

CLEAT:

**A Classification, Enhancement and
Analysis Toolkit
for
Heterogeneous Document Image Collections**

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Who are we?

LAMP History

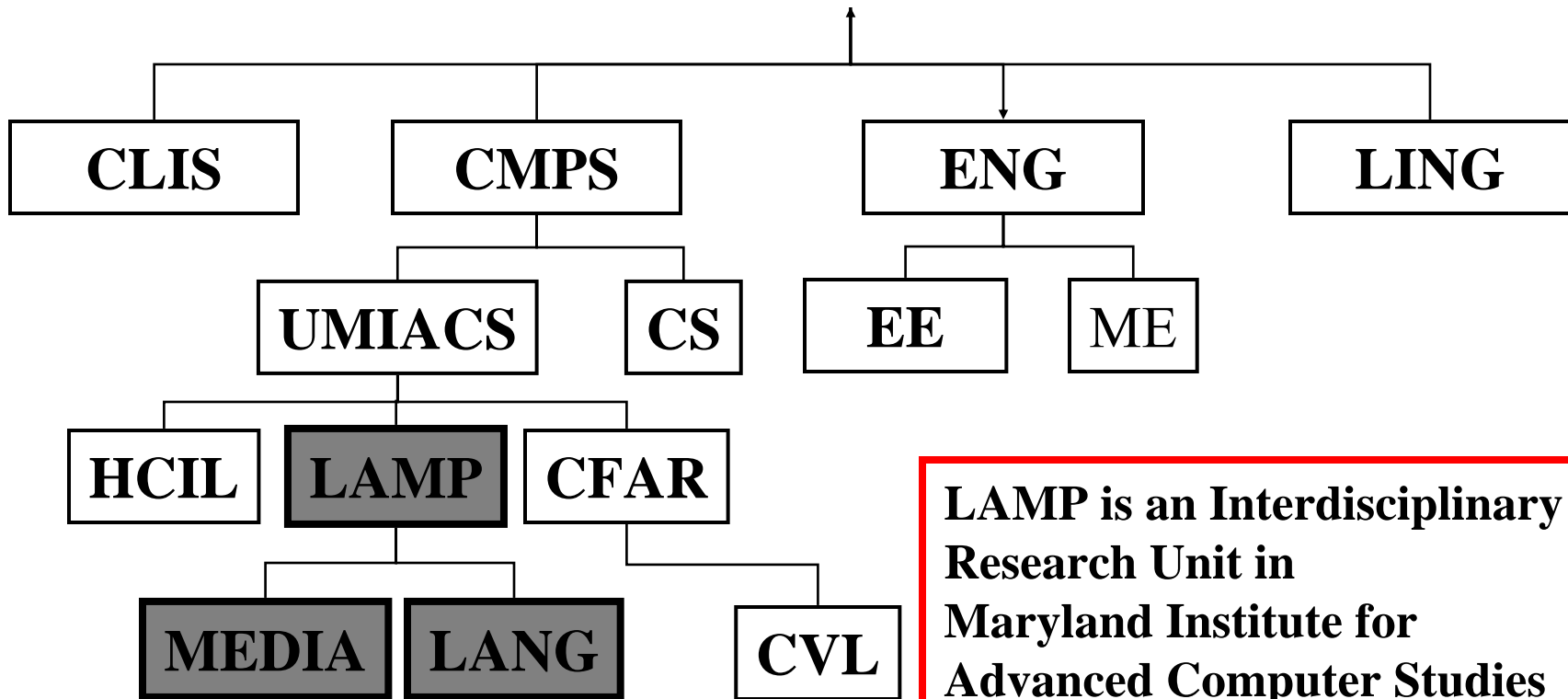
- Began in 1996 with a focus on documents
- Produced 9 PhD (2 more expected in 2007)
- Over 200 scientific publications
- Almost 50 Students (Undergrad-Graduate)
- Numerous Technology Transfer Opportunities



Mission

To conduct research and education in analysis and processing of multimedia information sources including documents, images and video, to develop natural language tools for real world applications, and to foster collaboration in these areas between researchers at the university and representatives of government agencies and industry





LAMP is an Interdisciplinary Research Unit in Maryland Institute for Advanced Computer Studies (UMIACS)



Outreach

- Bi-Annual SDIUT Conference
 - Soon to be included in Google Books Project
- Host of workshops and short courses
- Editorial Office of IJDAR
- Data Collection and Evaluations
- LAMP Seminar Series
- Chairing Program Committee for ICDAR 2007
- Organizing Arabic OCR competition at ICDAR'07



Research Focal Areas

- Document image analysis
 - Providing fundamental tools for the enhancement, summarization, navigation, indexing and retrieval in document image databases
- Content based video analysis
 - Providing access to video content through extraction, structure representation, classification, visualization and indexing
- In General
 - Ability to access large heterogeneous collections of material
 - Adaptable systems – OCR, MT
 - Low density to resource poor languages
 - Enhancing low quality input – document images, OCR



Intelligence Value Estimation

- How can we take **large, noisy, unstructured, heterogeneous** collections of image and video data to:
 - Mine the nuggets?
 - Bubble the important things to the top?
 - Provide tools for Information Discovery?

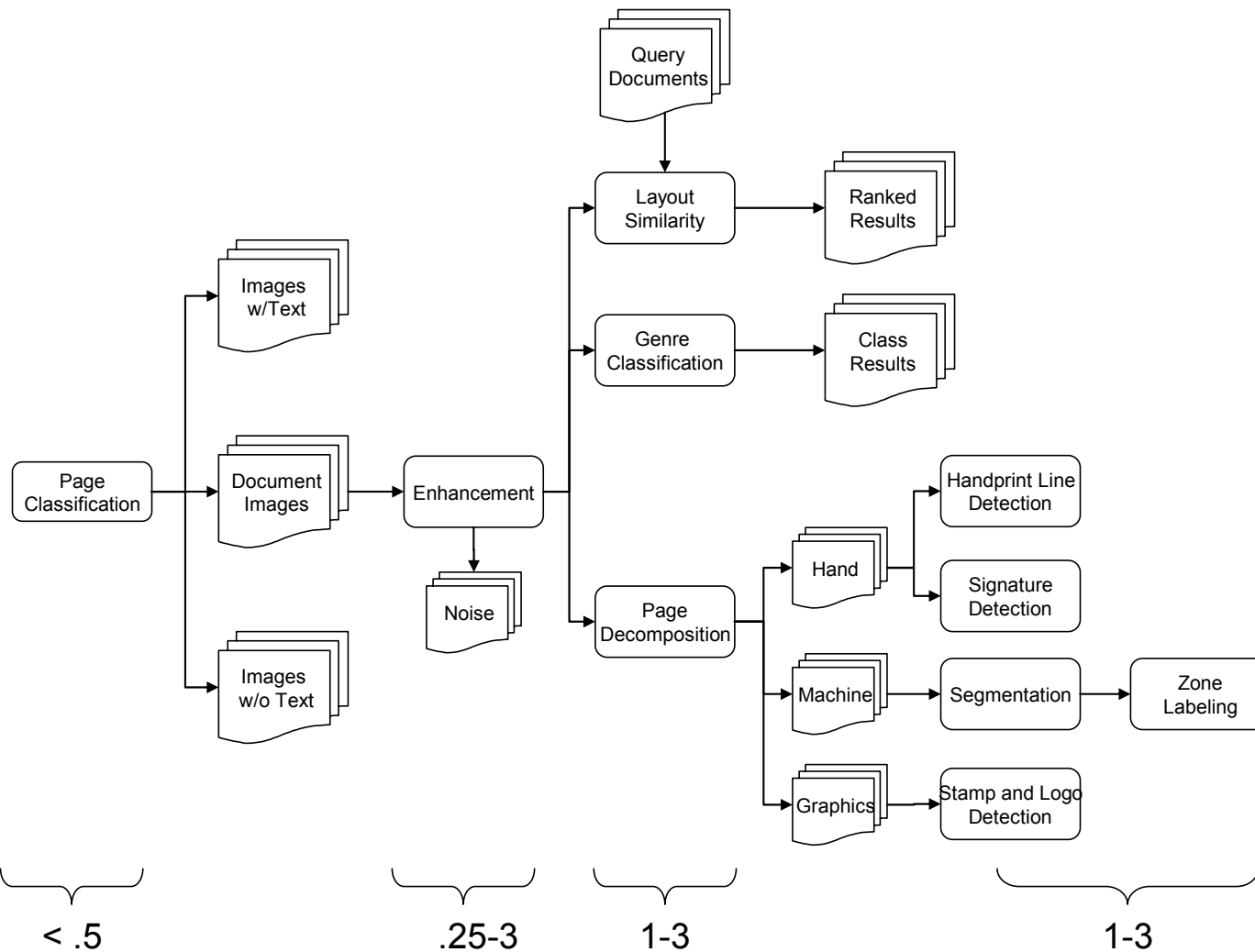


Approach

- Build robustness to noise into algorithms
 - Train noise as its own class
 - Integration of recognition and segmentation
- Provide mid level tools to organize collections
 - Genre Classification
 - Logo, Stamp and Signature Detection/Recognition
- Focus on Ranking rather than “conversion”
 - Page Layout Similarity
- Provide tools necessary for efficient research and evaluation
 - Datasets
 - GEDI – Groundtruth and Evaluation



Project Overview



Target Processing Speed in Seconds



Task Objectives

- Task 1: Data Collection**
- Task 2: Ground Truthing**
- Task 3: Evaluation Framework**
- Task 4: Evaluation and Visualization Tool**

- Task 5: Page Classification Module**
- Task 6: Enhancement Module**
- Task 7: Layout Analysis Module**
- Task 8: Content Labeling module**

- Task 9: Evaluation**
- Task 10: Training**



Performance Goals

Task	Performance Goal
Page Classification	80% precision across all three classes
Enhancement	10-30% increase in accuracy of downstream processes – segmentation, detection
Layer Separation	90% coverage at the pixel level
Segmentation (Print and Hand)	85% using implementation of existing methods
Logo and Stamp Detection	75% precision at 85% recall
Signature Detection	75% precision at 85% recall



GEDI – Java Interface

Image Window

The screenshot displays the DL-GEDI software interface. The title bar reads "00010005.TIF - DocLib GroundTruthing - Editor and Document Interface (DL-GEDI)". The menu bar includes "File", "Edit", "View", "Modify", "Preferences", "Window", and "Help". The toolbar contains icons for Merge, Split, Save, Open, Scale (Fit To Window), Drag, and a zoom level of 1. The main window shows a document with Arabic text and a red stamp. The interface is divided into several panels:

- Browser Window:** A table listing files with columns for Name, Image, and Xml.
- Type Window:** A table showing the properties of the selected zone, including Name, Color, Key, Visibility, and Count.
- Attribute Window:** A table showing the attributes of the selected zone, including gedi_type, coordinates, Overlap, Quality, and Shape.
- Selected Zone Info:** A text box displaying the coordinates and name of the selected zone.

Browser Window

Type Window

Attribute Window

Current File: 00010005.xml*

Name	Image	Xml
00010003	✓	✓
00010004	✓	✓
00010005	✓	✓
00010006	✓	✓
00010007	✓	✓
00010008	✓	✓
00010009	✓	✓
00010010	✓	✓
00010011	✓	✓

NAME	COLOR	KEY	VISIB...	COU...
DLStamp	Red	None	✓	1
DLSignature	Black	None	✓	1

Attribute	Value
gedi_type	DLStamp
(row,col)(width,hei...	(379,7)(452,300)
Overlap	partial
Quality	poor
Shape	elliptic

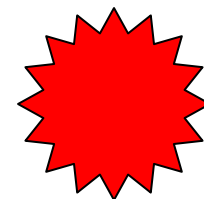
Selected Zone Info
(379,7)(831,307)
DLStamp

Data Collection and Evaluation

Type	Number
Class 1: Traditional Document Images	9000
Class 2: Camera captured, Text in Scene, and Color documents	500
Class 3: Non-document Images	500
Genre	Number
Forms, Drawing, Tables	1000
Business Documents, Memos, Letters	2500
Journal and Conference Papers, Articles	2500
Newsletters, Flyers	1000
Structured Documents – phone books, dictionaries	1000
Handwritten	1000
Foreign Language – handwritten and machine printed	1000
Highly Degraded	500
Mixed Annotation	2000



New Data



- 25,000 pages ground truthed to the zone level
- Sampled from the Tobacco Litigation Corpus of 49 Million pages



25,000 pages ground truthed

	<u>DOCS</u>	<u>PAGES</u>			
dt_calendar	44	90	dt_email	973	1151
dt_photograph	227	461	co_tables	1049	1980
dt_questionnaire	188	461	dt_form	1582	2265
dt_bibliography	175	530	co_foreign	1669	2300
dt_periodical	479	693	dt_notes	2288	2925
dt_list	405	710	co_illegible	2598	3983
dt_advertisement	519	894	dt_graphic	2061	4307
dt_newspaper	688	921	dt_letter	3145	4601
co_fax	830	1150	dt_report	2213	4604
co_drawings	638	1150	dt_memo	2762	4611
			co_handwritten	4894	6903
			co_marginalia	10665	17251



DocLib Architecture

- **Efficient Technology Transfer**
 - software compatibility
 - balance of academia, government, and industry needs
 - common framework for document processing
- **Scalability**
 - rapid prototyping of new methods
 - simple algorithm comparison
- **Robustness and Stability**
 - high quality standards
 - platform-independence
 - accommodation of frequently changing requirements



DocLib Status

- Core DocLib components matured and stable (in use by a variety of government installations)\
- Addons being integrated/implemented, primarily by developers
- Freely available to government researchers
- Core supported on Solaris, Linux and Windows



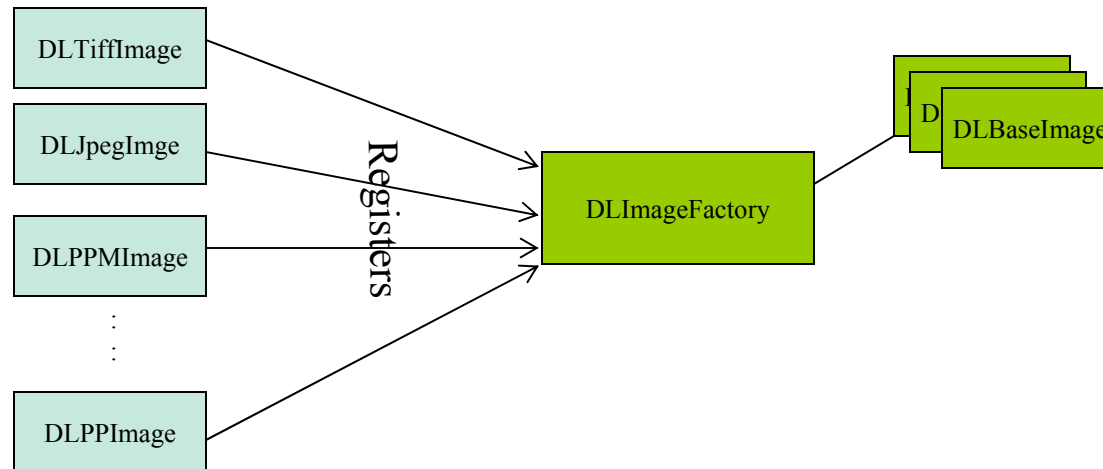
Core vs Add-ons

- Core components are loosely defined as necessary building blocks for ANY document analysis process
- Addons are tools and applications for specific types of analysis

We try to put as few constraints on the representations as possible.



Image Factory



Design Factors:

- Image Type objects are static/singleton objects created on startup
- DLImageFactory is a static/singleton object
- Image Type objects registers itself with the DLImageFactory during startup
- DLImageFactory keeps a list of supported Image objects as each image type calls the register function
- Additional image types can be plugged into DOCLIB without modifying existing DOCLIB code.

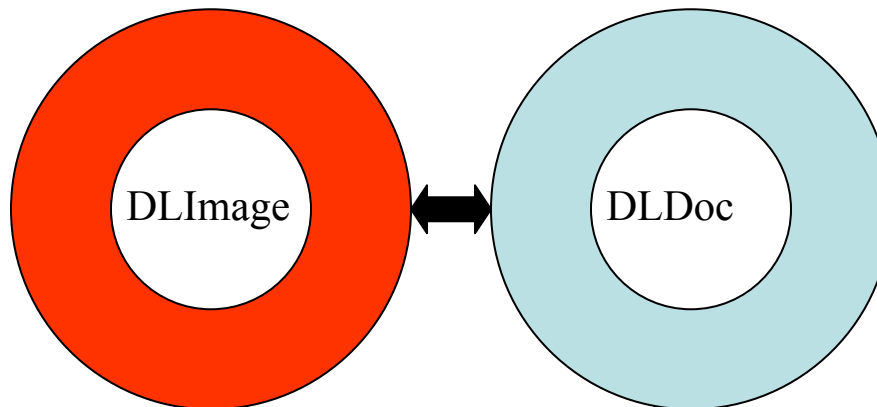


DocLib Architecture

DocLib's architecture rests on two pillars:

DLImage:

➤ **Image Processing**



e.g.

- **image rotation**
- **image deskewing**
- **image conversions**
- **cc calculation**
- **shape drawing**

DLDocument:

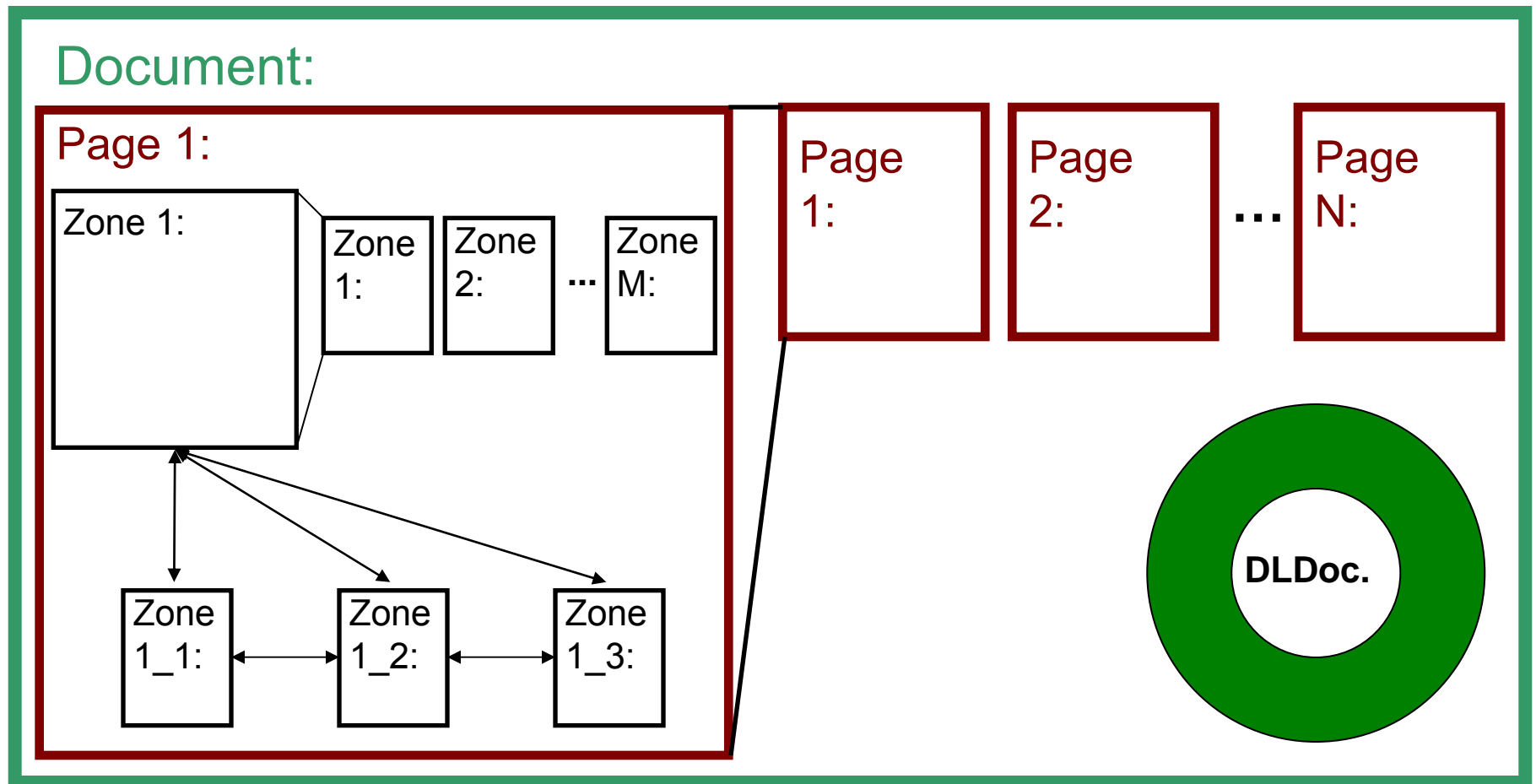
➤ **Document Processing**

e.g.

- **page segmentation**
- **text line extraction**
- **logo detection**
- **XML input/output**
- **page layout analysis**



Document Hierarchy



Recent Modules

- Thinning
 - Rotation
 - Deskewing

 - XML i/o
 - Degradation
 - OCR Scansoft interface (Windows)
 - Docstrum

 - Logo detection
 - Signature processing
- LogoDetect
 - TokenMatch
 - Machine vs. Handwritten
 - Jargon
 - Text Line Detection



XML Output Extension

```
<?xml version="1.0" encoding="UTF-8" ?>
<!-- GEDI is developed at Language and Media Processing Laboratory,
      University of Maryland. -->
<GEDI xmlns="http://lamp.cfar.umd.edu/GEDI" version="1.0">
  <USER name="Elena" date="Sun, 14 Oct 2007 8:28 PM" />
  <DL_DOCUMENT src="aaa27e00.tif" docTag="xml" NrOfPages="2">
    <DL_PAGE gedi_type="DL_PAGE" src="aaa27e00.tif" pageID="1«
      width="2560" height="3296">
        <DL_ZONE gedi_type="STAMP" id="None" col="1174" row="495“
          width="447" height="132" />
        <DL_ZONE gedi_type="LOGO" id="None" col="274" row="569"
          width="346" height="159" contents="" />
        <DL_ZONE gedi_type="MACHINEPRINT" id="None" col="647"
          row="626" width="1372" height="105" contents="" />
        <DL_ZONE gedi_type="MACHINEPRINT" id="None" col="2410"
          row="2479" width="511" height="110" orientation="-
          1.6295521495106193" contents="" />
      </DL_PAGE>
    </DL_DOCUMENT>
```



Technical Presentations

- Page Segmentation (and rule line separation)
- Logo Detection and Recognition
- Signature Detection
- Stamp Detection

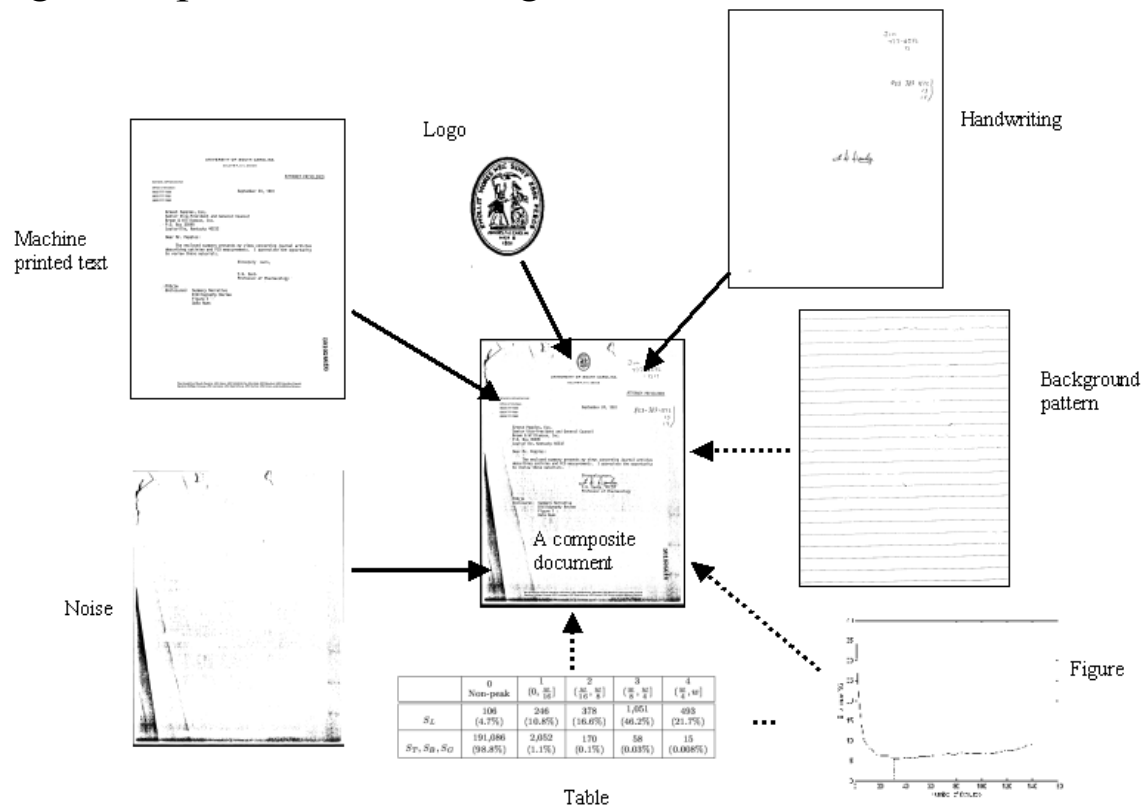
- Document ID/Script ID
- Page Layout Similarity

- Video Research
 - Tracking and Analysis of People
 - Video Content Classification



Page Layer Segmentation

- Document image generation model
 - A document consists many layers, such as handwriting, machine printed text, background patterns, tables, figures, noise, etc.

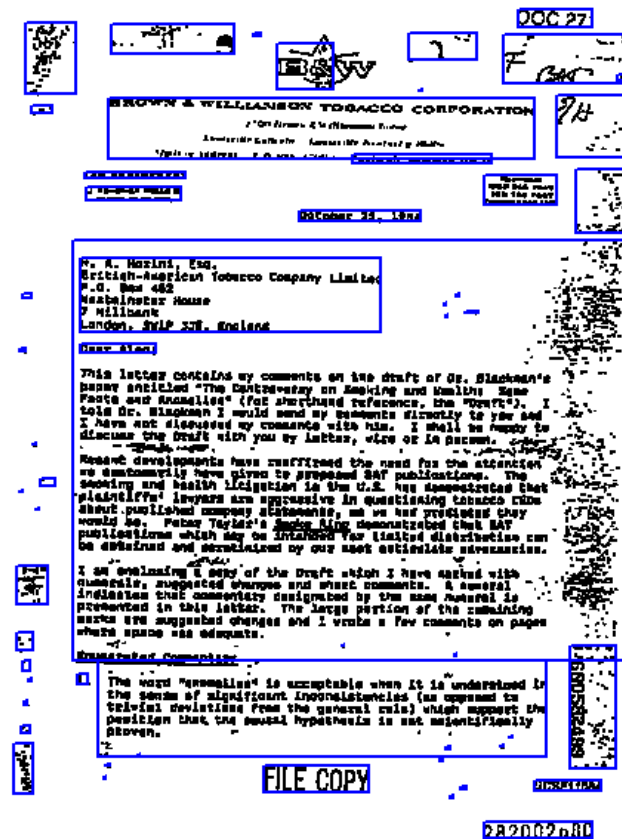
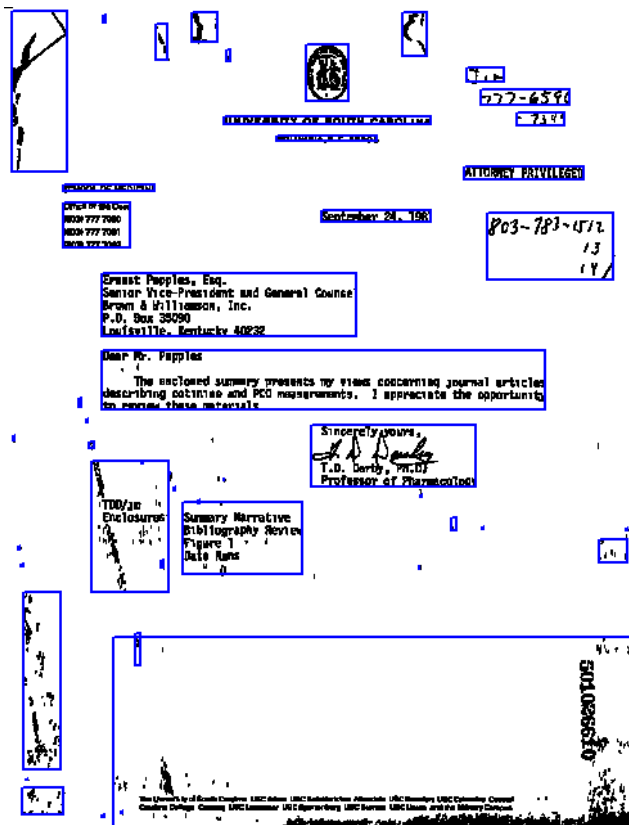


Motivation

- Document analysis has been viewed as a solved problem in clean, well-constrained documents.
- However, the performance degrades significantly when a small amount of noise is introduced.
- We further separate handwriting from machine printed text.



Page Segmentation for Noisy Documents



* Docstrum page segmentation technique is used



Overview of Our Approach

- Segment the document to word level using connected component based, bottom-up approach.
- Classify each segmented block into noise, handwriting or printed text, based on extracted features and the Fisher classifier.
- Using MRF (Markov Random Field) to refine the classification result.



Feature Extraction and Selection

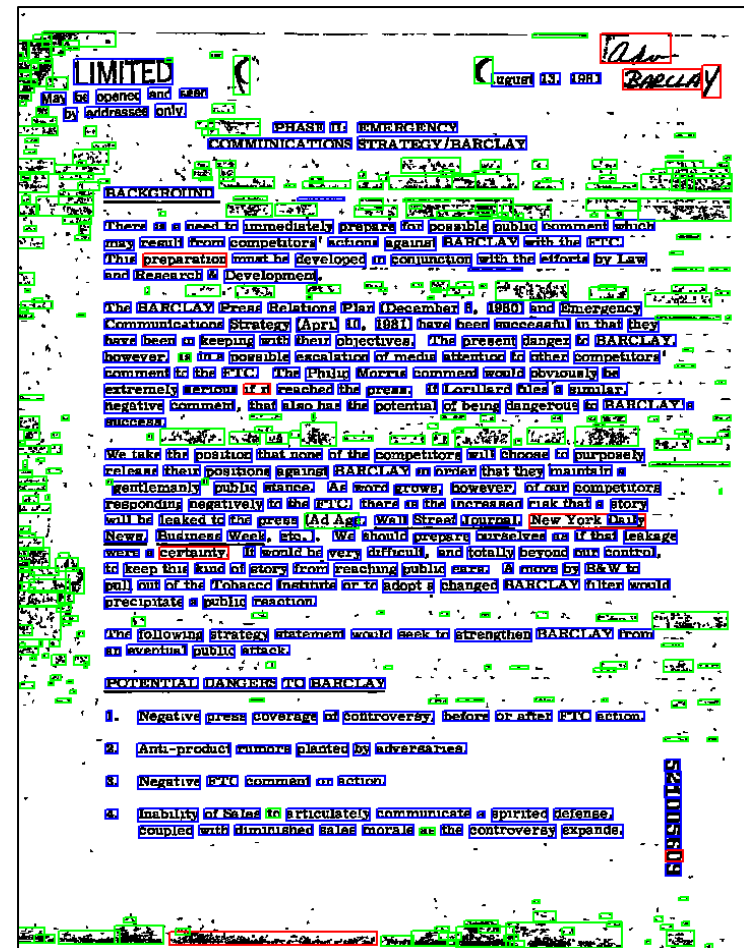
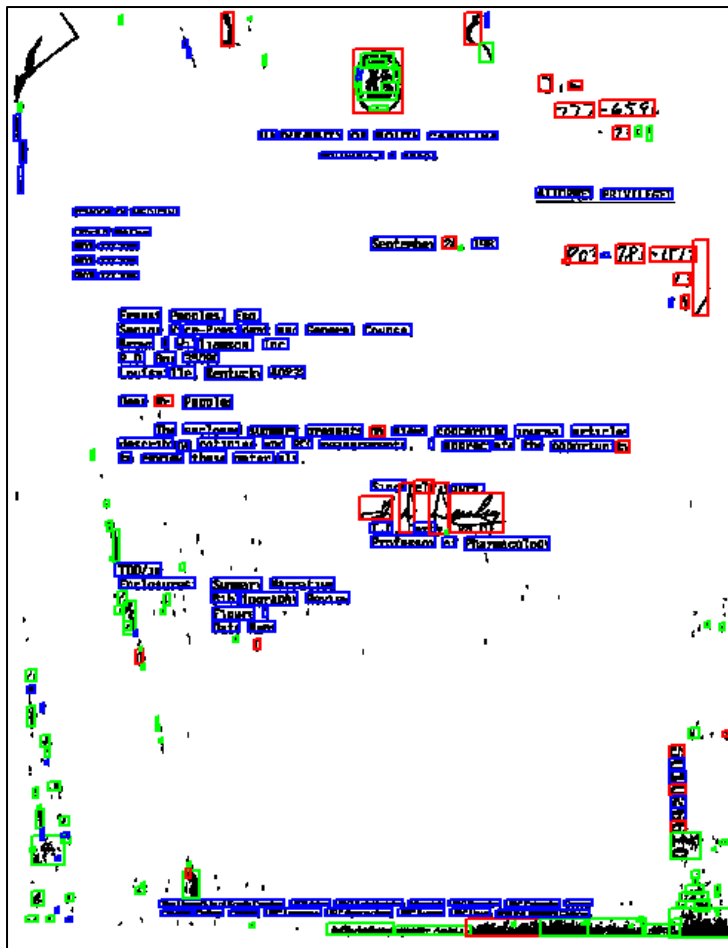
- We extracted 140 features and 31 of them are selected to train the

	Usage description	Dimensio	Selected
Structural	Region size, connected components	18	9
Gabor filter	Stroke orientation	16	4
Run-length histogram	Stroke length	20	5
Crossing counts histogram	Stroke complexity	10	6
Co-occurrence	Texture	16	2
2×2 gram	Texture	60	5
Total		140	31



Classification Results with Fisher Classifier

Printed text
Handwriting
Noise



Using Context

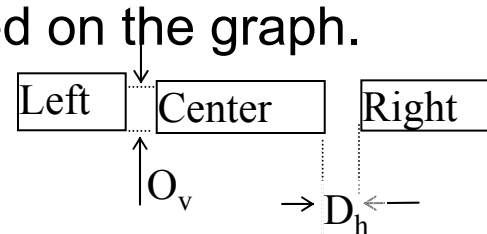
- The results are reasonable with a few mis-classification due to the overlapping of different classes in the feature space.
- Context can be used to refine classification results further
 - Words of printed text tend to lie on the same line.
 - Noise block are likely to overlap each other.
- This kind of local dependency among neighboring components can be described with the Markov Random Field (MRF).



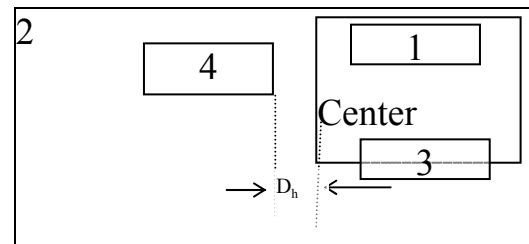
Clique Definition

- Low level MRF is defined on regular lattice (pixel)
- Our high level MRF is defined on a graph.
 - After defining the connection between word blocks, a graph is generated.
 - Neighborhood of MRF is defined on the graph.

- Clique C_p for printed text

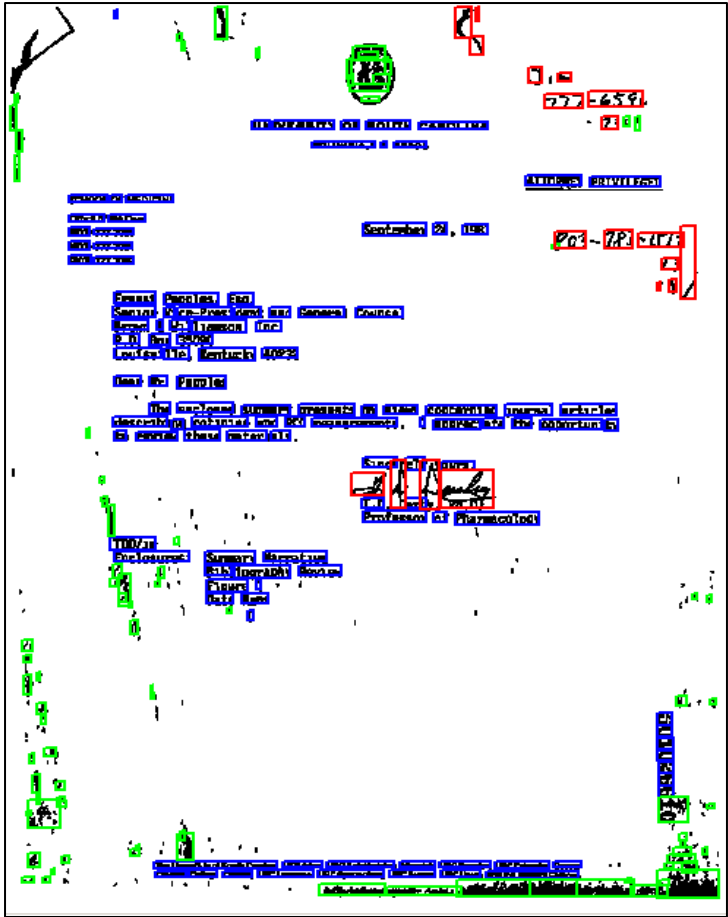
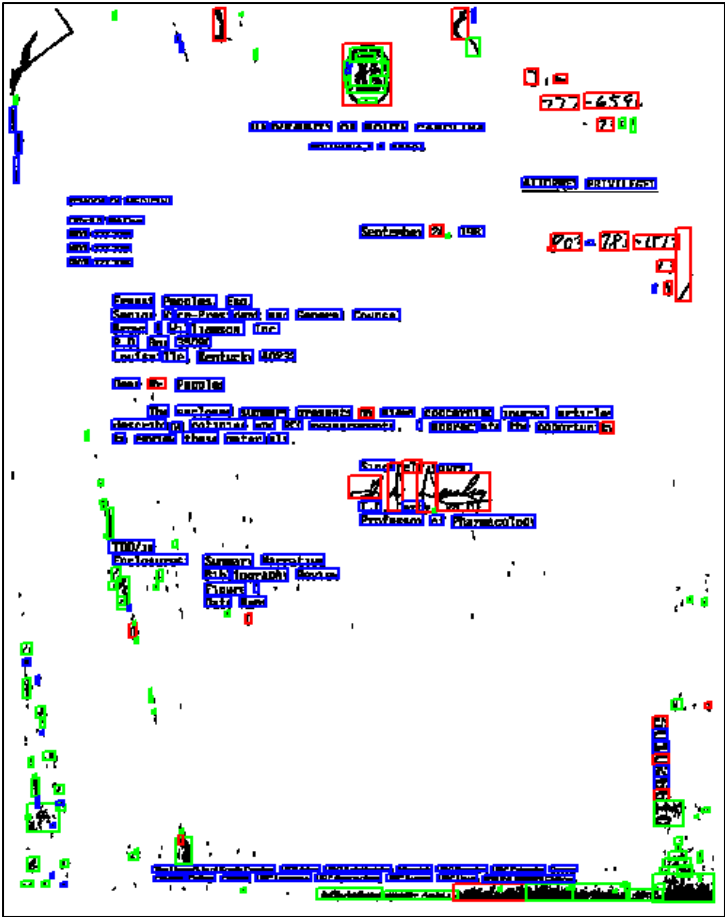


- Clique C_v for Noise



MRF Postprocessing Example

Printed text
Handwriting
Noise



Before MRF-based postprocessing

After MRF-based postprocessing



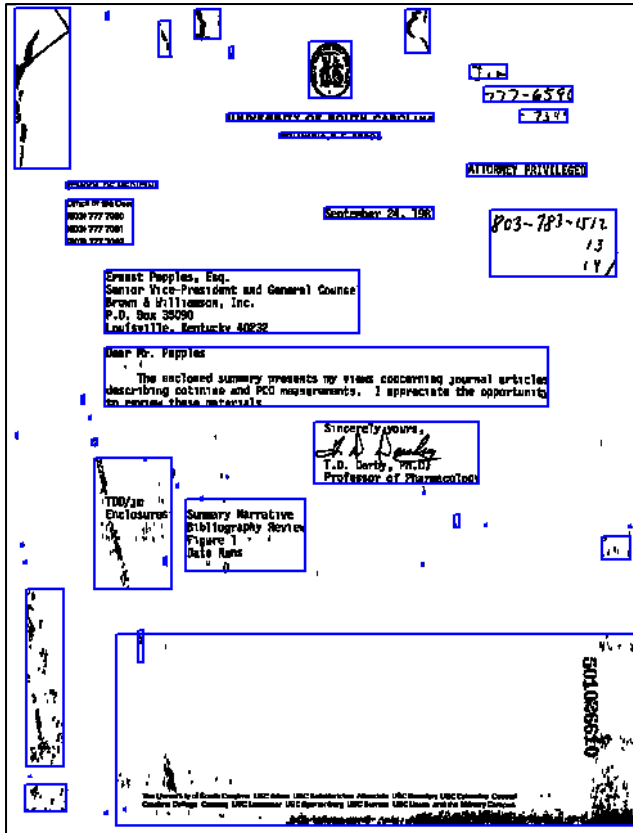
Evaluation

- Data Collection
 - 318 documents provided by the tobacco industry.
 - 94 documents of testing, the other for training.

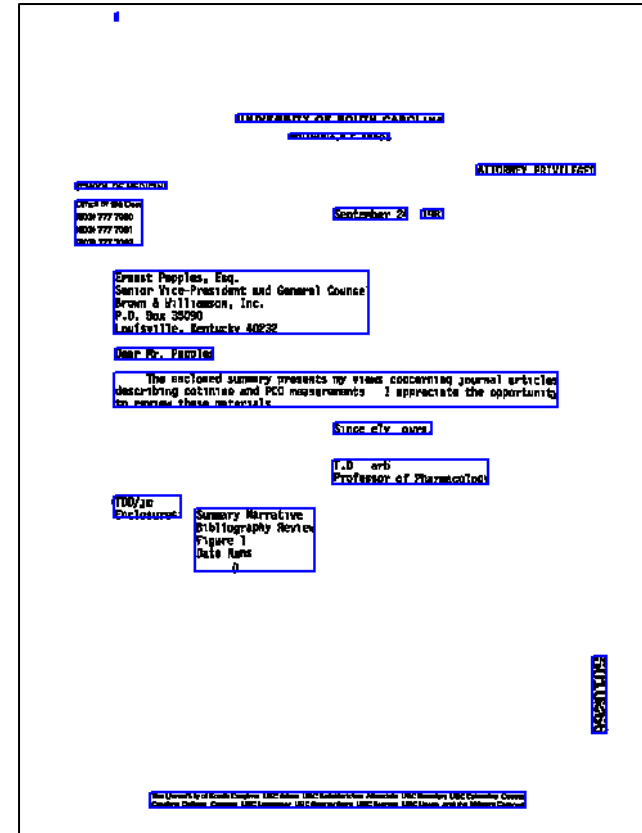
	#Total	Percentage	Before Post-processing		After Post-processing	
			Accuracy	Precision	Accuracy	Precision
Printed Words	19,227	66.9%	95.9%	99.5%	98.0%	99.7%
Handwritten Words	701	2.4%	93.2%	62.9%	93.0%	83.3%
Noise Blocks	8,802	30.7%	96.8%	93.0%	98.6%	96.0%
Total	28,730	100%	96.1%	N/A	98.1%	N/A



Application to Page Segmentation



Before enhancement



After enhancement



Evaluation

- Database
 - 168 Arabic documents with a total of 3,870 groundtruthed lines.
 - 100 images for the training of the HMM model, 68 images for the testing.
- Quantitative evaluation (evaluation metrics are discussed in the paper in detail).

QUANTITATIVE EVALUATION OF THE RULE LINE DETECTION RESULT.

	Groundtruthed Lines	Detected Lines	Correct	Partial Correct	Missed	False Alarm
Training Set	2,274	2,319	2,212 (97.3%)	56 (2.5%)	6 (0.3%)	51 (2.2%)
Test Set	1,596	1,631	1,545 (96.8%)	49 (3.0%)	2 (0.1%)	37 (2.3%)



Technical Presentations

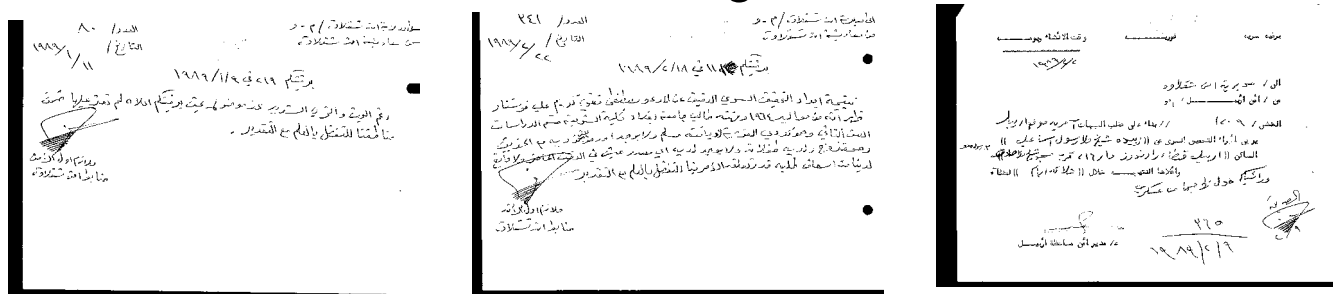
- Page Segmentation (and rule line separation)
 - Signature Detection
 - Logo Detection and Recognition
 - Stamp Detection
 - Document ID/Script ID
- } **Metadata Extraction**
- Page Layout Similarity
 - Video Research
 - Tracking and Analysis of People
 - Video Content Classification



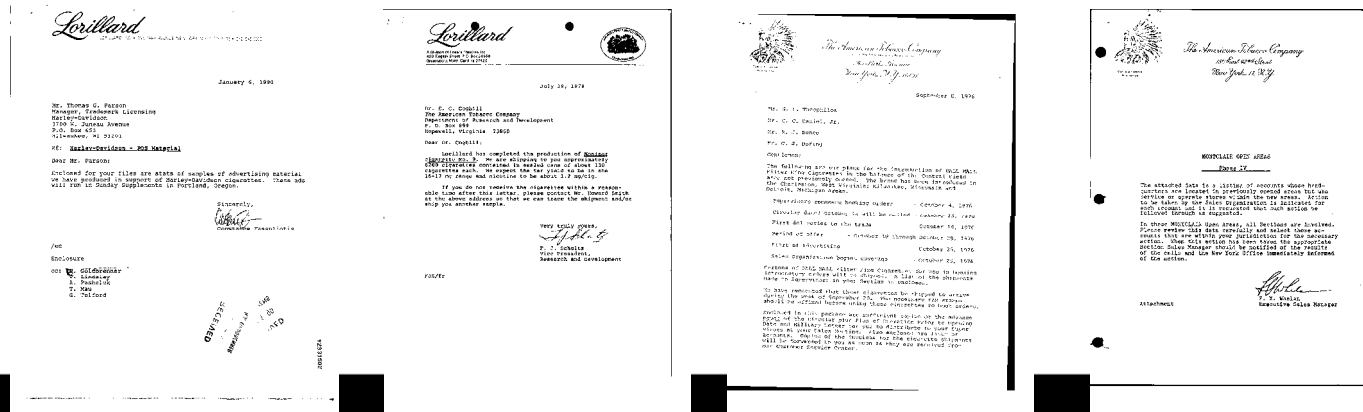
Problem Statement

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?



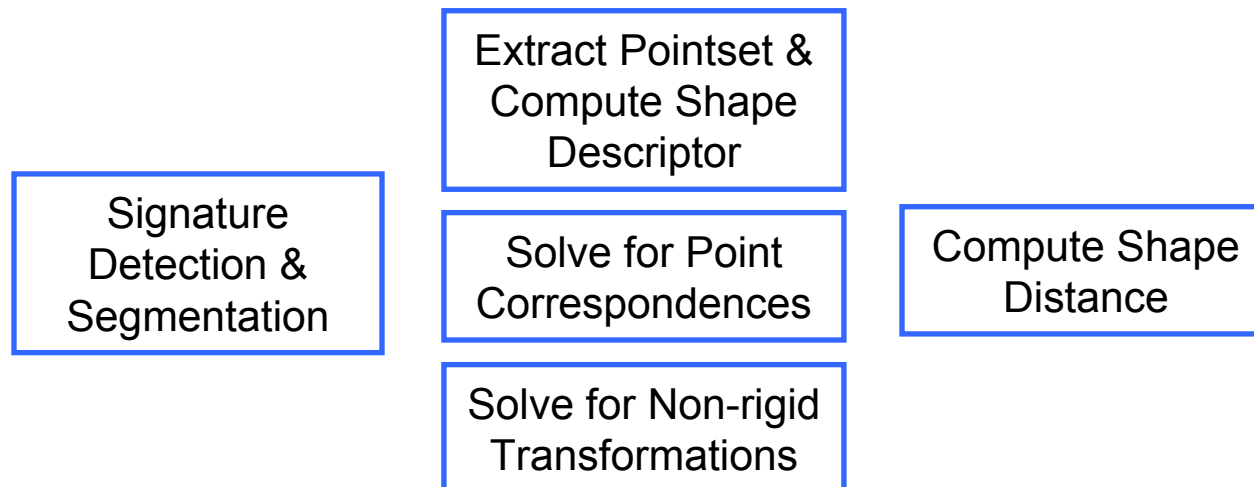
Motivation

- 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



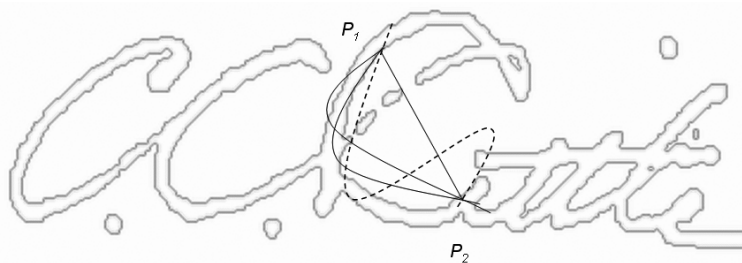
Our Tasks

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



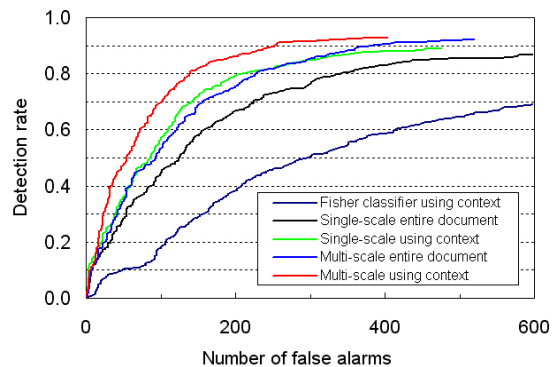
Overview of our approach

- 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

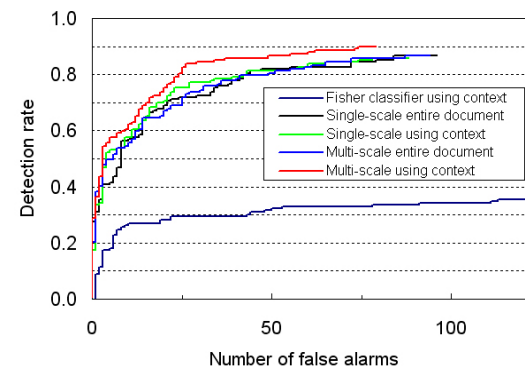


Evaluation

- 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

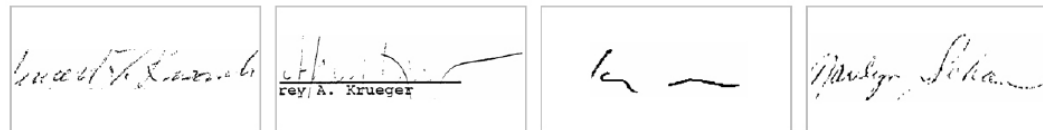


Examples of detected signatures from Maryland Arabic dataset and their saliency maps.

Evaluation



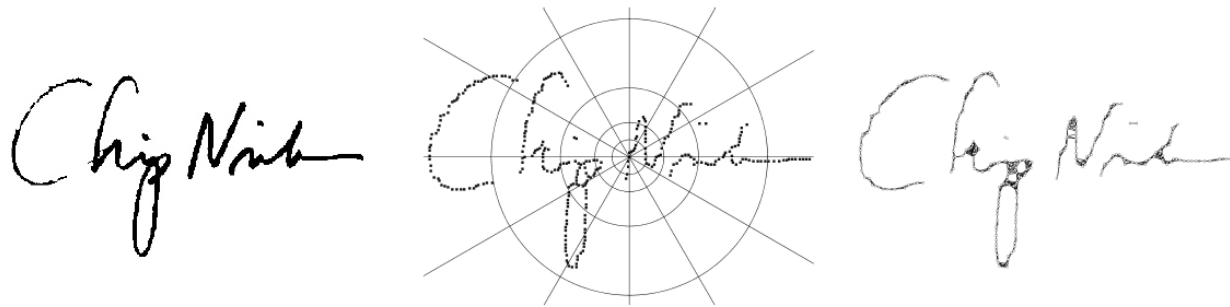
(a)



(b)

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

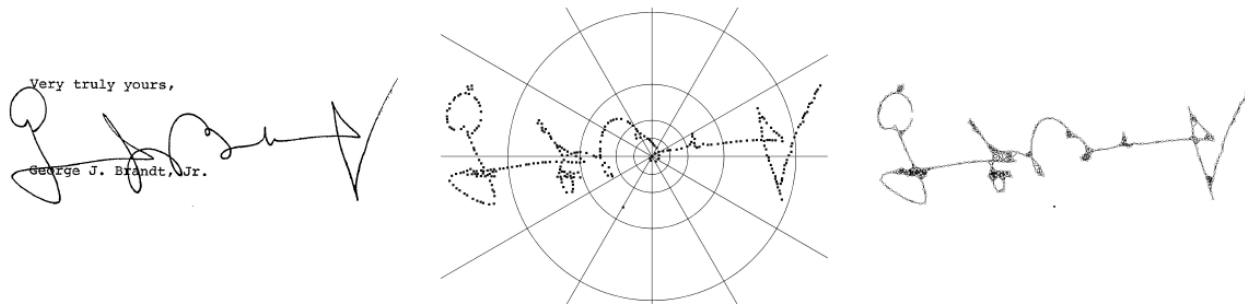
Shape representation



(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



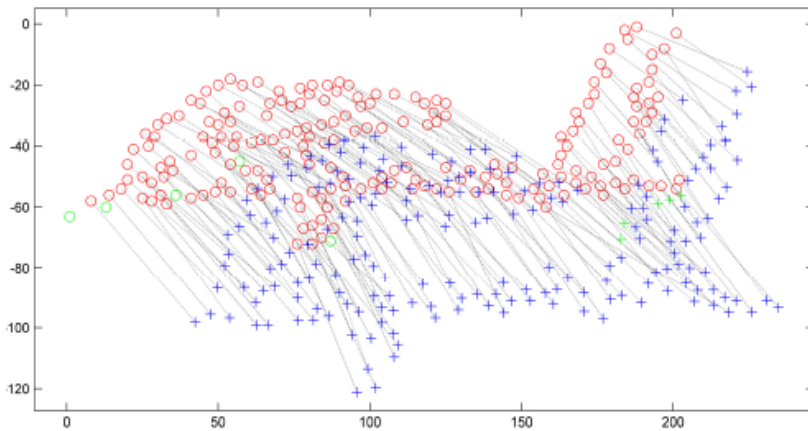
(a)

(b)

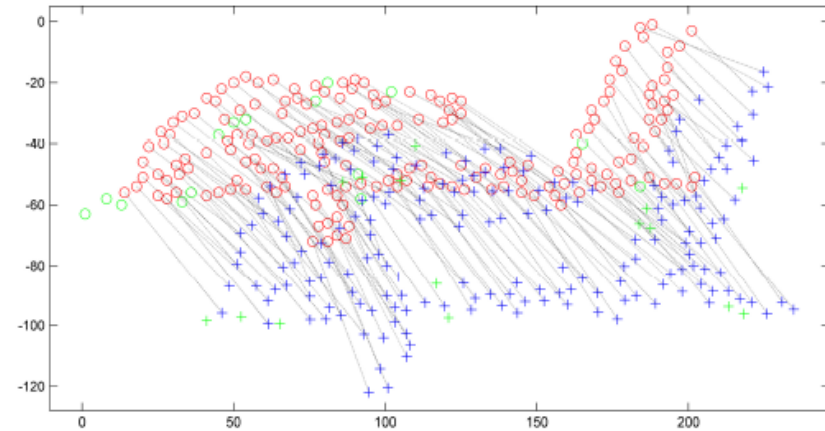


(d)

(e)



(g)

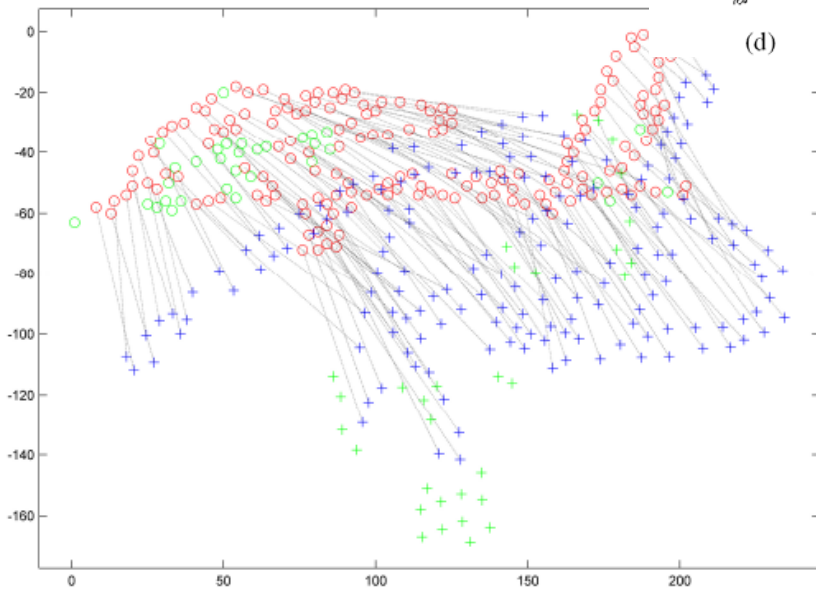
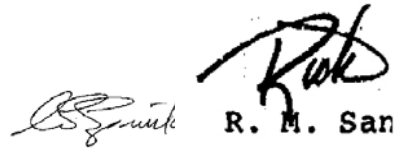


(h)

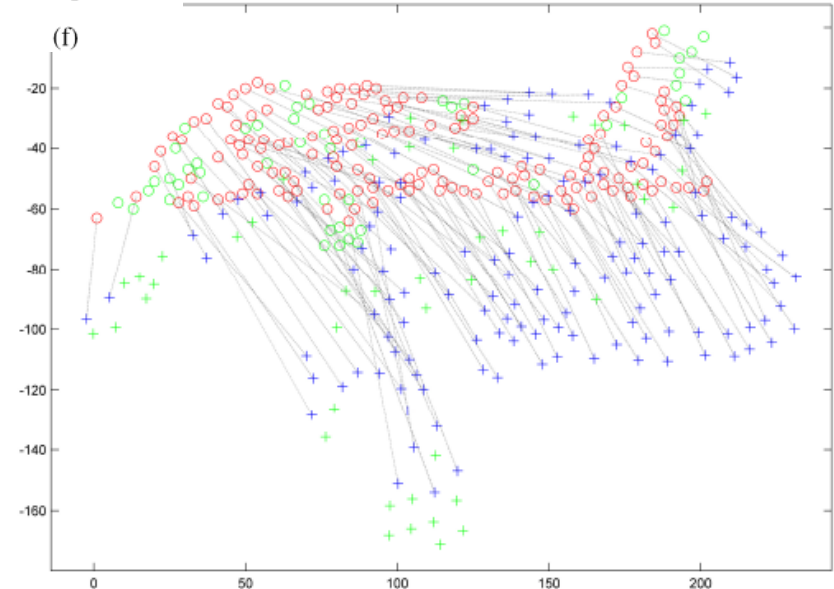
Illustration of signature matching using shape contexts and local-neighborhood-graph



Shape matching



(i)



(j)



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

Shape matching evaluation

A query with eight relevant signature instances

Sincerely,
Hallie S. Jessup
Hallie S. Jessup

Top eight retrieved in the ranked list

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

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%
$D_{sc} + D_{be}$	78.7%	74.3%
$D_{sc} + D_{af} + D_{sc} + D_{be}$	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%



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



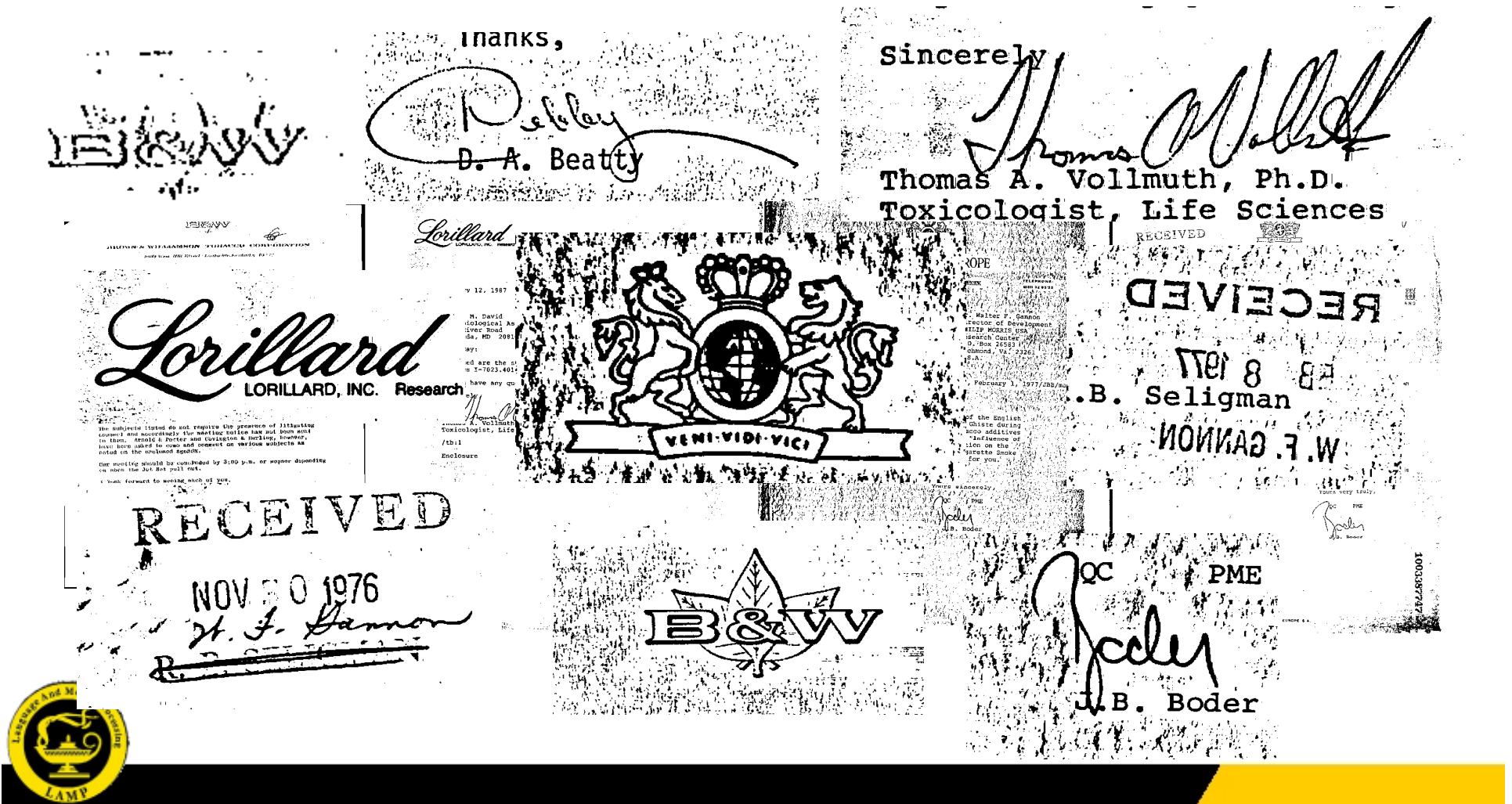
Challenges

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



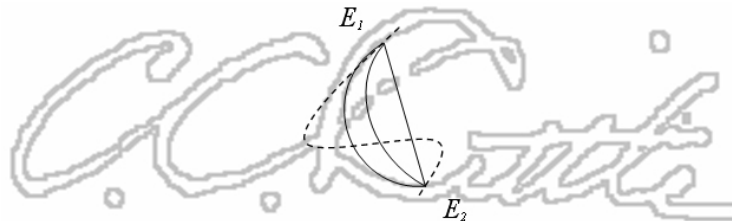
Claim #1

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



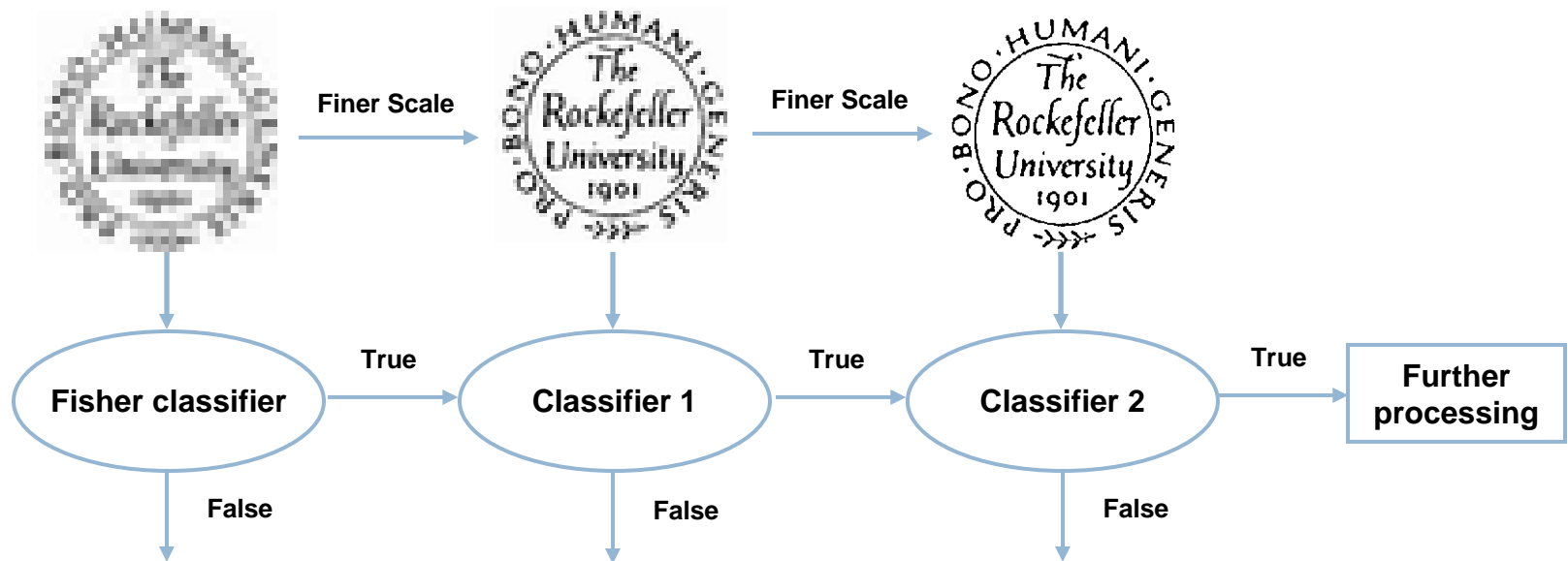
Claim #2

- 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.



Multiscale Detection

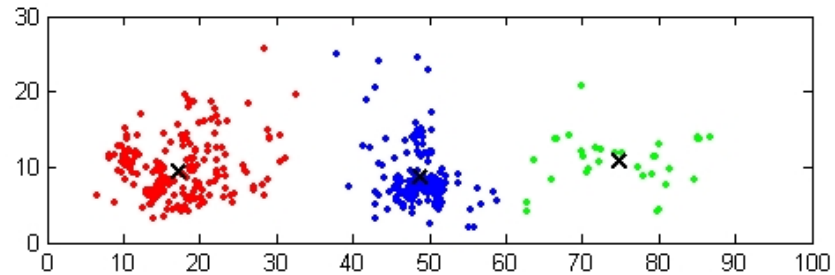
- Each logo candidate region is further classified at successively finer image scales by a cascade of simple classifiers



- 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 ($k = 3$)

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

- We define context distance as

Context Distance	Area	Symmetry
Spatial Density	Aspect Ratio	Text Uniformity



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 (determined from shape matching approach – Zhang. PAMI 2006)

Summary of logo detection performance on the Tobacco-800 dataset

	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

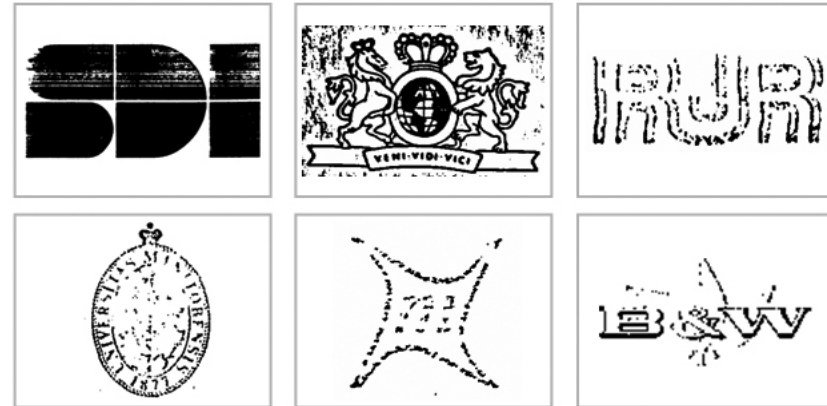
Evaluation



(a) Over/under-segmented logos



(b) Non logos



Examples of missed logos

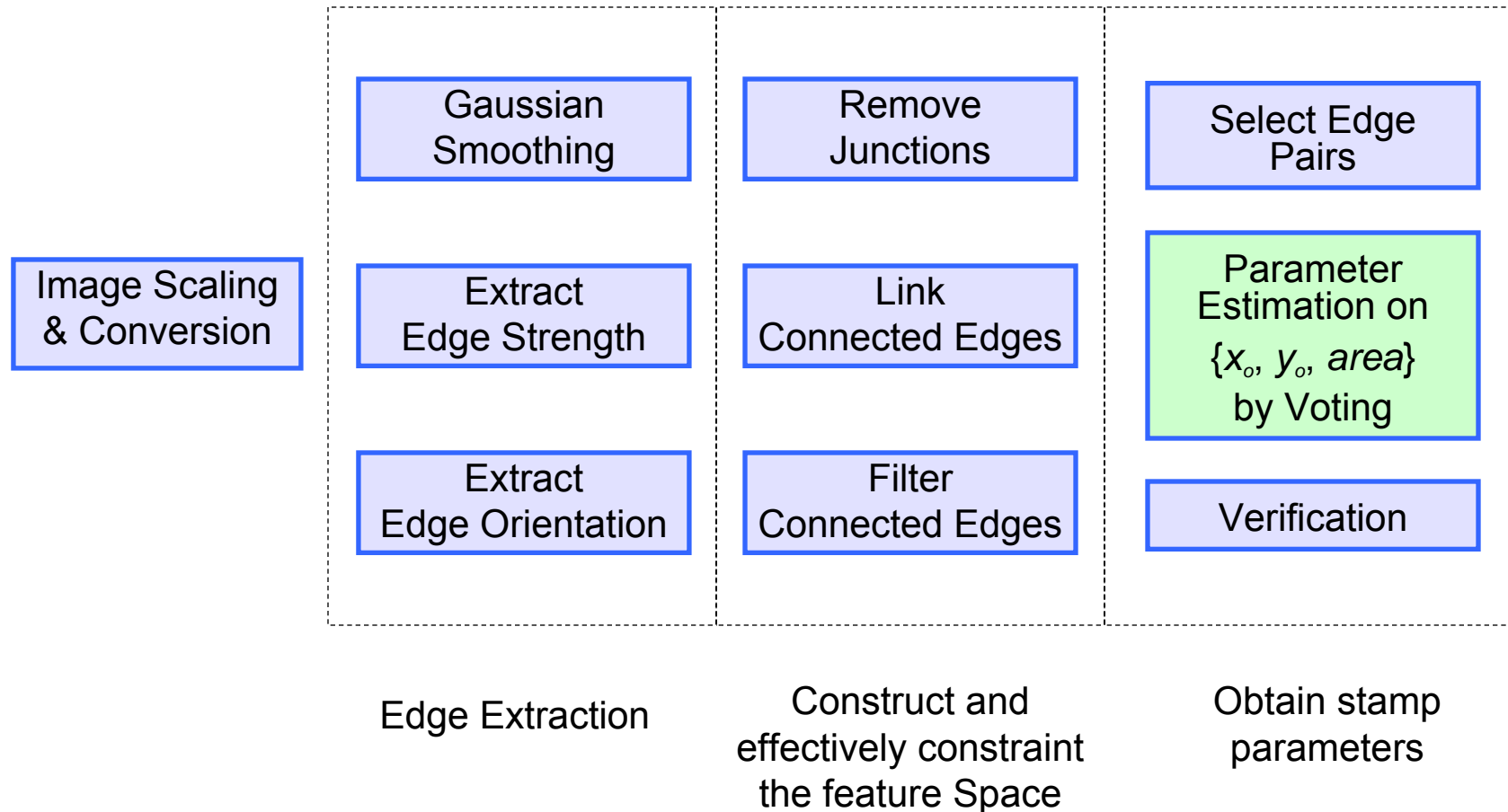
Examples of incorrectly detected logos

Challenges in stamp detection

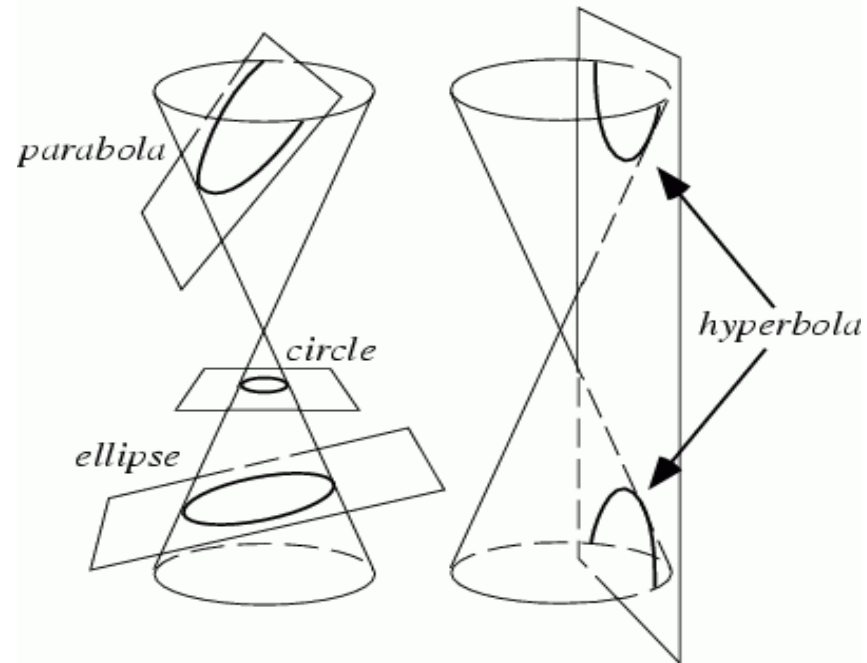
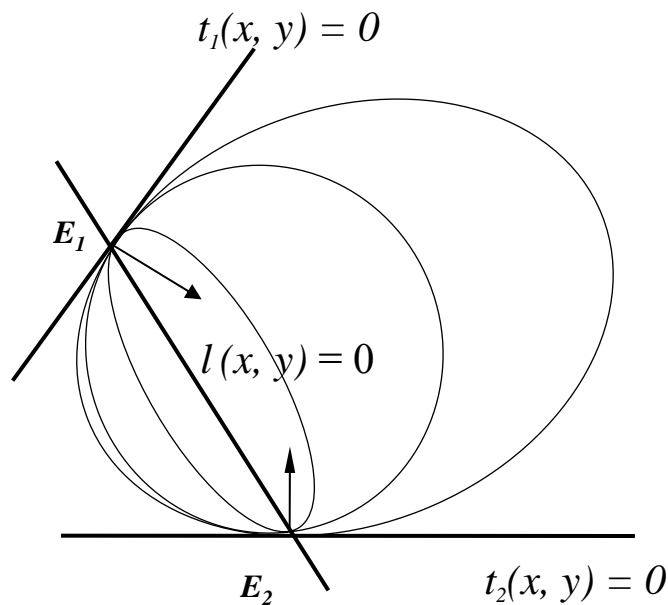
- Unique characteristics of stamps
 - Unstable and unpredictable patterns in documents
 - Outliers and occlusions are typical
 - Much lower spatial density compared to logo
 - Stamp instances appear as weaker regions within a full spectrum of background – text, figures, tables, watermark
 - Not generally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



Our stamp detection approach



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 $t_2(x, y)$.

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.

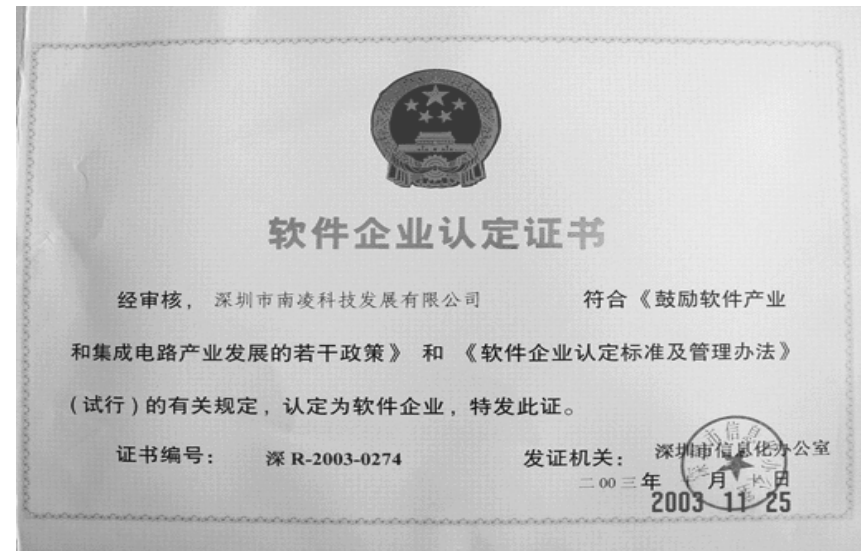
Gustavo pursues professional development opportunities. He is in the process of earning a doctorate, no small feat while teaching full time. In addition, he actively involves himself on the academic side of the profession. He presented a workshop at last year's EARCOS Teachers Conference and he is scheduled 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 Smith
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>



Demo

مركز استشارات السلبيات
بالتجارية
٢٠١٢
٢٠١٢
٢٠١٢

مركز استشارات السلبيات
بالتجارية
٢٠١٢
٢٠١٢
٢٠١٢

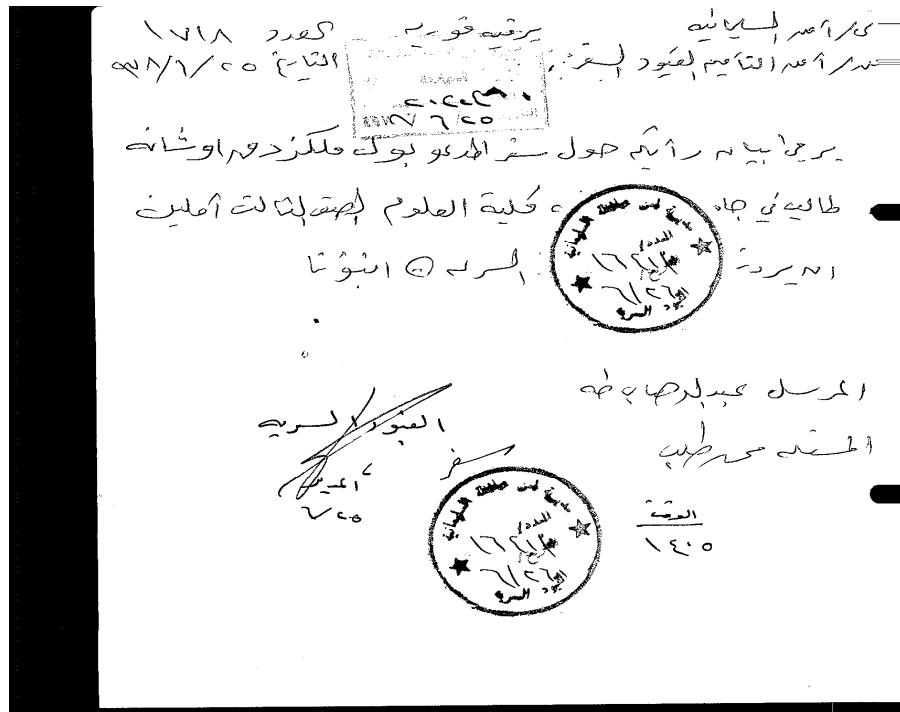
مركز استشارات السلبيات
بالتجارية
٢٠١٢
٢٠١٢
٢٠١٢

مركز استشارات السلبيات
بالتجارية
٢٠١٢
٢٠١٢
٢٠١٢



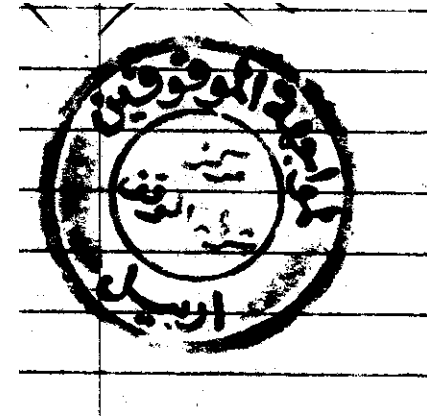
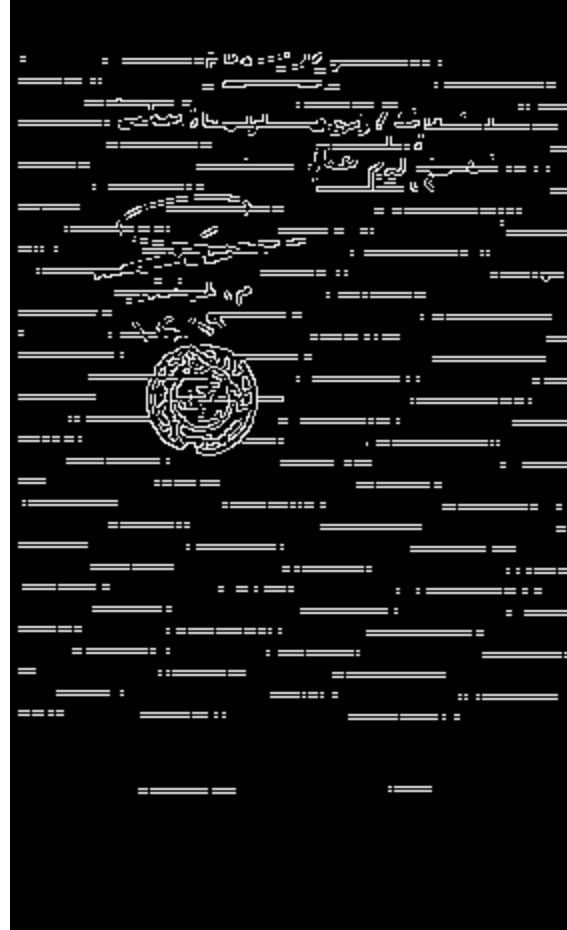
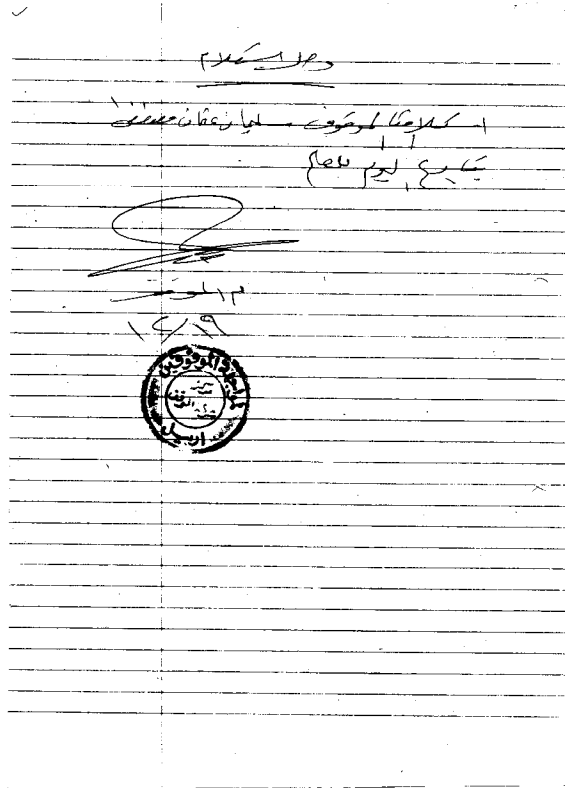
Demo

Capability to detect multiple stamp instances



Demo

Capability to detect stamp instances in diverse backgrounds



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

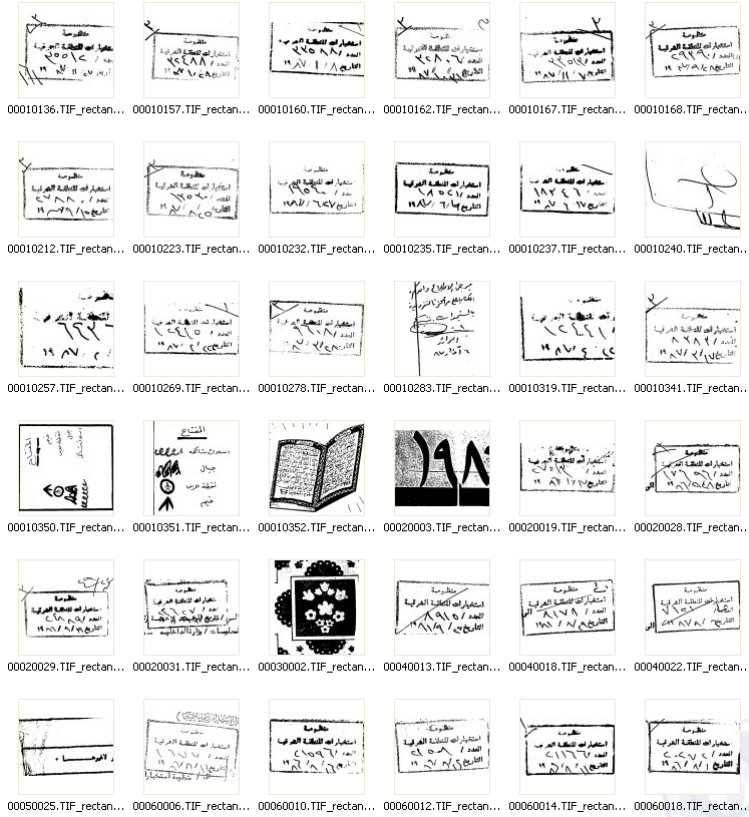
The screenshot displays four overlapping browser windows, each showing the documentation for a different Doclib add-on module. The windows are arranged in a grid-like fashion, with the top-left window being the largest and most prominent.

- DLTestDOCLIB Documentation:** The top-left window shows the documentation for DLTestDOCLIB v1.0. It includes a navigation menu on the left with options like 'Main Page', 'Class List', and 'File List'. The main content area contains text describing the module's purpose and usage.
- DImageResize Documentation:** The middle window shows the documentation for DImageResize v1.0. It features a similar navigation menu and content area.
- SignatureDetect Library v1.0 Documentation:** The bottom-right window shows the documentation for SignatureDetect Library v1.0. It includes a navigation menu and text describing the signature detection algorithm.
- LogoDetectDOCLIB Documentation:** The bottom-left window shows the documentation for LogoDetectDOCLIB v1.0. It features a navigation menu and text describing the multi-scale logo detection approach.

Each window has a title bar with the browser's address bar and navigation buttons. The overall layout is a collage of these four documentation pages, illustrating the software releases.

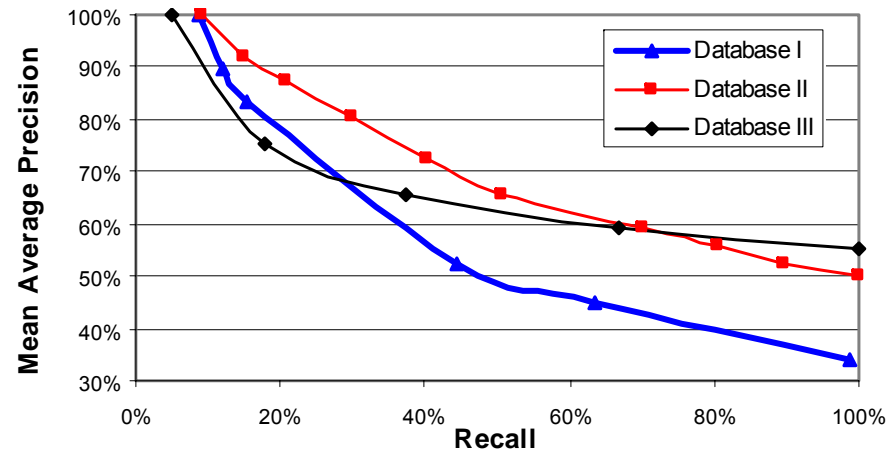


Demo



Experiment

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



Script and ImageID

- ScriptID
 - Given a set of handwritten document images, identify the scripts.
 - Dataset: UMD handwritten dataset + Arabic dataset
- ImageID
 - Given an arbitrary image, identify that it is
 - document image
 - image with text
 - Image w/o text
 - Dataset: ~3700 images from Internet.



The Observation

朱雀桥边野草花，

乌衣巷口夕阳斜。

旧时王谢堂前燕，

飞入寻常百姓家。

꽃을 감금하게 차

1 들어 있는 것

어릴 것 같았네

어고 있었다

شعر حسن المصنف
عند رصافه
عبد الرحمن بن عبد الله

स्वायत्त विनियोग
जो राष्ट्रीय आय
वर्तमान आधिक्य
न धारित होता है।



The Observation (con't)

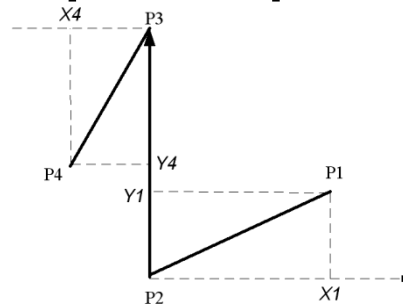
- The relationship of connected edges could be used for description;
- The dominant descriptors for different scripts could be different;
- The statistics of the descriptors could be used for discriminating different scripts.



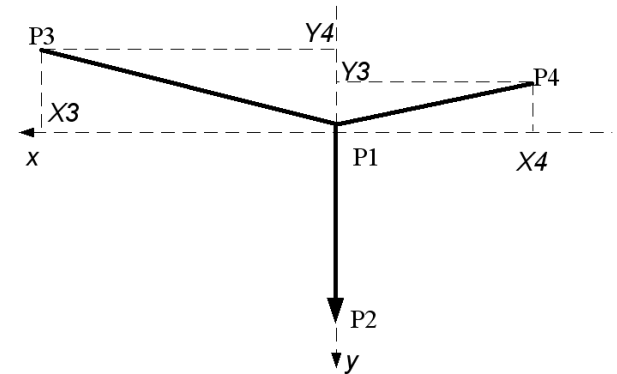
The descriptor

- Fit edges to small lines
- Adjacent lines: encode the relative coordinates w.r.t pivot point.

– C / Z shape



– Y shape



The codebook for the descriptor

- The advantage of the codebook
 - Generic
 - Quantization -> fast
- generate the codebook
 - A large dataset
 - Extract descriptor
 - Cluster the descriptor



The implementation

- Given a document image
 - Preprocessing
 - Binarize if necessary
 - Skeletonize
 - Clean the image using mathematical morphology.
 - Extract descriptors
 - Extract line segments
 - Compute shape descriptors
 - Quantize the shape descriptors and compute their histogram.
 - Train and classify



Result

- Confusion matrix (experimental result, july 2007)

	Arabic	Chinese	Hindi	Korean
Arabic	11 (74%)	1	2	1
Chinese	0	10 (77%)	0	3
Hindi	1	1	10 (83%)	0
Korean	1	3	0	9 (70%)

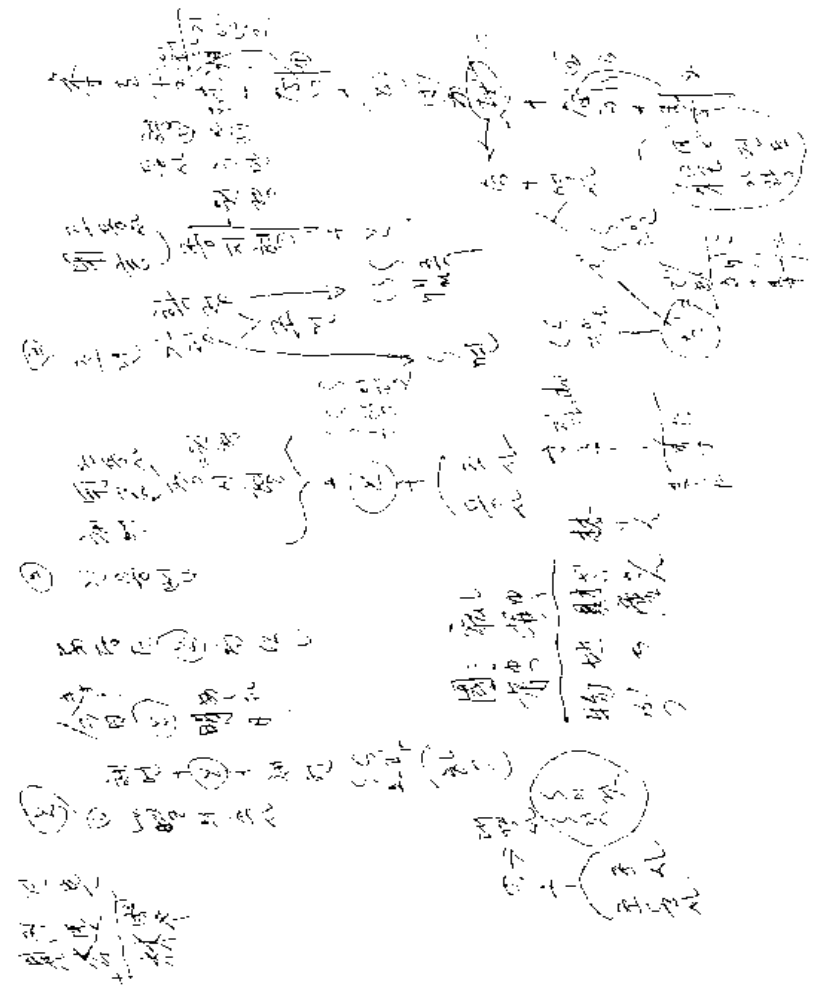


Failed examples

Arabic

Chinese

30-3. साधारण सुप्रसिद्धी की रचना, आप
 किसी एक उपयोग का प्रतिनिधि
 30-2. चित्र की दृष्टि अनुसार यह एक
 साधारण आवधिक शीशा है जो सुप्रसिद्ध
 पदार्थों की देखने के नाम जाता
 है वह कम फोकस इरी वाला
 जल लेंस होता है, जिसे एक
 होल में फिल कर लेंस है।
 आपत्तिका → एक किसी पदार्थ AB
 की जल लेंस की मुख्य नाड़ी
 F प्रकाश केन्द्र O ले कीच रखते हैं
 जो पदार्थ का जमी और बड़ा आभासी
 और सीधा प्रतिबिम्ब बनाता है
 रस प्रकार प्रतिबिम्ब A'B' काफ़ी
 बड़ा बना होता है।
 उपयोग → (i) घड़ी - यह रखी घड़ी



Failure example (Korean)

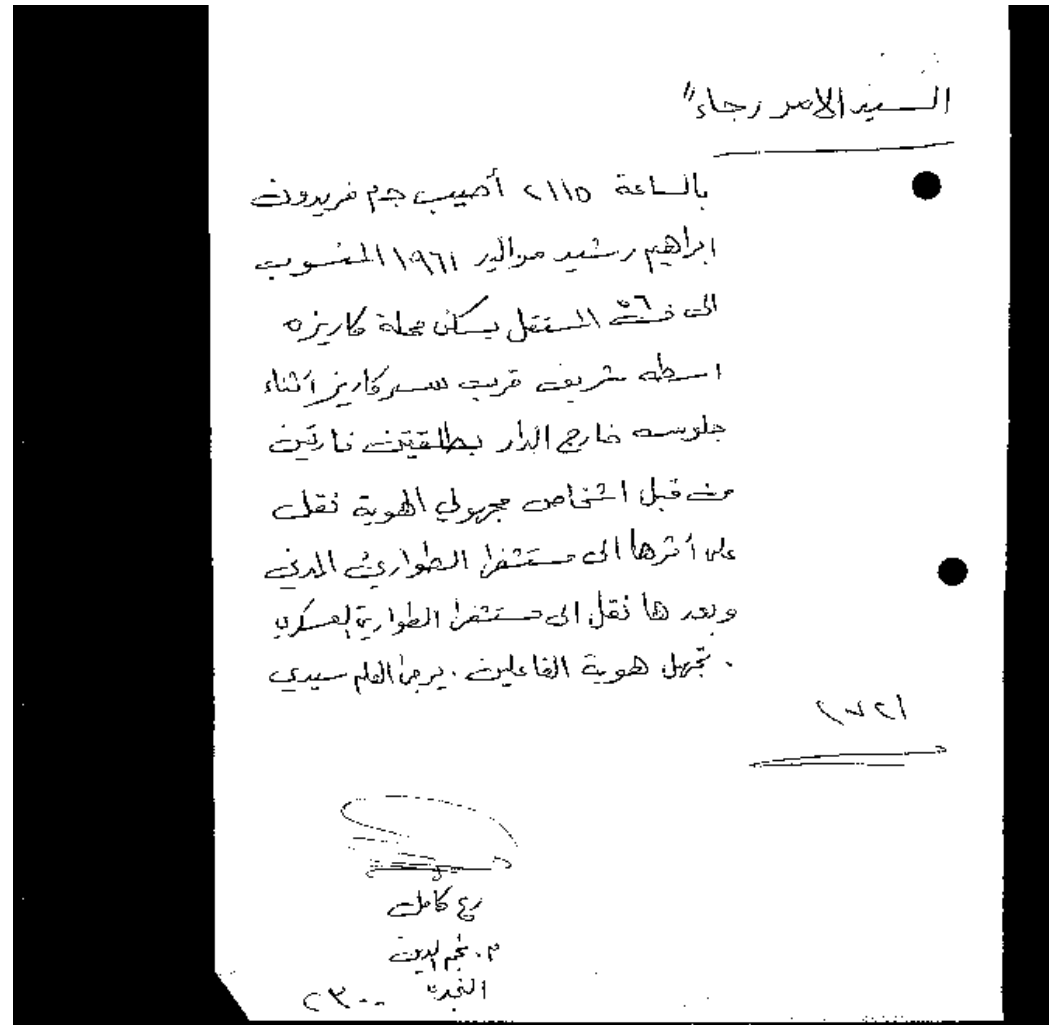


Image ID

- Determine which class:
 - Text, Image w/text, or image
- Adopt different vision modules
 - For different categories we can adopt different strategy in computer vision
- Improve efficiency
 - Use the category as prior.
- Speedup OCR module in real world environment.



The Challenge

- Images are arbitrary
 - Appearance model cannot be used for the classification.
 - We use the same shape descriptor because the code book is generic.
- Ambiguity
 - “images / text vs images”, e.g., Coke can.
 - “doc vs images / text”, e.g. “publication cover” usually has figures.



Dataset for ImageID

- Collected from Internet, through search using different keywords
- Manual inspection, removal of duplicate images.

Page Classification Datasets (Google Image)

Document	797
Image with Text	1695
Non-Document	1275
Total	3767





google_concert_tic
ket_46.tif



google_docum...



google_docum...



google_docum...



google_docum...



google_docum...



google_docum...



google_docum...



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google_cd_cover_0.tif



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google_cd_c



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google_cd_c



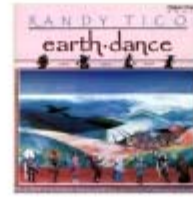
google_cd_cov...



google_cd_cov...



google_cd_cov...



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google_cd_cov...



google_cd_c



google_cd_cov...



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google_cd_cov...



google_cd_cov...



google_cd_cov...



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google_cd_c



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google_cd_cov...



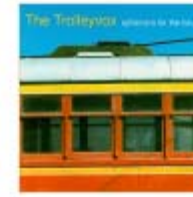
google_cd_cov...



google_cd_cov...



google_cd_cov...



google_cd_cov...



google_cd_cov...



google_cd_c



google_apple_0.tif

google_apple_1.tif

google_apple_2.tif

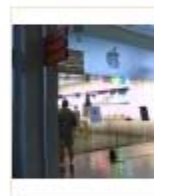
google_apple_5.tif

google_apple_9.tif

google_apple_1...

google_apple_1...

google_apple



google_apple_1...

google_apple_1...

google_apple_1...

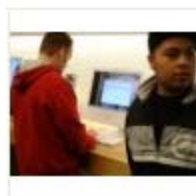
google_apple_2...

google_apple_2...

google_apple_2...

google_apple_2...

google_apple



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google_apple



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google_apple_5...

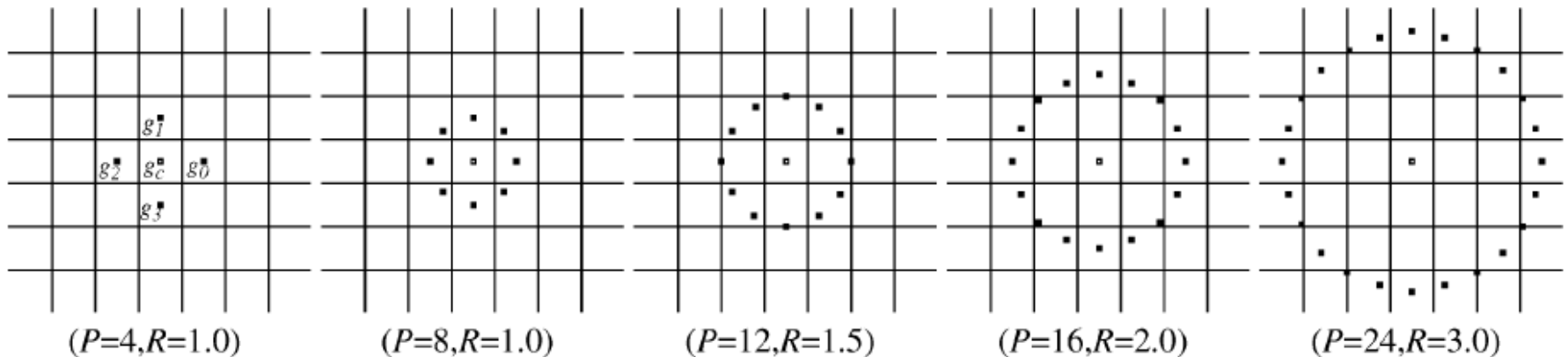
google_apple

LBP: Local Binary Pattern

- Define
 - Texture: Joint distribution of center g_c given neighbor sampling $(g_p \ (p=0, \dots, P-1))$

$$T = t(g_c, g_0, \dots, g_{P-1})$$

- Example



The performance

- Confusion matrix

	Doc	Image w/	Non doc
Doc	0.8557	0.1340	0.0103
Image w/	0.1725	0.6011	0.2264
Non doc	0.0444	0.1422	0.8133

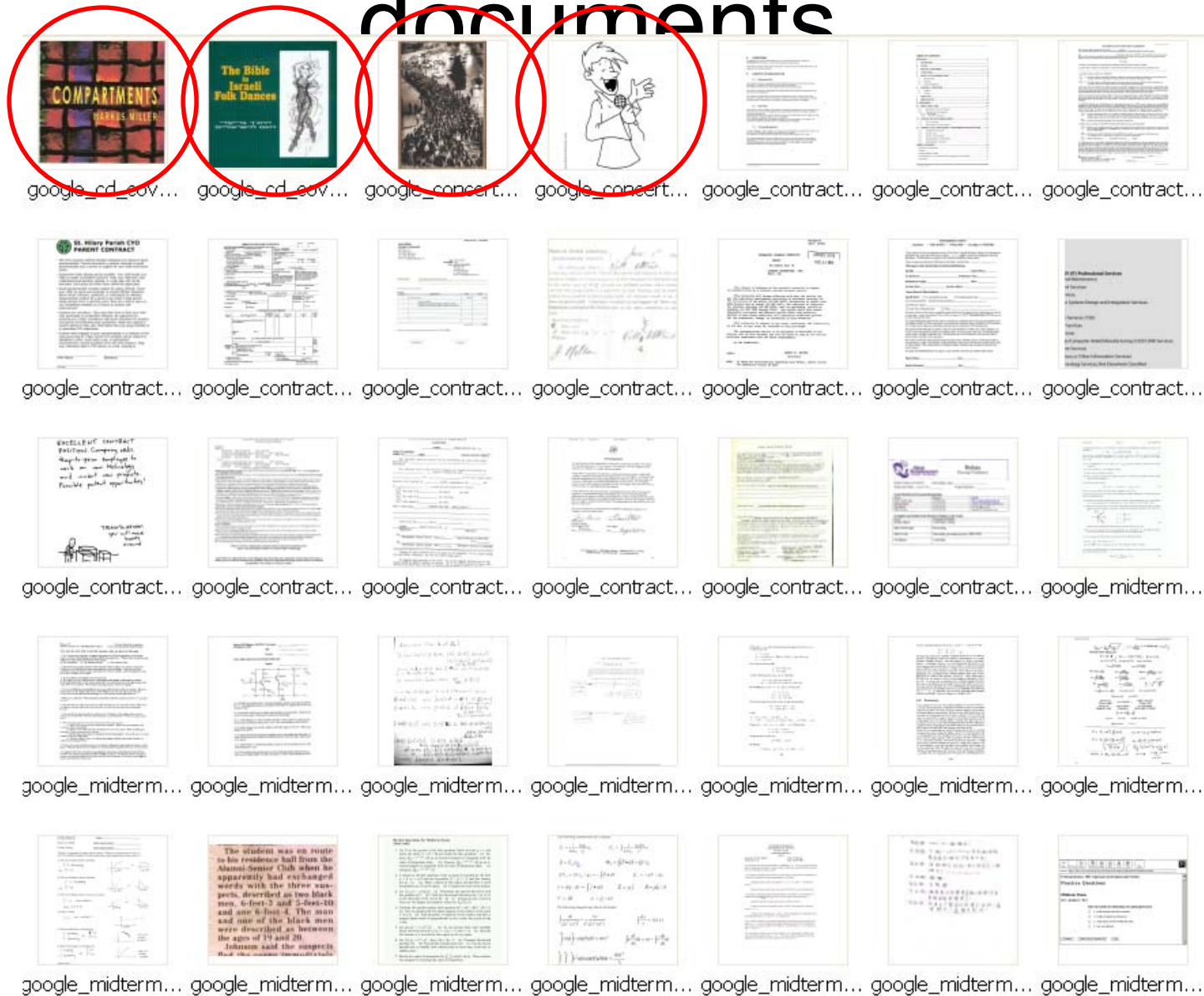


The Module

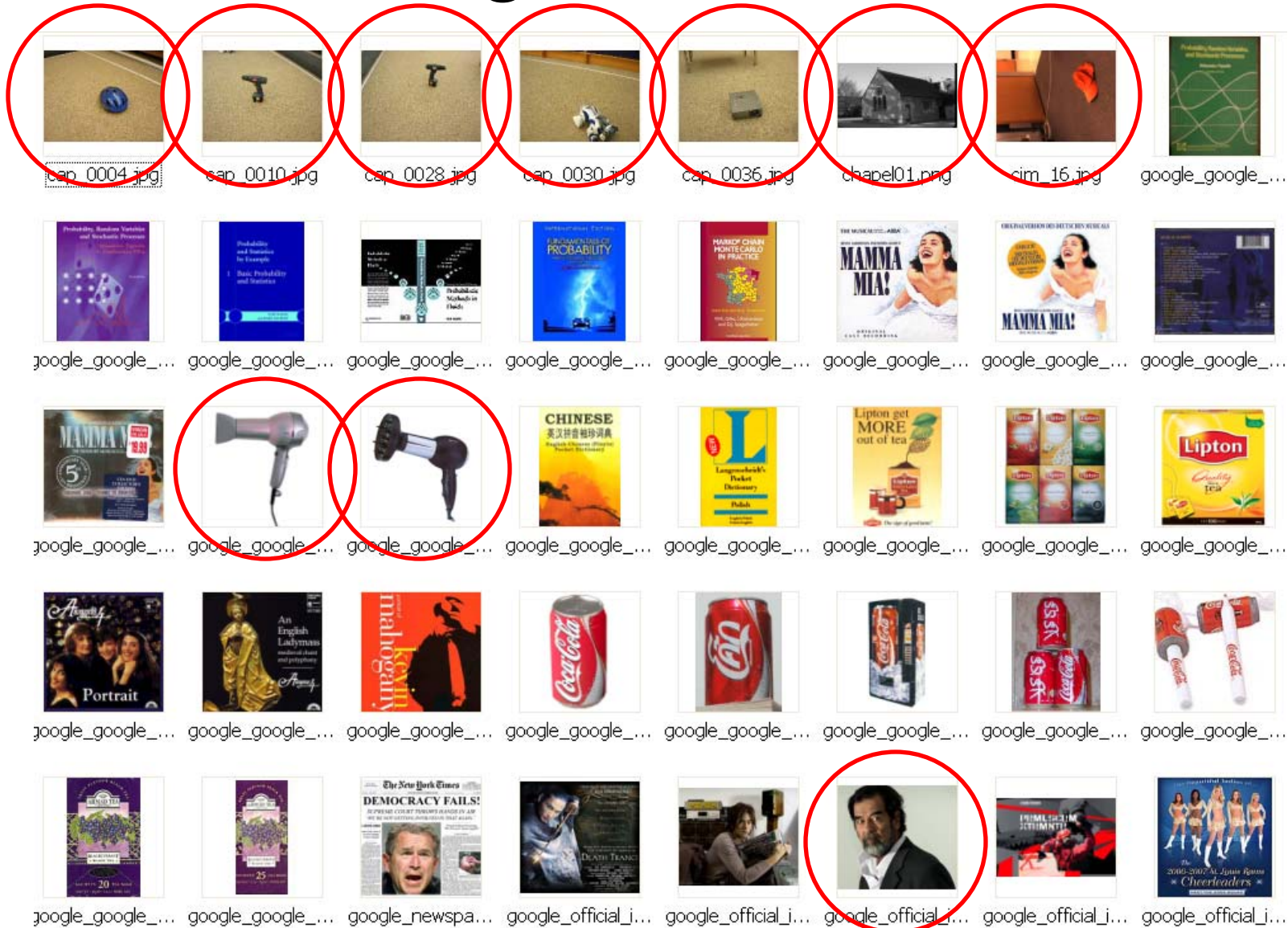
- Input
 - Training: an text file contains a list of training images.
 - Testing: a filename to an image.
- Output
 - Training: an SVM classifier (model.txt)
 - Testing: XML format (JEDI readable) for corresponding input image.
- Performance
 - 700 seconds for 3000 images
 - Similar speed for every image
 - No exceptions and memory leaks



Results – classified as documents



Images w/ text



Images



Technical Presentations

- Page Segmentation (and rule line separation)
 - Signature Detection
 - Logo Detection and Recognition
 - Stamp Detection
 - Document ID/Script ID
 - Page Layout Similarity
 - Video Research
 - Tracking and Analysis of People
 - Video Content Classification
- } Document Ranking

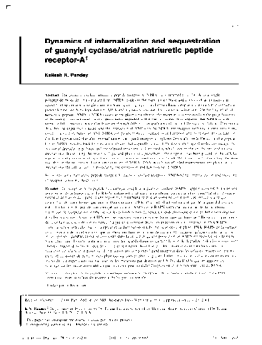


Motivation

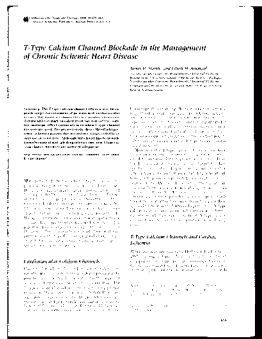
- *In a large collection of documents (forms, academic papers, handwritten letters, checks, receipts, etc.), most times people need to handle only those with some specific layout.*
- **Drawback** of our previous system for document ranking based on layout : *training is restarted from beginning each time a new layout comes*
- **Reason:** *we do not give an explicit definition of layout, the system learns no concept of layout, but image content.*
- **Proposal:** Let the system itself figure out important dissimilarities for layout classification.



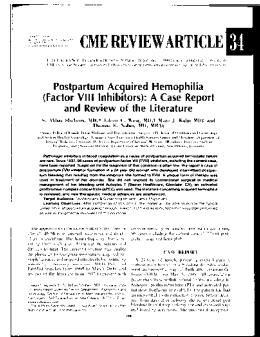
Layout Examples



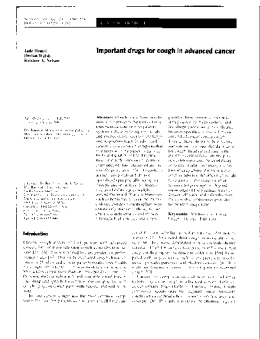
1C



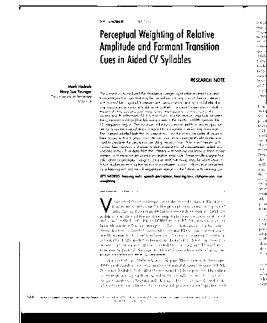
2C



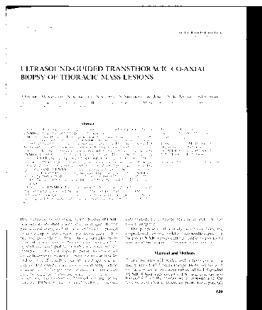
1r2C



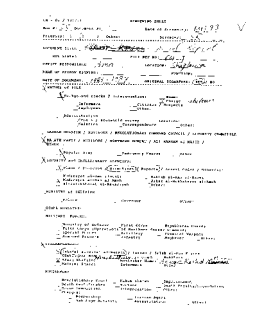
3C



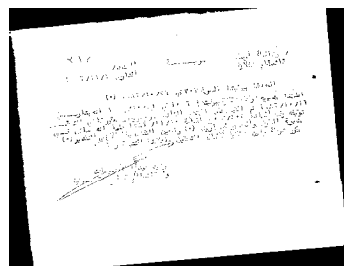
2c_asym



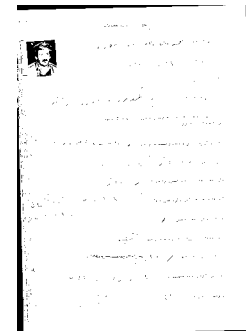
2c2c_asym



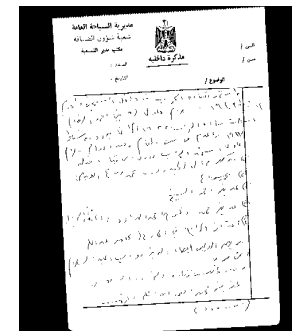
class1



class2



class3



class5



Document Representation

-- Building blocks

- Text lines extracted by TB library (endpoint coordinates, line orientations)

~~1040 U.S. Individual Income Tax Return 1988~~

For the year Jan.-Dec. 31, 1988, or other tax year beginning 1988, ending

Label
Use the label. Otherwise, please print type.

L Your first name and initial (if joint return, also give spouse's name and initial) Last name
~~Derry, K & Lorraine A. Boyle~~

R Present home address (street, apt. or box, and city, town or post office, state, and ZIP code) (Print on separate page if necessary.)
~~73 Mason Street
Camden, NC 28222~~

W State and social security number
~~AS7 80 3582
AS7 82 9700~~

F For Federal and State Payment Reduction Act (see instructions)

Presidential Election Campaign Do you want \$2 to go to this fund?
If joint return, does your spouse want \$2 to go to this fund?

Yes	<input checked="" type="checkbox"/>	No	<input type="checkbox"/>
Yes	<input type="checkbox"/>	No	<input checked="" type="checkbox"/>

Filing Status

<input checked="" type="checkbox"/> Single
<input type="checkbox"/> Married filing joint return (even if only one had income)



Quadrilaterals from text line pairs

- A document := {Quadrilaterals}

1040 Department of the Treasury Internal Revenue Service 1988
U.S. Individual Income Tax Return

For the year Jan.-Dec. 31, 1988, or other tax year beginning 1988, ending 1988

OMB No. 1545-0047

Label Your first name and initial (if joint return, also give spouse's name and initial) Last name Year social security number
MURPHY, K. & LINDA A. HAYES 1957 00 3582

Home phone number, street, and apt. no. (if applicable) (Do not use page 2 of instructions) Spouse's social security number
3 Hudson Street A37 02 762

City, town or post office, state, and ZIP code
Cambridge, MA 02139

For EFTPS, not on separate instructions. See instructions.

Presidential Election Campaign Do you want \$1 to go to this fund? Yes No Note: Checking "Yes" will not change your tax or reduce your refund.

If joint return, does your spouse want \$1 to go to this fund? Yes No

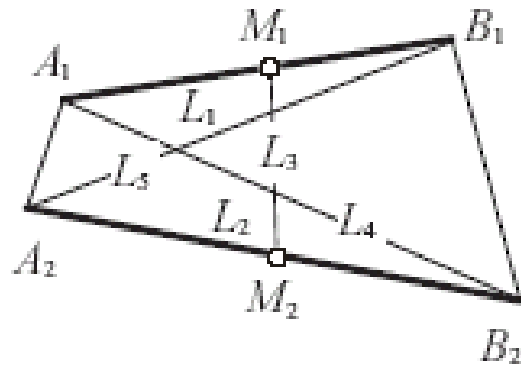
Filing Status 2 Married filing joint return (even if only one had income)

- Merits:
 - Text line properties (length, orientation) are defined implicitly by their relative contribution to the quadrilateral shape
- Drawbacks:
 - $O(n) \rightarrow O(n^2)$



Quadrilateral Shape Vector

- 5D shape vector



L_1, L_2 : text lines

L_4, L_5 : diagonals

L_3 : midpoints connection line

- Vector uniquely defines the quadrilateral shape
- Text line correspondence guaranteed
- Efficient clustering
- Document represented this way is translation and 180° rotation invariant



Dictionary of Quadrilaterals

- We need to establish correspondences between quadrilaterals so that documents comparison can break down into quadrilateral comparison.
- Clustering in 5D space using range search, each quadrilateral cluster is regarded as a word in the dictionary
- Need a rich dictionary to avoid too many unknowns in a query
- From 101 documents, we built a dictionary with 976 words



Score a query document

- Each document has a signature S like

1	0	0	1	0	1	1
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- Each layout class has a relaxed signature RS averaged from training samples. (consistency)

0.9	0.1	0.12	1	0.07	0.875
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- Each classifier has a performance value P on validation set. (discriminativity)

0.75	0.8	0.66	0.55	0.7	0.6
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- Score of a query against layout class i

$$\text{Score}_i = \sum_k F(S_k, RS_{i,k}) * P_k$$

$$C = \text{argmax}_i \text{Score}_i$$



Evaluation Scheme

- Mean Average Precision (MAP)
 - $P_i = (\sum_{i \leq j} P_j) / (\sum_{i \leq j} 1)$
- Average Relevance Rank (ARR)
 - $I = (\sum(R_i - (N_t + 1)/2)) / (N * N_t)$
 - R_i : rank of one wanted testing document.
 - N : testing size
 - N_t: wanted testing size
 - $I \in [0, 1 - N_t/N)$, the lower the better



Experimental Results

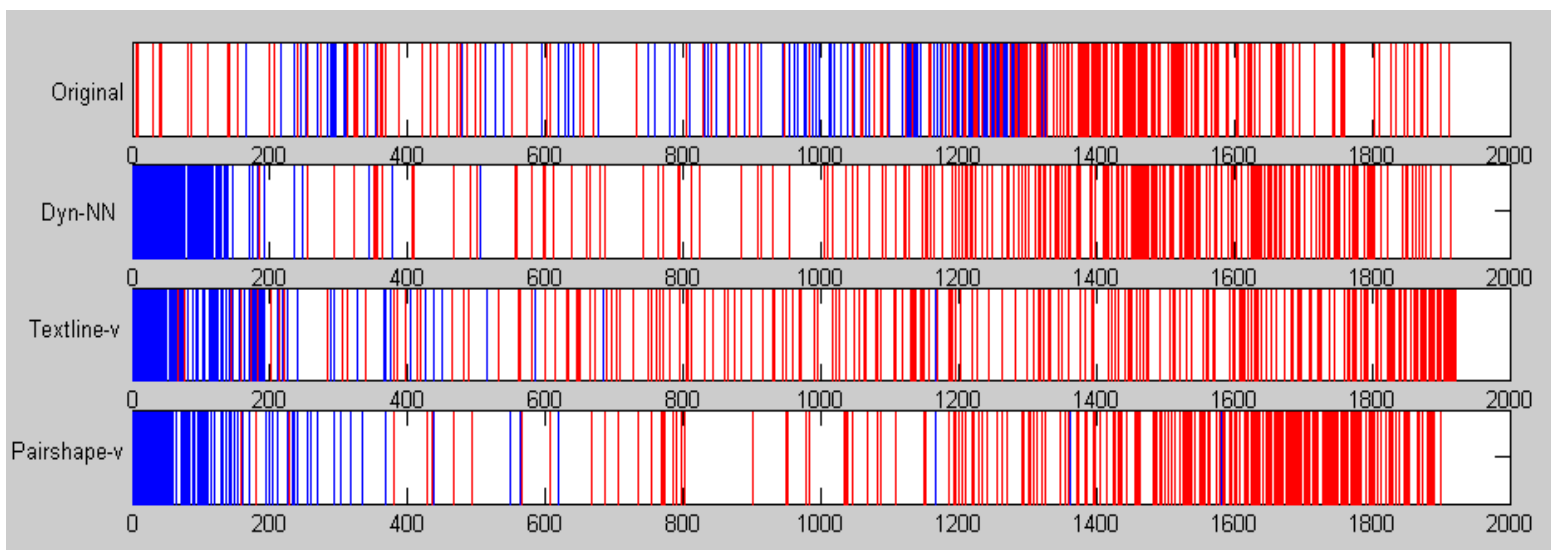
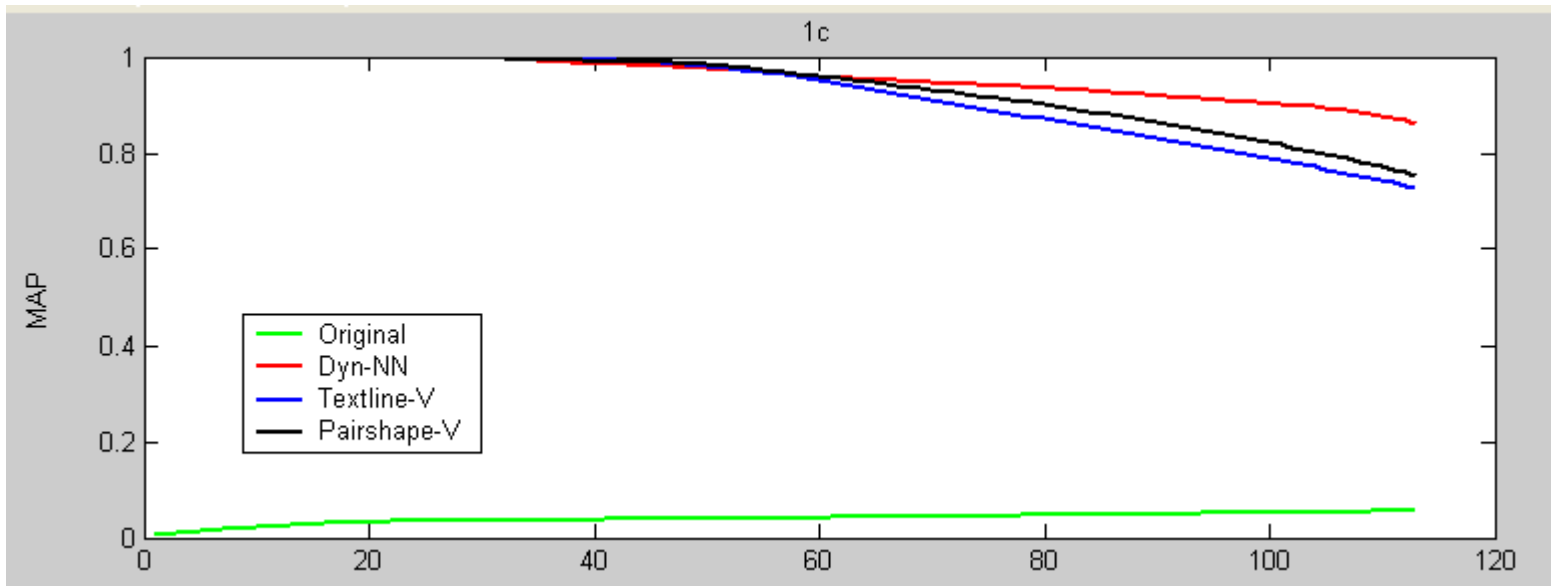
--Confusion Matrix

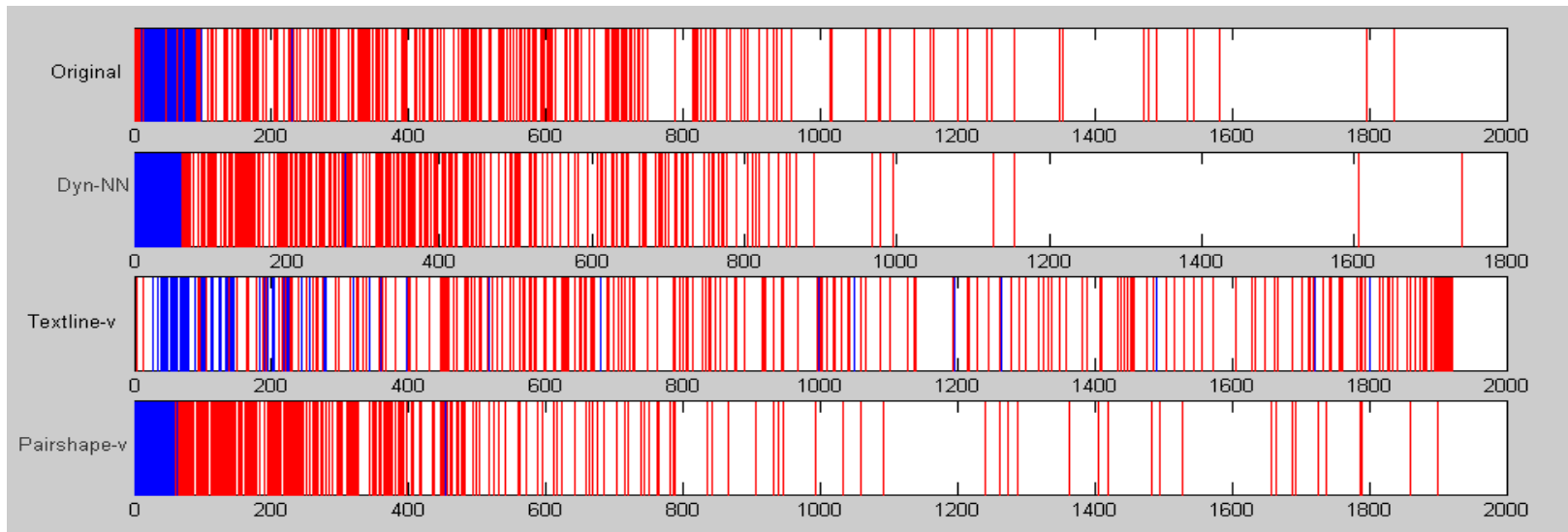
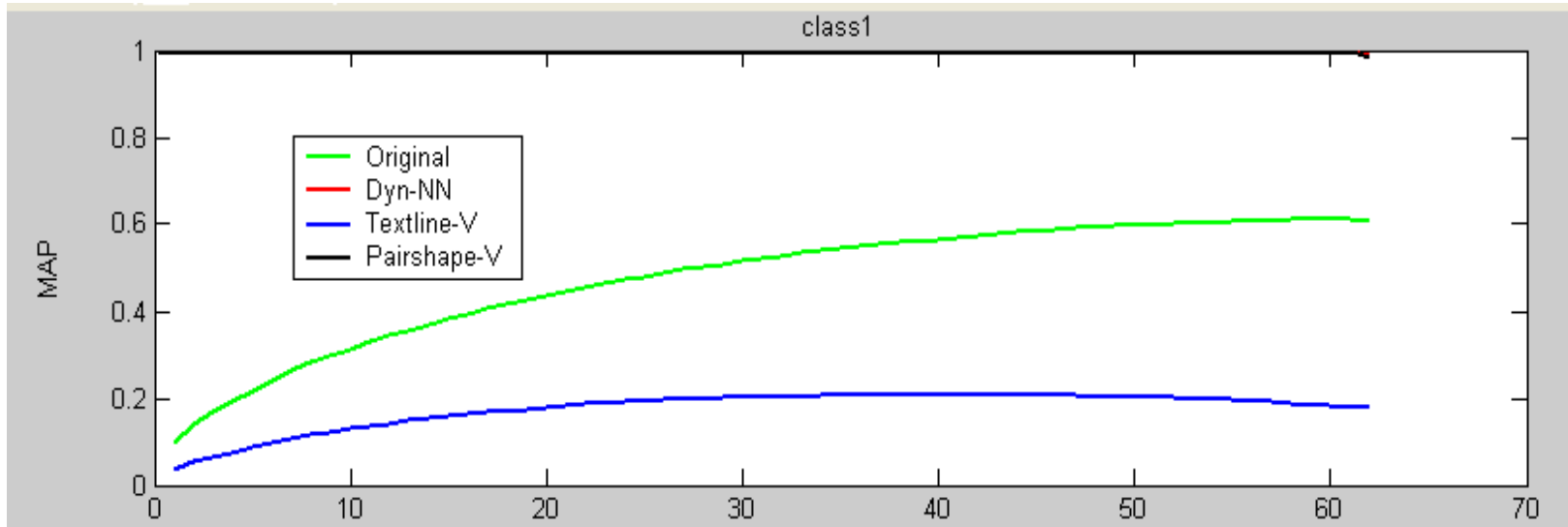
	1c	2c	1r2c	3c	2c_a sym	2c2c_ asym	class 1	class 2	clas s3	clas s4
1c (113)	87	8	16		2					
2c (144)		133	4	1		5	1			
1r2c (431)	9	168	246			8				
3c (23)				23						
2c_asym (6)					3	3				
2c2c_asym (45)		1				44				
Class1 (62)							62			
Class2 (264)	3					2	3	230	2	24
Class3 (121)	1			1			13	2	101	3
Class4				1		1	17	27	7	52

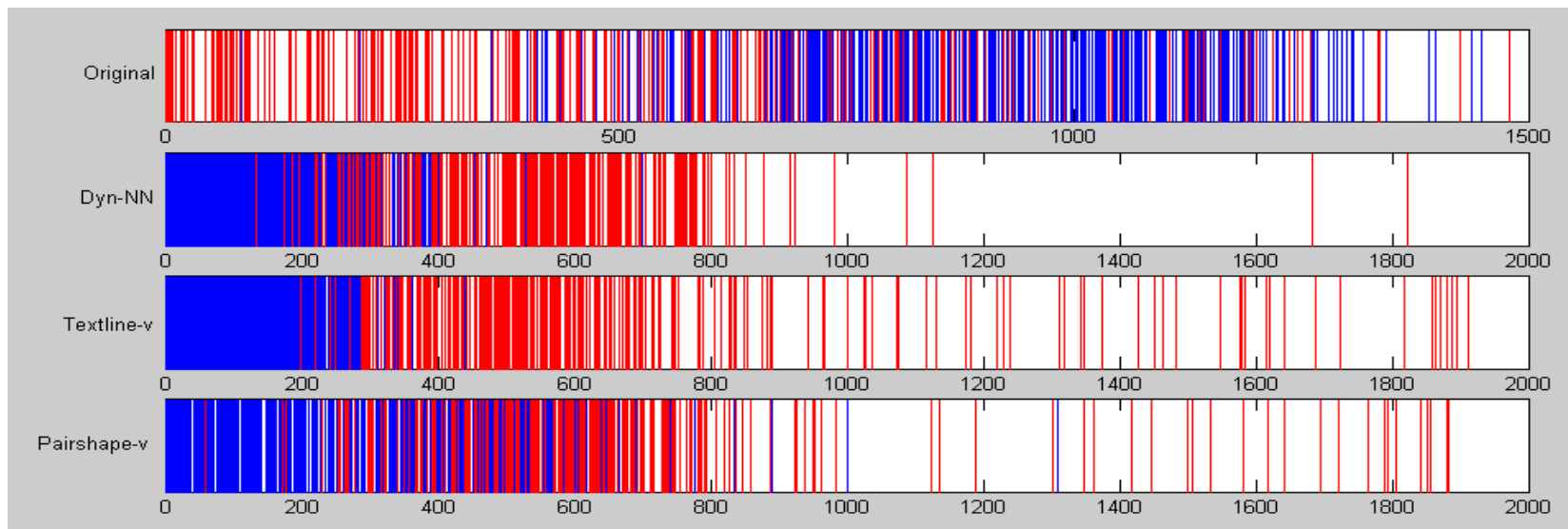
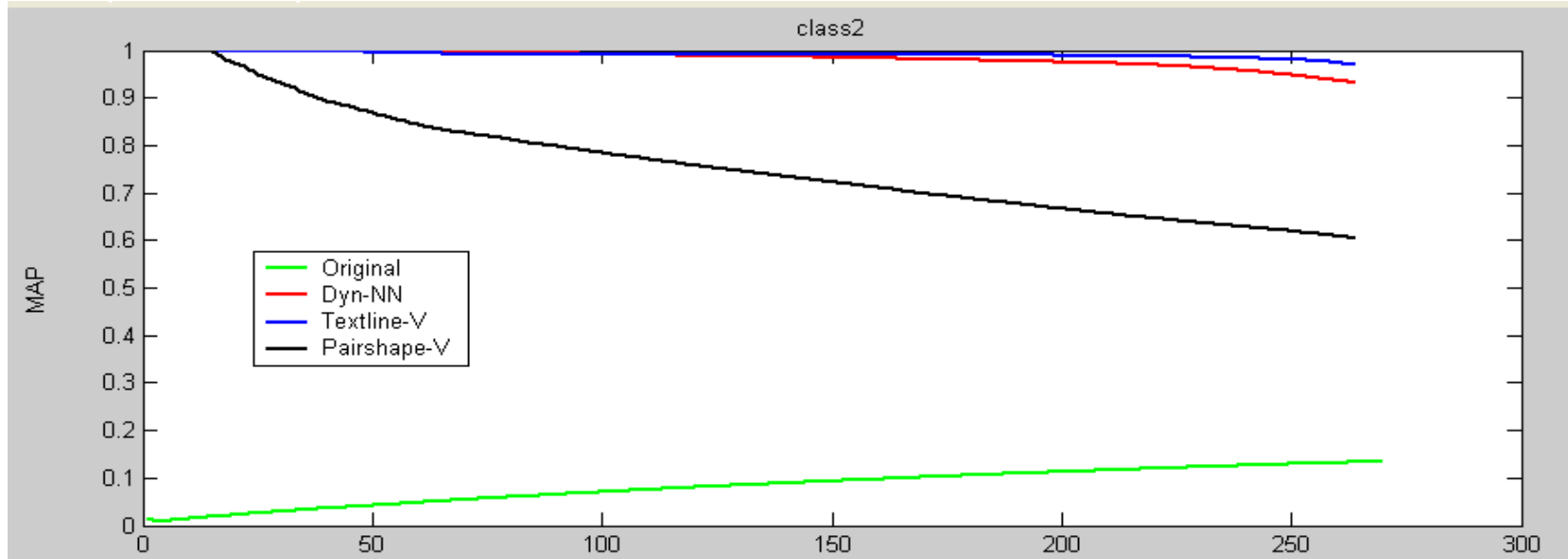


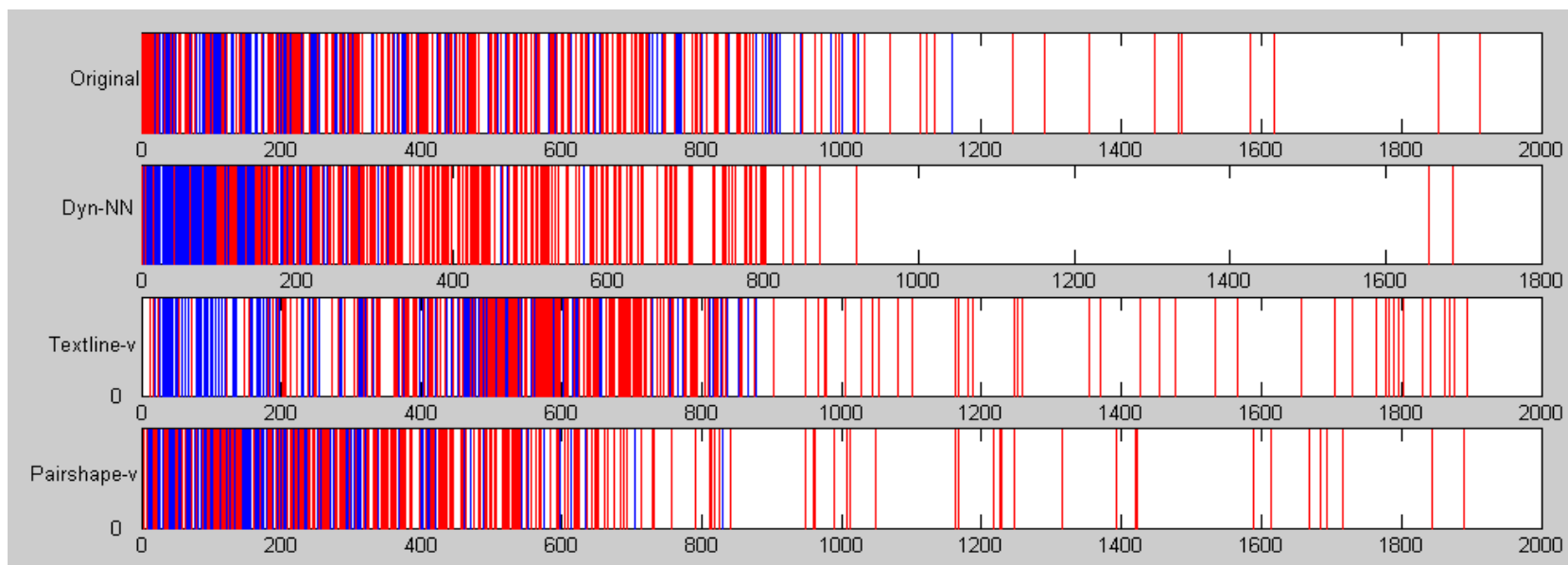
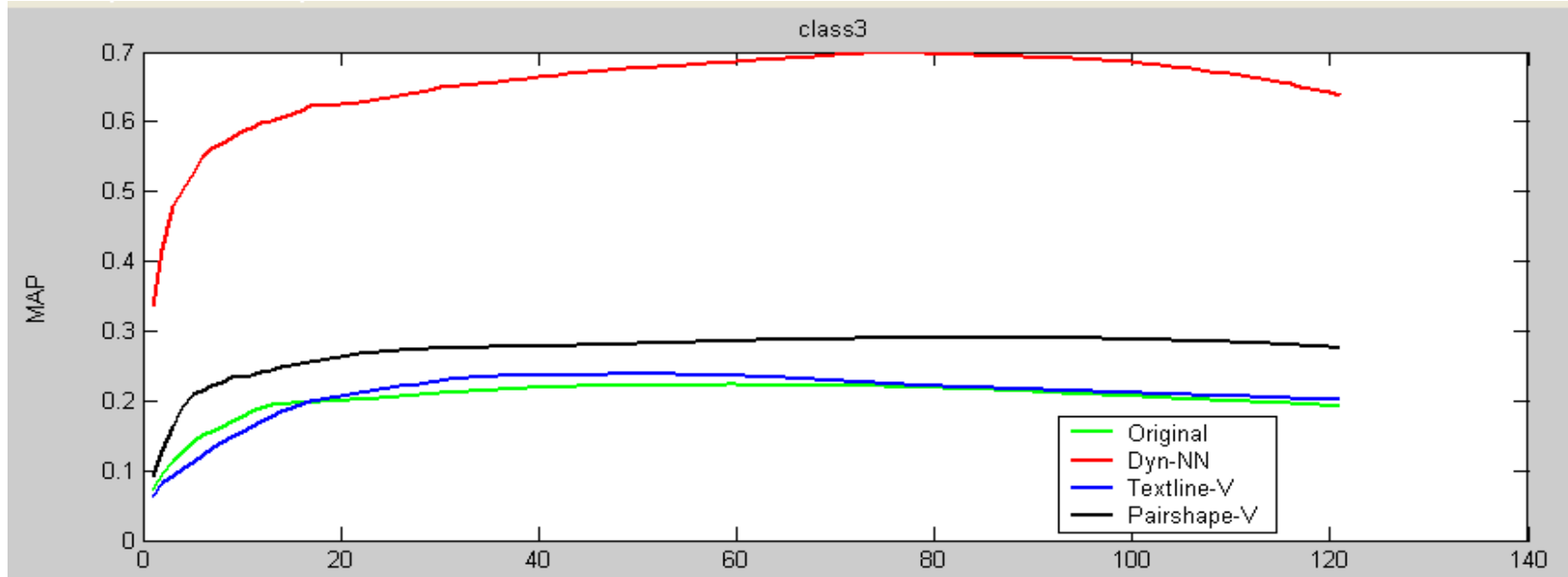
Experiments – ARR Results

	Original	Dyn-NN	Text-V	Pair_V
1c	0.450	0.011	0.038	0.043
2c	0.062	0.010	0.324	0.087
3c	0.028	0.0002	0.504	0.013
1r2c	0.148	0.063	0.245	0.105
1r1r2c	0.159	0.010	0.103	0.045
1r2c2c	0.121	0.067	0.186	0.139
2c_asym	0.137	0.025	0.360	0.039
2c2c_asym	0.025	0.0002	0.097	0.010
class1	0.009	0.002	0.133	0.003
class2	0.398	0.011	0.004	0.075
class3	0.160	0.026	0.146	0.090
class5	0.302	0.056	0.103	0.085









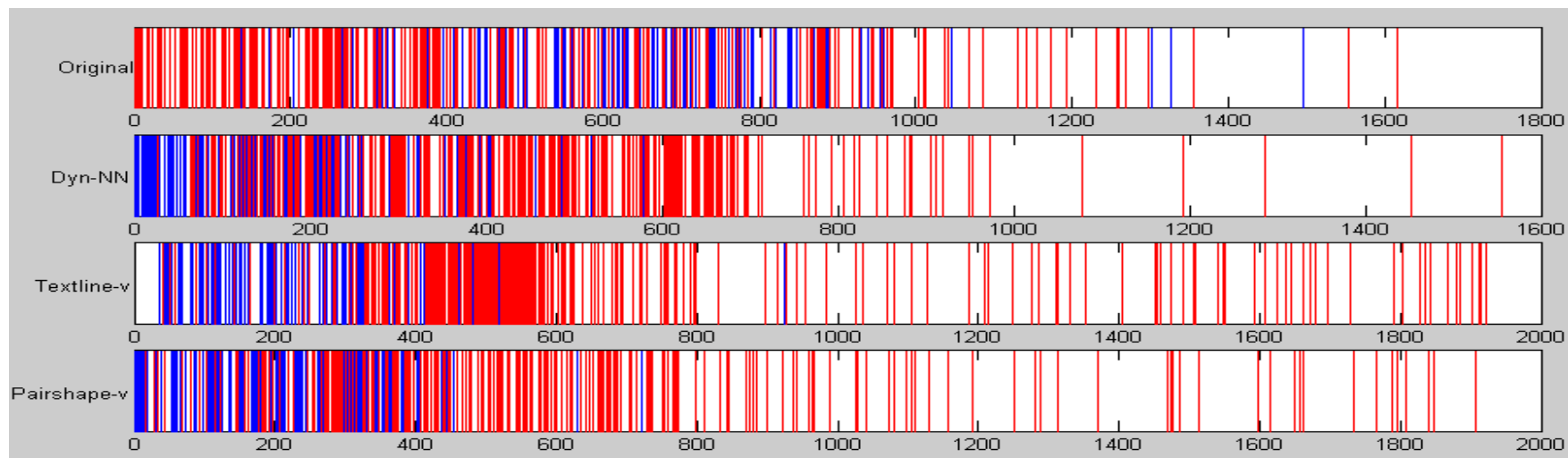
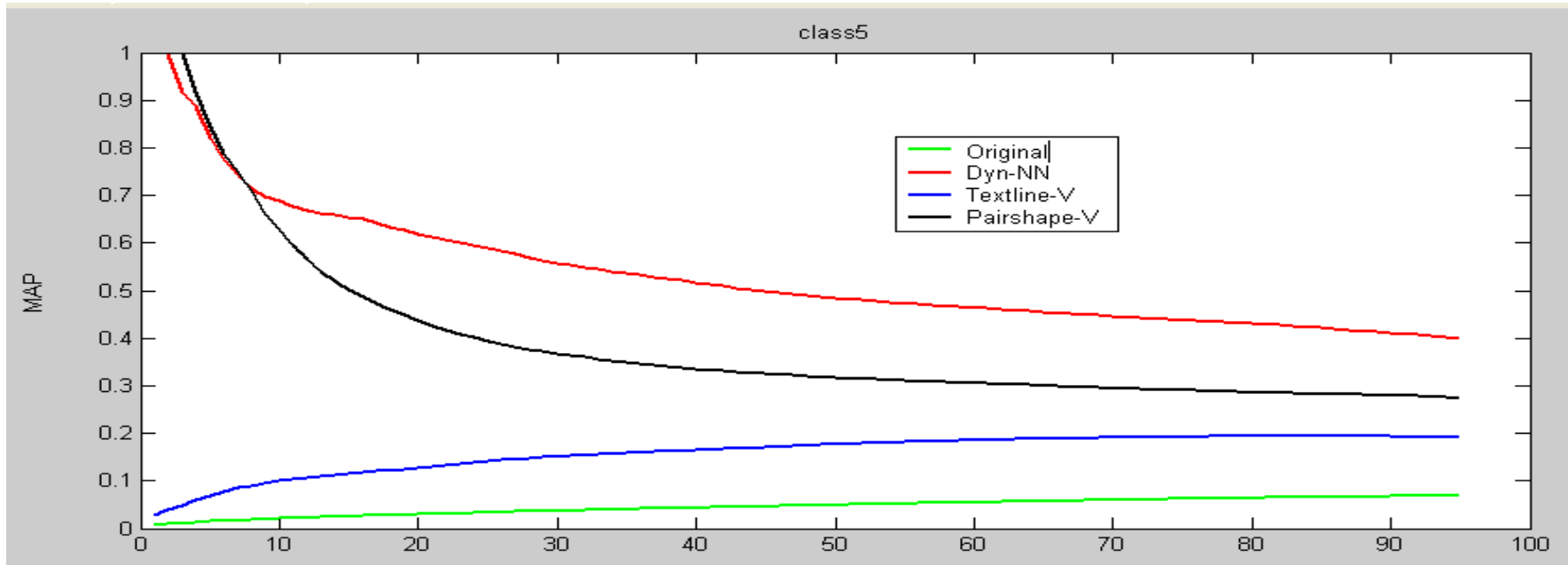
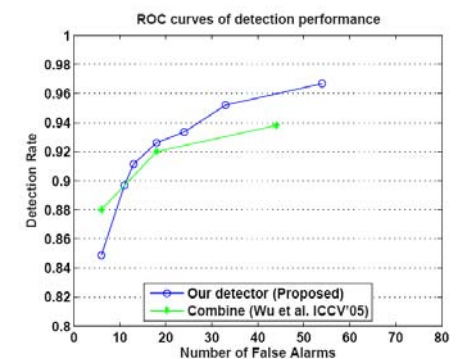
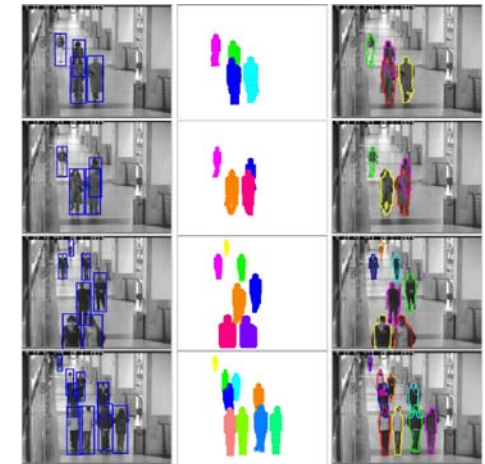
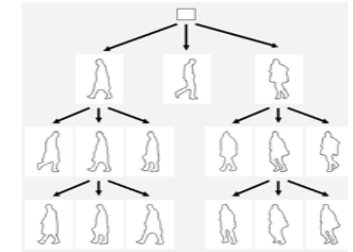
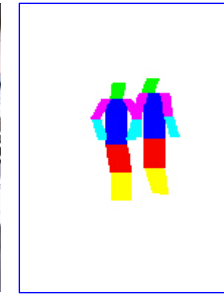


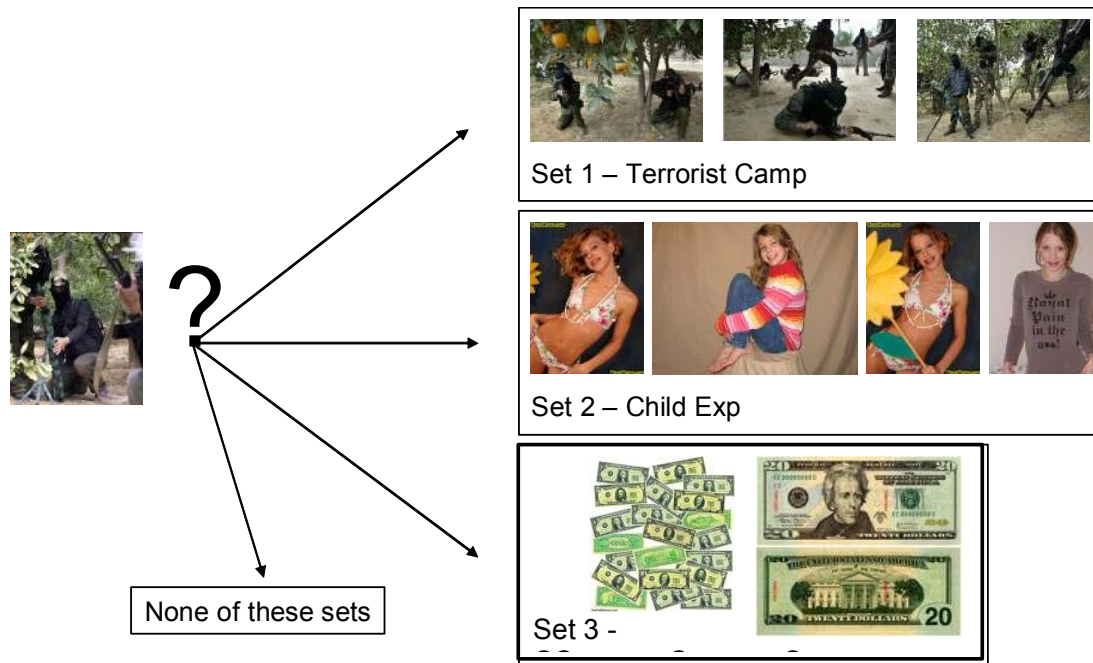
Image and Video Research

- Surveillance Video
 - People Tracking
 - Appearance Modeling
 - Pose Estimation
- Partial Image Matching
 - Robust to changes in view point
 - Able to match partial images



Forensic Image Search

- Consider a “search pack” which contains a “model” of a set of images of interest
- Hard Drive is searched and produces a report without revealing the search content



High Speed Image Classification

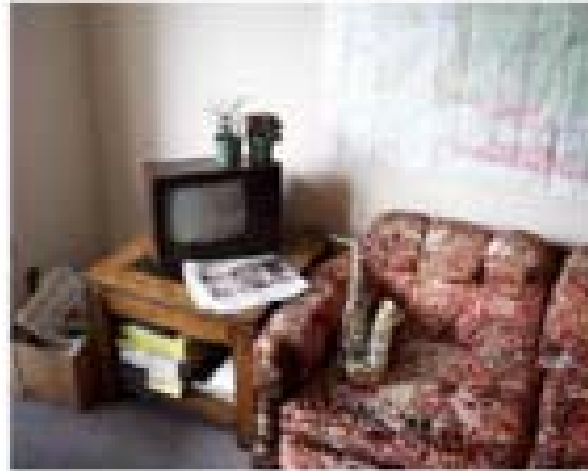
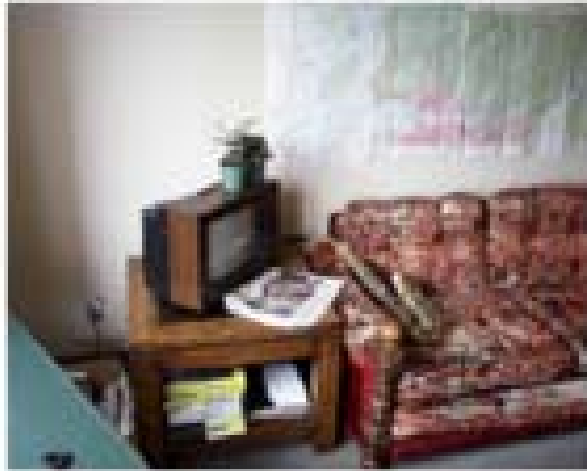
- The purpose of this project
 - To create a new content based image retrieval (CBIR) algorithm that will remove some of limitations of the state of the art
- The task description
 - A user provides a set of training images belonging to several known categories (called SearchPak) and a set of test images.
 - For a test image, the user wants to know if it is similar to one of the SearchPak categories and otherwise classify it as “non-SearchPak image” or “junk image”.



Using what features?

- Histogram, correlogram of color, edge, texture...?
- A good feature: keypoint
 - A feature based on neighborhood edge histogram that is scale and rotation-invariant
 - Independent of color
 - Approach is called SIFT (*Scale Invariant Feature Transform*)
 - Captures salient visual information
- Groups of keypoints are powerful description of objects in images and video





What Can we do with Keypoints?

- Searching (Video Google, Zisserman Oxford, K-means clustering)
- Mining (find most significant objects)
- Indexing (find anchor and cluster frames)
- Browsing
- Logo search
- Near-duplicate detection
- Face detection
- Building detection





Summary

- Focused on Integration with DocLib framework
- Need Software engineering support
- Detailed evaluation and evaluation tools as part of Prototypes.



Possible Research Extensions

- Increasing the speed of processing (software or hardware)
- Script independent word spotting
- Stamp and signature recognition
- Scene text recognition and super-resolution in video.
- Word level Script and Language ID

