



Recognition of Moving Patterns from Moving Observers

Rama Chellappa

Center for Automation Research

And

Electrical and Computer Engineering

University of Maryland



Issues

- Simultaneous object and observer motions.
- Illumination and pose variations.
- Behavior-based recognition is possible.
- Recognition of a rare event.
- Time is of the essence!
- Unambiguous ID of objects and activities possible
- Motion – Shape – Recognition- How they influence each other
- Basic survival skill



Opportunities

- Persistent observations – continuous sensing, tracking and identification.
- Peek-a-boo, I see you – Surprising an object by an observer (Active sensing).
- Behavior modeling (Dynamic Bayesian networks).
- Advances in structure from motion.
- Old tools (from the 50's) in modern computers (MCMC techniques).
- Role of invariants/quasi-invariants understood better.



Simultaneous Modeling of Object and Observer Motions

- Is there one or more combinations of observer and object motions for best recognition ?
- Keeping the object in observer's cross wire.
- The problem of critical motion sequences
 - Motions that result in many reconstructions



Continuous Tracking and Recognition -1

- “Fingerprinting” the object. What and how many ?
- How to accumulate evidence as the object is persistently observed ?
 - Evidence accumulation may have to be non-monotonic
- Not all objects are of equal interest – costs of incorrect decision unknown and non-uniform across the object space.
- How many frames are needed for achieving the required performance ?
 - Need to generalize Wald’s Sequential Probability Ratio Test

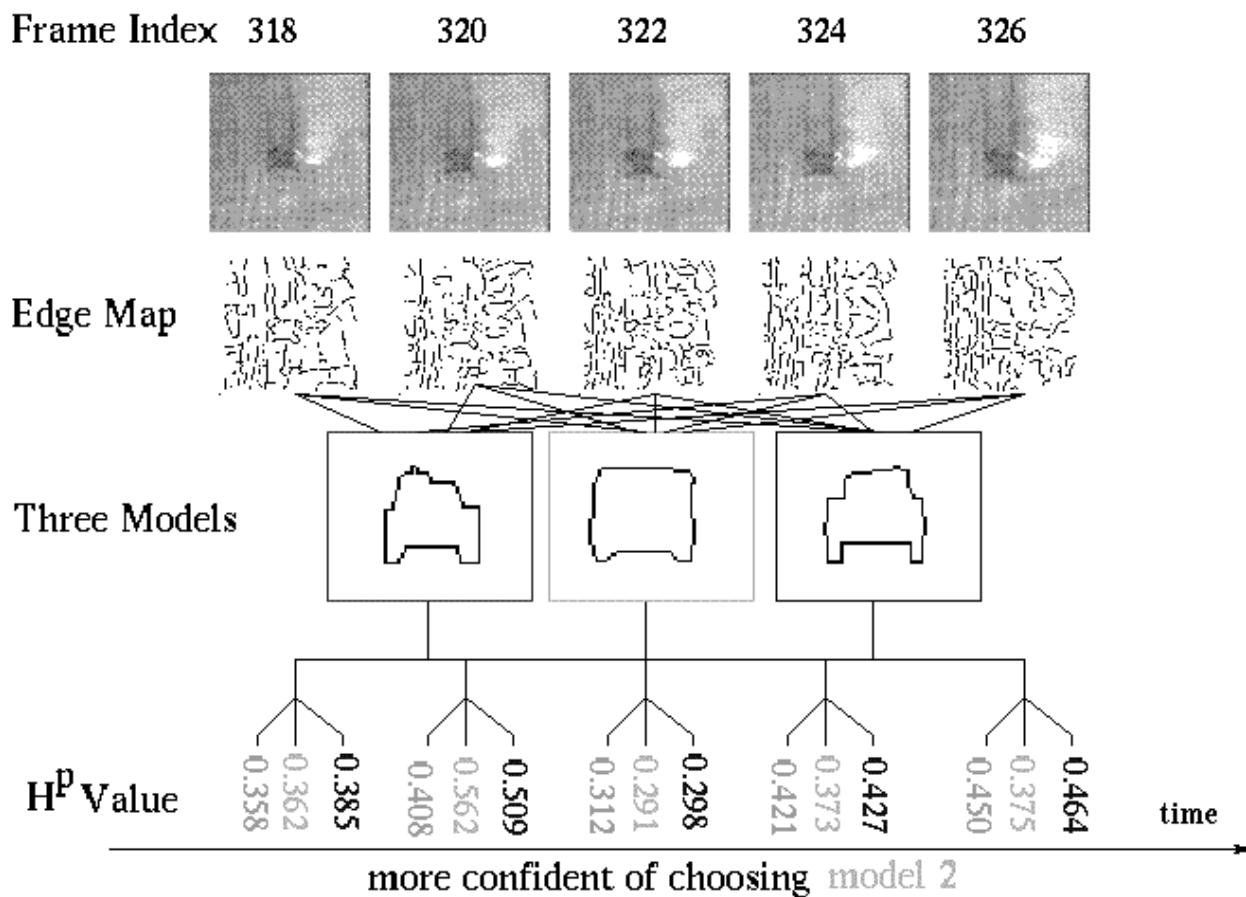


Continuous Tracking and Recognition -2

- Temporal Identification/Verification
 - Is this what I saw the last time?
 - How confident am I?
 - Recovery after temporary loss of tracking
- Hausdorff Metric
 - Measures the similarity between point sets
 - Using edge maps as input
 - Account for residual motion



Continuous Tracking and Recognition - 3





Continuous Tracking and Recognition -4

- MCMC (static) : a general method
 - Monte Carlo integration + Markov Chain
- Sequential importance sampling (SIS): dynamic MCMC
 - assuming the system is varying slowly
 - random samples at time t will be re-used at time $t+1$
 - have some good properties of both importance sampling and MCMC
 - a recent tool for analyzing non-Gaussian/nonlinear systems (e.g. Carlin *et al.* '92, Kitagawa '96, Gordon *et al.* '93, Isard *et al.* '96, Liu and Chen, 1998, Liu 2001)



Marginalization Over Motion

- Gallery: $H = \{I_1, I_2, \dots, I_N\}$
- Identity variable:
depicting the identity at time instant t n_t
- Motion state:
characterizing the dynamics at time instant t

t



Time Series Model for Recognition (II)

- Prior distribution:

$$p(n_0 | y_0) \quad p(n_0 | y_0)$$

- Noise distribution:

$$p(u_t) \text{ or state transition prob. } p(n_t | n_{t-1})$$

$$p(v_t) \text{ or likelihood } p(y_t | n_t, v_t)$$

- Statistical independence:

$$n_0, u_t, v_t, v_s, t, s$$



Galleries

Face Gallery



Upper Body Gallery





Tracking results





Continuous Tracking and Recognition - 5

- Original sequence



- Tracking results for true hypothesis



- Tracking results for false hypothesis





Continuous Tracking and Recognition -6

- Back-door camera captured a person entering a building





Continuous Tracking and Recognition - 7

Front-door
video





Structure from Motion: Help or Hindrance

- Flow-based method.
 - 43 FFT computations for structure recovery using two frames.
 - Fusion of depth maps using error covariance and stochastic approximation.
- Discrete feature based method using SIS.
- Tango between structure and motion – Critical motion sequences.
- How much of shape is needed for recognition ?
- Motion to recognition without explicit structure recovery?



Bayesian SfM Algorithm

- A single solution is not enough to describe the solution space of the SfM problem.
- To find the posterior distribution of the parameters is a better way.

$$\begin{aligned} P(\mathbf{x}_t | \mathbf{Y}_t) &= P(\mathbf{x}_t | \mathbf{Y}_t) \\ &= P(\{\mathbf{x}\}_{=1}^t | \{\mathbf{y}\}_{=1}^t) \end{aligned}$$

- Monte Carlo methods approximations to the posteriors.



SIS for SfM

$$\left\{ \binom{(j)}{t}, w_t^{(j)} \right\}_{j=1}^m \sim \binom{(j)}{t} \stackrel{SIS}{\sim} \left\{ \binom{(j)}{t+1}, w_{t+1}^{(j)} \right\}_{j=1}^m \sim$$

SIS steps: for $j = 1, \dots, m$,

(A) Draw $X_{t+1} = \mathbf{x}_{t+1}^{(j)}$ from $g_{t+1}(\mathbf{x}_{t+1} | \mathcal{X}_t^{(j)})$. Attach $\mathbf{x}_{t+1}^{(j)}$ to form \mathcal{X}_{t+1}

(B) Compute the "incremental weight" u_{t+1} by

$$u_{t+1}^{(j)} = \frac{\pi_{t+1}(\mathcal{X}_{t+1}^{(j)})}{\pi_t(\mathcal{X}_t^{(j)}) g_{t+1}(\mathbf{x}_{t+1} | \mathcal{X}_t^{(j)})}$$

and let $w_{t+1}^{(j)} = u_{t+1}^{(j)} w_t^{(j)}$.

$$g_{t+1}(x_{t+1} | \binom{(j)}{t}) = q_t(x_{t+1} | x_t)$$

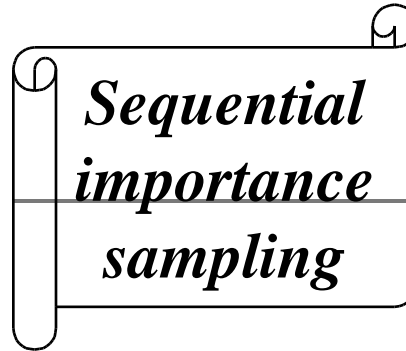
$$\begin{aligned} u_{t+1} &= \frac{p(y_{t+1} | \mathcal{X}_{t+1})}{p(y_{t+1} | \mathcal{X}_t)} \\ &= p(y_{t+1} | \mathcal{X}_{t+1}) \end{aligned}$$



3D Modeling from Video

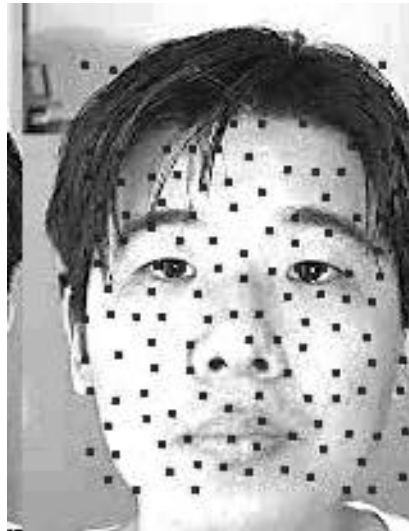
- A two-step strategy

*Feature
trajectories*



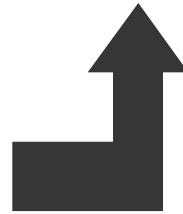


3D Face Modeling





Incorporating 3D Models





Quasi-invariants for Activity Recognition

- Most common human actions involve several body parts that align themselves in a plane: e.g. walking, running, sitting down, waving, jumping, etc.
- Pick phases in the action where a subset of body parts align themselves approximately in a plane.
- Pre-compute a pair of determinant form of invariants for each such ‘canonical’ pose in the action.
- Distributed sensors + overlapping quasi-invariants = Full invariants ?



Behavior-based Recognition

- Based not on who or what you are, but what you have been doing or what you intend to do.
- Knowledge about origin and destination may be useful.
- Modeling and recognition of abnormal activities.
- Dynamic belief networks (DBN)
 - Inference mechanisms understood for simple structures.
- DBN's with MCMC , a promising approach (Koller, 2001)
- How to incorporate source, sink priors and how long should one observe ?



Recognition of a Rare Event

- Normalcy distribution can be estimated.
- The rare event is a deviation from the normal hypothesis.
 - Outlier detection in an incompletely specified Markov process is hard.
- The FAA problem – monitoring the activities around an aircraft.
- Dictionary of normal activities.
 - Trash removal, catering services, fuel tank, baggage carts, a few authorized people, retraction of the jet way, etc.
- How to learn something that is rare ?



My 2 Cents!

- Representation for recognition in video is the key
 - Trade-off between shape and motion should be understood.
- Being able to learn from sparse samples is important.
- Detection of a rare event is critical.
- DBN + MCMC has potential
 - I love particle filters, but they are NOT the next best thing after the sliced bread!
- Scalability of stochastic grammar representation to video is a challenge