Effective Statistical Modeling Tools for Pattern Recognition and Dynamics Analysis of Visual Data

Kenneth Rose

Signal Compression Laboratory
University of California, Santa Barbara

March 11, 2008
Outline

- (A brief commercial: “What else we pursue in the lab”)
- Motivation: hard problems require powerful tools
- Statistical modeling with the hidden Markov model (HMM)
- The one dimensional HMM: modeling what we don’t understand
  - Tracking curvilinear structures (microtubules)
- The two dimensional HMM: major challenges and rewards
  - Pattern recognition and retrieval (examples with face image database)
Signal Compression Lab

- Video coding and communications:
  - robust encoding for lossy networks and wireless communications
  - scalable video coding
  - optimal delivery of pre-compressed video
- Audio coding:
  - nearly optimal encoding of MPEG-AAC audio (real-time and offline)
  - audio frame-loss concealment
  - scalable audio coding
- Pattern recognition and databases
- Distributed coding, sensor networks
Pattern recognition tools must model what is not well understood, e.g.:
  - Facial features for recognition
  - Speech features and dynamics

One important tool is the hidden Markov model
  - Speech recognition’s flagship
  - Captures temporal and spatial correlations from examples
  - Its flexibility allows application in extremely diverse fields
A “Hard Problem” Example

- Microtubules: importance and challenges
- Tubular structure with critical functions in the cell
- Are the focus of research on
  - Cancer
  - Alzheimer’s disease
- Dynamics (growth, shortening, stability) implicated
- Considerable technical challenges...
Microtubules Animation I (UC Berkeley, Nogales Lab)

To see click
UCB Nogales Lab: microtubules
Microtubules Animation II (Harvard University)

Includes microtubule animation. To see click:
Inner Life of the Cell
And Now – Reality

- What biologists actually work with:
And Now – Reality

▶ Zooming in:
Hidden Markov Model

- Markov Chain:
  - The system goes through a sequence of states

![Diagram of Markov Chain](image)

- Governed by the “transition probabilities” $P(S_j | S_i)$

![Diagram of Transition Probabilities](image)

- Models evolution of signals in time or space
Hidden Markov Model

- “Hidden”:
- States are not directly observable
- We only have access to observation data that depend on the state

- Governed by the “emission” probabilities: \( P(o_t|q_t = S_i) \)
- Model for underlying process that explains observations
- Used for:
  - Modeling (design model to fit observation data)
  - Classification (class models compete to explain observations)
  - Decoding (find the underlying sequence of states)
1D-HMM “Decoding”

- The “trellis”

- A path in the trellis is a sequence of states
- Decoding: find the path that best explains observed data
- Number of paths enormous, but efficient search: “Viterbi decoding”
Open Contour Tracking: 1D-HMM

- Tracking challenges:
  - Noisy images
  - Clutter
  - Illumination variations

- Deformable Trellis
Open Contour Tracking: 1D-HMM

- Initial and end states model growth and shortening
Microtubule Tracking In Vivo
Microtubule Tracking In Vivo
Microtubule Tracking In Vitro
Extension: 2D HMM

► Markov chain:

► HMM:

► No efficient way to find best path in the high-dimensional “trellis” (no 2D Viterbi decoding)!
Convert to 1D HMM?

- Use “super states”
- Apply Viterbi decoding to the 1D HMM.
- Catch: complexity is in the super state...
- Najmi-Gray (’00) proposal:
  - Limit number of super states considered to some feasible $K$
  - Approximation quality depends on $K$
Turbo-HMM Decoding (Eurecom-UCSB ’05)

- Iterate between vertical and horizontal 1D HMM decoding
- Horizontal and vertical scans “communicate” through the posterior state probabilities
- Bootstrapping leads to a solution leveraging 2D evidence
- Limitation: Assumes overall transition probabilities are separable (product of the horizontal and vertical transition probabilities)
Conditional Iterative Decoding

- Turbo-HMM revised:
2D-HMM - Synthetic Data

![Graph showing Avg. Log. Lik. vs. Iterations for different K values: K=16, K=32, K=64, K=128, K=256, K=512, K=1024, K=2048. Each curve represents a different model, with CID, THMM, and PCVSV models indicated. The graph captures the convergence of the Avg. Log. Lik. over iterations.]
2D-HMM for Face Recognition

- Design 2D HMM to model the “warping” needed to map between photographs of same person
  - State = local translation
  - Transition probabilities favor neighborhood consistency in translation
  - Emission probabilities penalize errors in local features after warping
- System has access to one template image per subject in the database
- Given a query image, identify subject by template whose warping HMM would most likely “emit” the query image.
- Yale Face database: 165 face images (15 subjects)
- Methods compared for preliminary results:
  - Our conditional iterative decoding (CID)
  - ”Bayesian subspaces” (Moghaddam ’02)
2D-HMM for Face Recognition

<table>
<thead>
<tr>
<th></th>
<th>%ER</th>
</tr>
</thead>
<tbody>
<tr>
<td>CID</td>
<td>3.3</td>
</tr>
<tr>
<td>BS</td>
<td>7.7</td>
</tr>
</tbody>
</table>

Query Image

Warped Images

Warped Mesh Images

Template Images
2D-HMM Retrieval Experiment

Query Image

Rank Ordered Retrieval
2D-HMM Retrieval Experiment

![Graph showing log likelihood over iterations with a note indicating the first "incorrect" retrieval.](image-url)
Summary / Conclusion

- Statistical modeling tools are needed to solve hard, noisy, uncertain or partially understood problems
- Hidden Markov models are effective tools to statistically capture evolution in time and space
- Turbo techniques are efficient and enable practical extension to 2D-HMM applications
- New 1D and 2D HMM techniques were shown to be effective in:
  - Tracking curvilinear structures (microtubules) – 1D HMM
  - Face recognition and content-based retrieval in image databases – 2D HMM