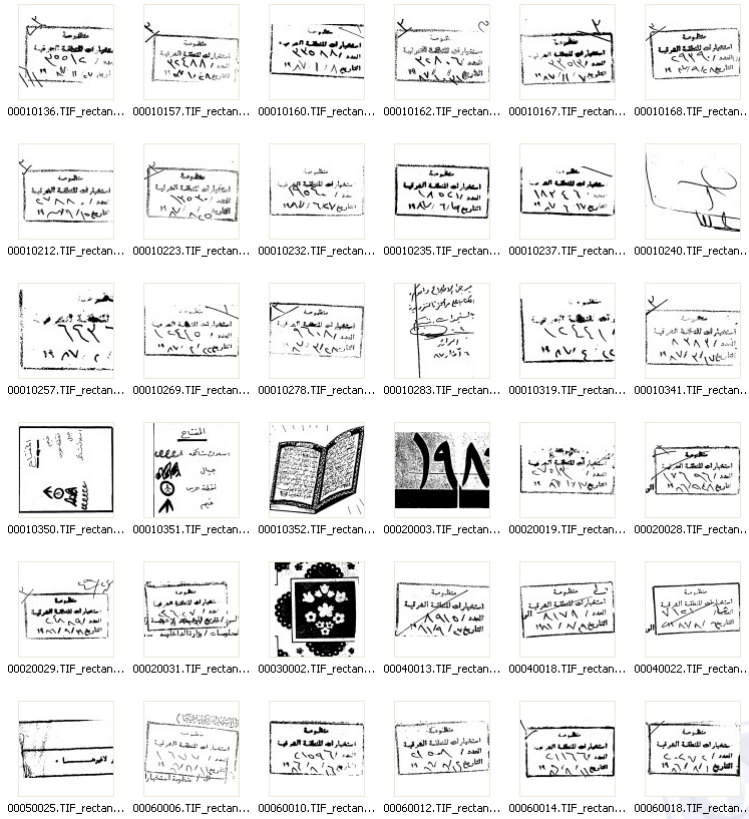
Demo



Capability to detect stamp instances in diverse backgrounds



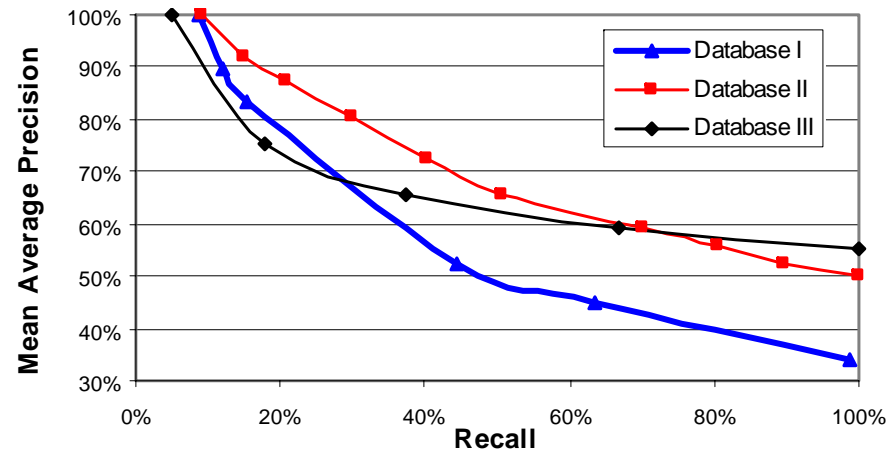
Demo



Experiment



Test Databases	Total Images	Images with The Retrieved Stamp
Database 1	436	92 (Circular)
Database 2	193	68 (Elliptic)
Database 3	287	102 (Rectangular)



Summary for stamp detection



- The stamp detector proves to be robust against outliers and occlusions in degraded documents using only limited a priori information
- The speed of detection is 2-3 seconds on 2000×2500 pixel images. Improvements can reduce the running time further by carefully constraining the feature space
- Production retrieval tests on real Arabic document databases, each with about 5000 binary images.
- It can be used as real-time shape detectors in video
- We are also working on robust techniques that are able to achieve auto recognition of logos/stamps



Technical Presentations

- └ Page Segmentation (and rule line separation)
- └ Page Layout Similarity
- └ Document ID/Script ID

This afternoon

- Signature Detection
- Logo Detection and Recognition
- Stamp Detection
- Font OCR



October 24, 2007