Studying Digital Imagery of Ancient Paintings by Mixtures of Stochastic Models

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Applications

- Compare Artists
- Retrieve images based on similarity of stroke styles
  - Stroke styles may be the key difference between images.
Outline

- Background
- The approach
  - Feature extraction
  - Mixture of stochastic processes
- Experiments
- Conclusions and future work
About 50-100 paintings are collected each for some of the most renowned artists in Chinese history.
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A Stochastic Modeling Approach (Overlook)

- Every subimage of 64x64 is one instance of a certain stroke style.
- Every subimage is divided into 8x8 blocks.
- A feature vector is extracted for each block at each resolution.
- A stroke style is characterized by a 2-D multiresolution hidden Markov model (MHMM).
Wavelet Transform

Wavelet coefficients in high frequency bands reflect characteristics of strokes:

- Orientation
- Abruptness of variations
Multiresolution features

- At the crudest resolution, one feature vector is formed for the block.
- At the next higher resolution, the block is divided into 2x2 child blocks and a feature vector is formed for each child block.
Feature Extraction

For each block at each resolution, a 3-dimensional feature vector is formed by the LH, HL, HH coefficients.
Model: 2-D MHMM (Overlook)

- Represent images by local features extracted at multiple resolutions.
- Model the feature vectors and their inter- and intra-scale dependence.
- 2-D MHMM finds “modes” of the feature vectors and characterizes their spatial dependence.
2D HMM

Regard an image as a grid. A feature vector is computed for each node.

- Each node exists in a hidden state.
- The states are governed by a Markov mesh (a causal Markov random field).
- Given the state, the feature vector is conditionally independent of other feature vectors and follows a normal distribution.
- The states are introduced to efficiently model the spatial dependence among feature vectors.
- The states are not observable, which makes estimation difficult.
2D HMM

The underlying states are governed by a Markov mesh.

\((i', j') < (i, j)\) if \(i' < i\); or \(i' = i\) & \(j' < j\)

\[
P(s_{i,j} \mid s_{i',j'}, u_{i',j'} : (i', j') \in \Psi) = a_{m,n,l},
\]

where \(\Psi = \{(i', j') : (i', j') < (i, j)\}\)

and \(m = s_{i-1,j}, n = s_{i,j-1},\) and \(l = s_{i,j}\).
2D MHMM

- An image is a pyramid grid.
- A Markovian dependence is assumed across resolutions.
- Given the state of a parent node, the states of its child nodes follow a Markov mesh with transition probabilities depending on the parent state.
2D MHMM

- First-order Markov dependence across resolutions.

\[
P\{s^{(r)}_{i,j}, u^{(r)}_{i,j}; r \in \mathcal{R}, (i, j) \in \mathbb{N}^{(r)}\} = P\{s^{(1)}_{i,j}, u^{(1)}_{i,j}; (i, j) \in \mathbb{N}^{(1)}\} \cdot P\{s^{(2)}_{i,j}, u^{(2)}_{i,j}; (i, j) \in \mathbb{N}^{(2)}| s^{(1)}_{k,l}; (k, l) \in \mathbb{N}^{(1)}\} \ldots
\]

\[
P\{s^{(R)}_{i,j}, u^{(R)}_{i,j}; (i, j) \in \mathbb{N}^{(R)}| s^{(R-1)}_{k,l}; (k, l) \in \mathbb{N}^{(R-1)}\}
\]
2D MHMM

- The child nodes at resolution $r$ of node $(k,l)$ at resolution $r-1$:

  $$\mathbb{D}(k,l) = \{(2k,2l), (2k+1,2l), (2k,2l+1), (2k+1,2l+1)\}$$

- Conditional independence given the parent state:

  $$P\{s_{i,j}^{(r)} : (i,j) \in \mathbb{N}^{(r)} \mid s_{k,l}^{(r-1)} : (k,l) \in \mathbb{N}^{(r-1)}\} = \prod_{(k,l) \in \mathbb{N}^{(r-1)}} P\{s_{i,j}^{(r)} : (i,j) \in \mathbb{D}(k,l) \mid s_{k,l}^{(r-1)}\}.$$
Mixture of 2-D MHMMs

- It is restrictive to assume a single stroke style for an artist.
- Model each artist by a mixture of 2-D MHMMs, each characterizing one type of stroke.
- One stroke style is assumed through each subimage.
Model Estimation (Training)

- Training data: collection of subimages.
- Use Maximum Likelihood (ML) criterion and the EM algorithm.
- Relies on the ML estimation of 2-D MHMM.

Cluster subimages based on the mixture of 2-D MHMMs

Cluster 1 | Cluster 2 | Cluster M
---|---|---
Train 2-D MHMM | Train 2-D MHMM | Train 2-D MHMM
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Experiments

- A typical image is of rough size 3000x2000.
- Five Chinese artists are studied:
  - Ming Dynasty: Shen Zhou, Dong Qichang
  - Qing Dynasty: Gao Fenghan, Wu Changshuo
  - Late Qing to Modern: Zhang Daqian
- Number of images in the collection:
  - Zhang Daqian: 91
  - The others: around 45
A mixture of 2-D MHMMs is trained for each artist.

Subimages can be clustered into different MHMMs.

Images can be compared based on the percentages of subimages belonging to each stroke style.
Zhang’s stroke style

Swift, thin strokes

Flat controlled strokes
Zhang’s stroke style

Heavy and thick wash

Straight, light wash with some vertical lines

Smooth region
Zhang’s stroke style

Small dark strokes

Sharp lines and straight wash

Pale and diluted wash
Image Similarity

Retrieval of most similar images among Zhang’s paintings
Image Similarity

Retrieval of most similar images among Zhang’s paintings
Artist Similarity

- Similarity between an image and an artist’s style can be assessed by the likelihood of the image under the mixture model of the artist.
- The following paintings of Zhang are identified as most different from Shen’s painting style.
Artist Similarity
Shen Zhou’s Paintings

East village painting, by SHEN Zhou (1427-1509), Ming Dynasty

Relaxed tour painting, by SHEN Zhou (1427-1509), Ming Dynasty

Mountains-and-waters painting, by SHEN Zhou (1427-1509), Ming Dynasty

Mountains-and-waters in Wu painting, by SHEN Zhou (1427-1509), Ming Dynasty

Mountains-and-waters (mimic DONG Ju) painting, by SHEN Zhou (1427-1509), Ming Dynasty

Bridge over the Ba River in snow painting, by SHEN Zhou (1427-1509), Ming Dynasty

SHEN Zhou: One of the Four Great Masters in the Ming Dynasty. Landscape painter. His flower and bird paintings created the new style of freehand drawing. [info, signature, paintings]
Zhang Daqian’s Paintings
Zhang Daqian’s Paintings

<table>
<thead>
<tr>
<th>Image</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image 1" /></td>
<td>Chinese painting, by <strong>Zhang Daqian</strong> (1899-1983), Qing Dynasty to China. <strong>Zhang Daqian</strong>: Blend Western painting style with Chinese painting style. [info, signature, paintings] <strong>SIMPLICITY &gt;</strong></td>
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<tr>
<td><img src="image2.png" alt="Image 2" /></td>
<td>Chinese painting, by <strong>Zhang Daqian</strong> (1899-1983), Qing Dynasty to China. <strong>Zhang Daqian</strong>: Blend Western painting style with Chinese painting style. [info, signature, paintings] <strong>SIMPLICITY &gt;</strong></td>
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<tr>
<td><img src="image4.png" alt="Image 4" /></td>
<td>Chinese painting, by <strong>Zhang Daqian</strong> (1899-1983), Qing Dynasty to China. <strong>Zhang Daqian</strong>: Blend Western painting style with Chinese painting style. [info, signature, paintings] <strong>SIMPLICITY &gt;</strong></td>
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Classify Artists

- About one third of the images are used in training.
- A subimage is classified to the artist whose profiling mixture model yields the highest likelihood.
- Majority vote is used to decide the class of the image.
- Mixture models with 1, 4, and 8 component MHMMs are examined.
- Comparison is made with the decision tree method (CART).
<table>
<thead>
<tr>
<th></th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accuracy (%)</strong></td>
<td><strong>Eight components</strong></td>
<td><strong>Four components</strong></td>
<td><strong>One component</strong></td>
</tr>
<tr>
<td>Shen</td>
<td>70</td>
<td>83</td>
<td>63</td>
</tr>
<tr>
<td>Dong</td>
<td>90</td>
<td>90</td>
<td>87</td>
</tr>
<tr>
<td>Average</td>
<td>80</td>
<td>87</td>
<td>75</td>
</tr>
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Conclusions

- Studied a stochastic modeling approach to extract and characterize stroke styles.
  - Feature extraction by the wavelet transform.
  - Mixture of 2-D MHMMs
- Explored various applications.
  - Image comparison
  - Artist comparison
Future Work

- Identify more art-related image analysis tasks.
- Advance modeling techniques.
  - Model complexity?
- Explore further applications.
- Evaluations of art historians.
- More …
More Information