

Models for Computer-supported Manuscript Analysis

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Computer Vision, Artificial Intelligence and Palaeography



Palaeographic Applications



"Can you help?"

Richter 2006: "Tentative Criteria for Discerning Individual Hands in the Guodian Manuscripts"





"Yes, we can!"



coarse image

contours

skeleton and axes



Centre for the Study of Manuscript Cultures

DFG Special Research Unit "Manuscript Cultures in Asia, Africa and Europe" Manuscripts as material entities, relations to social and cultural context

First phase 2011 – 2015

17 sub-projects in diverse areas of the humanities, organized in 3 project areas

- Paratexts
- Visual Organisation
- Manuscript Collections

3 "Scientific Service Projects"

- Recovering lost writing
- Reconstructing manuscript history with methods of Material Science
- Determining visual manuscript and character features using computer-based image analysis



Service Project Image Analysis

Project team in the Department of Informatics: Rainer Herzog, Arved Solth, Bernd Neumann

Work plan:

- A Application of image processing methods for projects of the humanities
- B Innovative image processing methods for manuscript analysis
- C Prototype of a work place for manuscript analysis



Second Phase 2015 - 2019

Same main topics as in Phase 1:

- Paratexts
- Visual Organisation
- Manuscript Collections

3 Working Groups (cross-section topics)

- Learning
- Ritual
- Agency

Same service projects

- Main goal of image analysis project: Development of Advanced Manuscript Analysis Portal (AMAP)
- * Different team: Siegfried Stiehl, Volker Märgner (PIs), N.N., N.N.



Interest in Computer Support for Manuscript Analysis at CSMC





Agenda

Retrieval

Layout Analysis

Content-based Image Retrieval

- Animated overview of scribe comparison
- Feature Extraction

Stroke Analysis

Grouping and Classification

Shape-Context Analysis

• Interpretation

Recognition of compositional structures Clustering

• Summary



What is Layout Analysis?

Determining the locations of

- text blocks (incl. paratexts)
- text lines (columns)
- characters
- (- strokes)
- non-textual elements

Arabic Manuscript Multaqā al-abḥār (1641) Ms.or.oct.261, p13v, Staatsbibliothek Berlin





Why use Computers?

Human eyes are very good at discerning text block and character boundaries.

Main purpose of computer methods is to handle large data volumes.

- Layout analysis provides inventory of main text blocks, paratexts and other layout elements.
- Layout analysis delivers useful information (line frequency, orientation) for word and character segmentation.
- Layout analysis allows rectification of text blocks and thus application of well-developed methods for analyzing horizontal or vertical lines:
 - Line Segmentation
 - Word Spotting
 - Writer Identification



Easy Cases

- Text lines parallel to image rows (columns)
- No overlap between characters



Section of the Fo shuo Tiwei jing 佛說提謂經 (British Library Or.8210/S.2051) Columns and characters automatically isolated (white lines)



Simple Processing Steps

Column structure





column boundaries at minima

character boundaries at minima



Localizing Overlapping Text Lines



aun non

Examples from Surinta et al. 2014: A* Path Planning for Line Segmentation of Handwritten Documents.



Planning a Path between Lines

A* Algorithm of Artificial Intelligence finds "minimal-cost" paths from initial state (left margin) to final state (right margin).



Judicious cost definition determines performance of algorithm.



Layout Analysis by Gabor Transformation

(Herzog et al. 2014)

- Location of text blocks in manuscript pages
- Line structure

Main idea:

Use local 2D Fourier Transforms (= Gabor Transform) to determine frequency and orientation of text lines.





What is a 2D Fourier Transform?

An image function may be considered a sum of spatial sinusoidal components of different frequencies and directions.

The 2D Fourier Transform computes the *spectrum* of the image function, which indicates the amplitudes, orientations and phases of the spatial sinusoidals contained in an image.

Principle:





What is a Gabor Transform?

A Gabor Transform is a Fourier Analysis applied to a circular local area, weighted by a Gaussian centered at the circle.



By applying the Gabor Transform at all image locations, the locally dominating line frequencies and orientations can be determined.



Processing Steps

- A Determine dominating frequency and orientation ("line signature") at each image location.
- B Determine local inhomogeneity by computing differences (gradient magnitudes) between adjacent line signatures.
- C Segment image into text blocks along inhomogeneity maxima.

If line distances are unknown or vary strongly, step A must be carried out with several sizes of the Gabor window.

Typical processing time for 2000 x 3000 manuscript page: 10min (in research infrastructure)



Determining Local Line Signatures



Section of an Arabic manuscript

Colour code of line orientations

Note: Orientations ± 180° are not distinguished





<image>

Orientation gradient magnitudes

Frequency (line distance) gradient magnitudes Combined inhomogeneity gradient magnitudes



Region Properties

Region boundaries can be derived from the inhomogeneity gradient image with segmentation methods from Computer Vision.

Used here: Watershed segmentation

1

Several region properties are available for further analysis, e.g.:

2000 2010 2010 2010	مسالان محرما می میدیم از معار استاع حکمار و معرف معرف وی در 19 کسی استفادیند کالاند و واقعها و اصفها و اکترا از و واقد و 1 مانونین معارف کالاو در ولان موجود معرف مید سالو کالمان ما	العدين العدين العدار الوقاة وبقير موتان ال موقعه واحد طاالتي ا
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	COG (x,y)		Line distance mean [Pixel]	Line distance variance	Line orientation mean	Line orientation variance		
Region 1	(545,1220)	45623	89.93	77.777	90.39	64.39		
Region 2	(645,300)	10421	44.95	221.5	93.25	317.08		
Region 3	(1050,620)	4412	45.78	85.6	29.58	156.48		
Region 4	(775,2150)	7108	35.35	60.97	164.12	134.98		
Region 5	(1140,1965)	3247	39.55	69.22	33.62	705.81		
Region 6	(1075,1380)	10920	40.67	112.92	114.88	977.64		
Region 7	(115,1070)	953	36.65	192.38	98.95	1474.81		
Region 8	(655,1045)	2226	49.53	133.38	90.43	245.09		



Examples (1)





Examples (2)







Examples (3)





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Content-based Image Retrieval

Determine occurrences of example image in large database







Word Spotting with Harris Corners (HCs)

Search and retrieval support for scholars of the Humanities

- User provides template with query pattern
- System determines classified HCs
 a) for query pattern
 b) for database (only once)
- System searches for similar patterns
 a) based on classified HCs
 - b) using elastic deformation of query pattern







What is a Harris Corner?

Response of the Harris Corner detector:



Measure of "cornerness" of an image region:



no change in all directions



no change along edge



significant change in all directions



Classification of HCs

Manually designed code chart for HC types



HCs are classified using a Support Vector Machine (SVM) trained with manually selected examples.







Example Databases (2)

Database B: Ca. 2000 Chinese characters

-11 同 不 有 F 60 日 恩 想 E 二句敬之与行 向 窬 同 厚 别差殊为 山人 合 九 沃 B 及 競 她 言 階 J 欲 火台 有 依 降 崕 俋 終み 果 105 游 B 阿 名 大口 如 本 赤 相 增

Database C: Ca. 1800 Newari (Sanskrit) characters





Displacements of Harris Corners



Displacements of corresponding HCs relative to character width, normalized to zero mean



Retrieval Results for Database A





Character	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
True Positives	13	2	0	5	?	10	28	2	16	2	0	7	4	0	5	1
False Positives	5	0	0	0	?	0	1	0	10	0	0	4	0	0	1	0
False Negatives	0	0	0	0	?	0	0	0	0	0	0	0	0	0	0	0

100% recall, 94% precision without warping.



Local Elastic Deformation









query pattern target pattern

matching regions before warping matching regions after warping

- Binarization required
- Local warping with Gaussian radial basis functions
- Hill-climbing for better match
- Mismatching HC pairs are ignored


Retrieval Results for Database B



Precision-Recall plots without warping (red) and with warping (green)



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Basic Stroke Finding Procedure

- Determine character contours (or silhouette)
 - Compute gradient magnitude image
 - Sub-pixel watershed segmentation

• Identify strokes

- Constrained Delaunay Triangulation
- Merge partial strokes at junctions

Compute stroke features

- Location of medial axis, length, orientation, width
- Relational properties



Determining Character Contours



Image of Chinese character

Gradient magnitudes after interpolation

Watershed edges

Final contour after removing insignificant edges



Subpixel Watershed Segmentation

- A Determine continuous image by Spline interpolation between pixels of discrete image
- B Determine watershed lines (mathematically: lines connecting maxima and saddle points)
- **C** Remove insignificant lines



5-th Order Spline interpolation

There exist numerous methods for determining object boundaries. Nice properties of watershed lines:

- closed boundaries
- no artefacts at junctions



Constrained Delaunay Triangulation (CDT) for Stroke Analysis

CDT is defined for points on a polygonal boundary such that no edge of a triangle crosses the boundary.

The density of boundary points can be chosen as fit for the application.

Three types of triangles according to the number of *chords* (edges not coinciding with the contour):

- junction triangles (3 chords, green)
- sleeve triangles (2 chords, blue)
- terminal triangles (1 chord, red)



Stroke analysis amounts to collecting the connections from terminal or junction triangles via sleeve triangles to other terminal or junction triangles.



Examples of Delaunay Triangles







junction triangle

sleeve triangle (top) terminal triangle (bottom)



Corners vs. Curves

Junction triangles are generated within a curve, if the stylus has performed a sudden (discontinuous) orientation change.



Exact conditions for junction:

- Dense boundary points
- Stylus radius S, center line curve radius R, and angle α meet inequality

$$R < S \frac{1 - \cos(\alpha/2)}{1 + \cos(\alpha/2)}$$



Triangulation Example





Chinese character for "come" with computed contour

Constrained Delaunay Triangulation



Influence of Contour Point Density

The spacing of boundary points must be chosen according to the details to be captured.





Influence of Distortions

"Distortions" may naturally arise from handwriting irregularities or background noise.

terminal and junction triagles at "distortions"





Junction Triangles





Junction triangles including spurious junctions due to handwriting irregularities

Cleaned up junction triangles



Merging Partial Strokes

Partial strokes are merged by searching for an optimal stroke configuration:

- smooth individual continuation
- best overall result





Evaluation (1)

339 Chinese characters, ca. 60 x 60 pixels each

沙 醉 奴 卧 者 4 身 面 胞 搭 神 者 聚 致 是 戎 門 其 皆 時 セ 奴 翡平 當 囚 耳 2 醉 无 出 皆 如 得 道 者 語 吹 弟子 ż 生 抡 用 是 1 便 TH 世 如 如 犯 吉 五 四者 酒 醉 呼 為 死 識 億 甘 被 獄 20 酒為思 世 分 者 疽 衝 遇 + 六 輕 中 狂 ん 病 六 間 明 人常當愚寢无 万 知 者 痿黄 醉 无 醉 顛 愣 常 失 歳 去 ++ 1 5 ス 者 輩皆從 山 醉 五 而 便 欲 便 P4 ++ 受形乃竟 佛 飲 如 可 PA 是 = 者 = 死 出 消 踞 执 識 醉 錘 便 順 說 訴 者 者 病 法 醉 + 浅 便 欲 桐 求 大口 酒 銅 皆 红 四 生 前 醉 醉 之 处 不 便 消 魂 世 世 酒 故 訖 者 吏或 沃 皆 散 汤 不 便 吐 便 魄 有 世 銅 世 諸 PF 者 者 元 醉 送 支 得 明 席 家 當 親 六 宿 大口 世 者 得 醉 醉 錘 水 厚 PF 悪 室 識 世 P 便 六 ap 狼 精 作 者 畏 賢 今 鞭 无 衫 D 便 便 驚妻子悪 失 JI-太 和 卧 硯 釋 飲 識 难 榜 或 者 所畏 睐 天 醉 現 地 L 庭 之 不 飲 酒 而 諸 覺 得 龍 地 E 不 循 有 **秋**得 玄 便 + 去 鬼 酒 醉 欲 れ 腹 雪 愚 弑 汞 鬼 臣卜 辟 時 中 如 西午 油 PF 20



Evaluation (2)

Stroke recognition rate decreases with character complexity





Faulty Stroke Reconstruction Due to Rounded Corners



The square-shaped contours actually consist of four strokes, only one has been identifies due to missing junction triangles at rounded corners.



Faulty Stroke Reconstruction Due to Segmentation Error



Two separate strokes were merged due to touching strokes in the image.



Application to Cursive Scripts



Tamil syllable lai



Triangulation resulting in six stroke segments







Three high-ranking reconstructions



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Discovering Clusters in Data

"Clusters" of data objects are hypothetical classes based on similarities and distances. Data objects should be as similar as possible within clusters and as distinct as possible between clusters.



Cluster 1: age 15 - 25, low income, high criminality ("youth criminality") Cluster 2: age 45 - 55, high income, high criminality ("white-collar criminality")

Data objects are viewed as points in a multi-dimensional feature space. Similarity of data is judged by distance measures.



Clustering in Manuscript Analysis

Grouping of manuscrips / sections based on a similarity measure

How does one measure the similarity of e.g.

- letters?
- layouts?
- writing style?



Quantitative features in feature space Symbolic features in relational structures

There exist numerous clustering procedures in commercial systems. <u>Warning</u>: Results depend on *weights* assigned to different features



Metrical Distance Measures

A distance measure is required to judge the difference between two samples. Mathematical definition of a <u>metric</u> d for points x, y, z must meet conditions:

d(x, x) = 0	points have distance 0
d(x, y) ≠ 0	different points have distance different from 0
d(x, y) = d(y, x)	symmetry
$d(x, y) + d(y, z) \ge d(x, z)$	triangular inequality

Metrics cannot always be easily defined:

- Angles
- Colors
- Shapes
- Texts



Examples for Distance Measures

Euclidean distance for numerical values

 $d^2 = \sum_i (x_i - y_i)^2$

e.g. for length, width and orientation of two shapes

Normalization may be required $b' = \frac{b}{\sigma_b}$ $h' = \frac{h}{\sigma_h}$ $\alpha' = \frac{\alpha}{\sigma_\alpha}$ for a meaningful comparison

• Absolute distance $d = \sum |(x_i - y_i)|$

$$\frac{1}{i} + \frac{1}{i} + \frac{1}{i} + \frac{1}{i}$$

- Maximal distance $d = \max_{i} |(x_i y_i)|$
- Hamming Distance $d = \sum_{i} d_{i}$ with $d_{i} = \begin{cases} 0 & \text{for } x_{i} = y_{i} \\ 1 & \text{for } x_{i} \neq y_{i} \end{cases}$



k-means Algorithm

Samples are represented as points in an N-dimensional feature space.

- A Choose arbitrary initial cluster centers
- B Determine cluster assignments of points according to distance to cluster centers
- **C** Move cluster centers to mean of assigned points
- D Repeat B and C until no further changes occur





Structural Distance Measures

- Levenshtein Distance ("Editing Distance") of symbol sequences (e.g. texts)
 - How many operations for
 - replacing a character / symbols
 - removing a character / symbols
 - inserting a character / symbols

are minimally necessary to concert one sequence into the other

<u>Example</u>: LEVENSHTEIN \leftarrow LEWENSTEIN \rightarrow d = 2

There exist efficient algorithms to determine the Editing Distance.

Structure Distance

Generalization of Editing Distance to relational structures

edges often express compositional information





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Datamining and Knowledge Discovery

Classical statistics Machine Learning Pattern Recognition

Data Mining and Knowledge Discovery are considered parts of AI (1990)

Identification of new, potentially useful patterns in large data sets

Data Mining: Analysis, hypothesis generation

Knowledge Discovery: Evaluation and interpretation



Datamining for Manuscript Analysis

Discovery of visual features to determine commonalities between manuscripts

Potential evidence for

- common region of origin
- common cultural epoche
- common writing style
- common hands

Thesis:

Computers may discover features and feature associations, which may have been overlooked or which are difficult to discover by humans.



Association Rules

Datamining offers mature and efficient procedures, developed e.g. for purchase analysis:

"Customers who purchase beer and pizza also tend to buy potatoe chips"

Transfer to manuscript analysis:

"Scribe A tends to use a smaller stroke angle in character Y more often than scribe B"

"There is a group of manuscripts

- where the cross bar in character X tends to be shorter than elsewhere, and
- where the strokes in the characters Y1, Y2 and Y3 tend to be slimmer than normal, and
- where the height of the signs is unusually constant"



. . .

Preparing Manuscripts for Datamining

• Select objects (characters, words) for comparison



• Determine features of large repertoire for each object

01	angle4	angle2	length4	compact3 size2	size2	relation3
o2	angle5	angle2	length3	compact1 size1	size3	relation2
о3	angle3	angle2	length4	compact2 size1	size3	relation3
04	angle4	angle2	length4	compact3 size2	size2	relation1
05	angle3	angle2	length4	compact3 size1	size2	relation3

• Start datamining with APRIORI Algorithm



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Compositional Patterns in Medieval Music Notation

Ac clara che arma feltura > methaned & Ahner canta une porta ar mind que et tola catalina I Am ab utama too marra grana & plena per numra ohm farta angehra . I hiherum ma a mus femp benecheta. Qui comes maira her reda 2 1 pm 4 1 4 9 4 900 100 1 9 9 10 4 9 4 9 Famma Vurnom nullain serve copulam Duam Cr quo drop na A fin incorrupt 171 (7) av plena fietmana. ma weden affant. I) ous offerens aductio wie ver mera en more elan And would

What is the significance of square and rhomb note ligatures?





Is there any meaning to different stem lengths?



Large data volume of > 1200 pages must be analyzed!



Challenging Pattern Recognition Problem



ligatures of same type have significantly different appearances

Search for compositional structures: patterns of parts related to each other by certain constraints.

Many examples of compositional structures in manuscripts:







Stroke radicals / \



How does one recognize a compositional structure in a standardized way?



Staffs

Staff Lines

Models for Compositional Structures

Stem

A compositional structure



can be visualized as a graph:

Note Heads

Nodes represent image parts or aggregates

Edges represent the relation "composed-of" (or "has-part")

Each aggregate node is described by

- aggregate name
- parent concepts
- aggregate properties
- parts
- constraints between parts

Name:	Climacus
Parent:	Ligature
Bounding Box:	< 150 x 200
Parts:	Staffs, Triple, Stem
Constraints:	Triple matches Staffs
	Stem touches upper left of Triple

Climacus

Triple

Climacus model



Recognition of Primitive Parts

"Primitive parts" = elements of a compositional structure which cannot be decomposed further

Here: staff lines, note heads, stems

Standard recognition procedures:

- Template matching
- Normalized Cross Correlation
- Feature-based Classification
- Specialized methods

Here: Distinguishing between

- square notes
- rhomb notes
- noise








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Recognition of Compositional Structures

There exist several standardized algorithms:

- Constraint Satisfaction
- Top-down Search
- Bottom-up Search
- Mixed Bottom-up Top-down Search

We used Mixed Bottom-up Top-down Search for ligature recognition:

- Find staff lines
- Find staff system, check staff system constraints
- Find note heads
- Find triples, check triple constraints
- Find stem
- Find ligature, check stem constraint

Standard bottom-up steps for aggregate nodes:

- Check constraints on parts
- Compute aggregate properties
- Assign aggregate to parent aggregates





Result Statistics



Manuscript	W1	W2	F
# Pages	379	508	798
# Ligature Type 1	2703	1089	3891
# Ligature Type 2	2	4	6
# Ligature Type 3	1398	549	1364
Ratio Type 1:Type 3	~2:1	~2:1	~3:1
Accuracy Note Classification	89,41%	96,44%	79,11%

W1 = Scottish Manuscript 1 (Herzog August Bibliothek Wolfenbüttel)
W2 = Scottish Manuscript 2 (Herzog August Bibliothek Wolfenbüttel)
F = French Manuscript (Notre Dame)



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Summary

Computer Vision and Artificial Intelligence provide powerful methods which can be harvested for palaeographic applications.

Computer support may range from sped-up palaegraphical methods to specially designed "black boxes".

You saw examples of

Restoration

Retrieval

Feature Extraction

Grouping and Classification

Interpretation

There are numerous methods for Digital Palaeography, how choose?



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Tool box of computer methods

"Different scribes!"

It is useful to understand the "idea" (model) of a computer method:

- What information is exploited, what is neglected?
- What are inherent limitations?
- How certain is a result?

Thank you for your interest!