Deformable Contour Tracking

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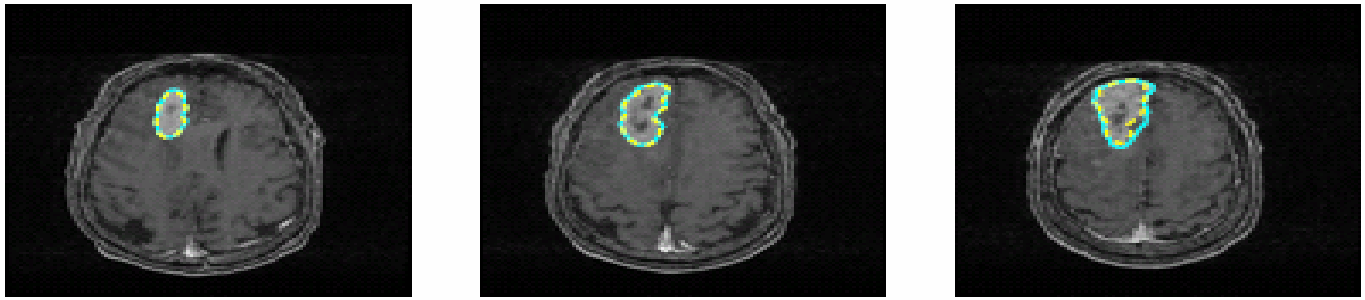
Becoming the best.

Goal

- Sequentially segment deforming objects or Regions of Interest (ROIs) from video or from spatial image sequences
  - Do this offline (“smoothing”) or online (“tracking”)
  - Output of a tracker is input to a smoothing algorithm

Brain MRI slices: Tumor sequence (actual deformations)



Partial occlusion of car by street light

Perspective effect: Plane tracked by UAV (frequent camera viewpoint changes)

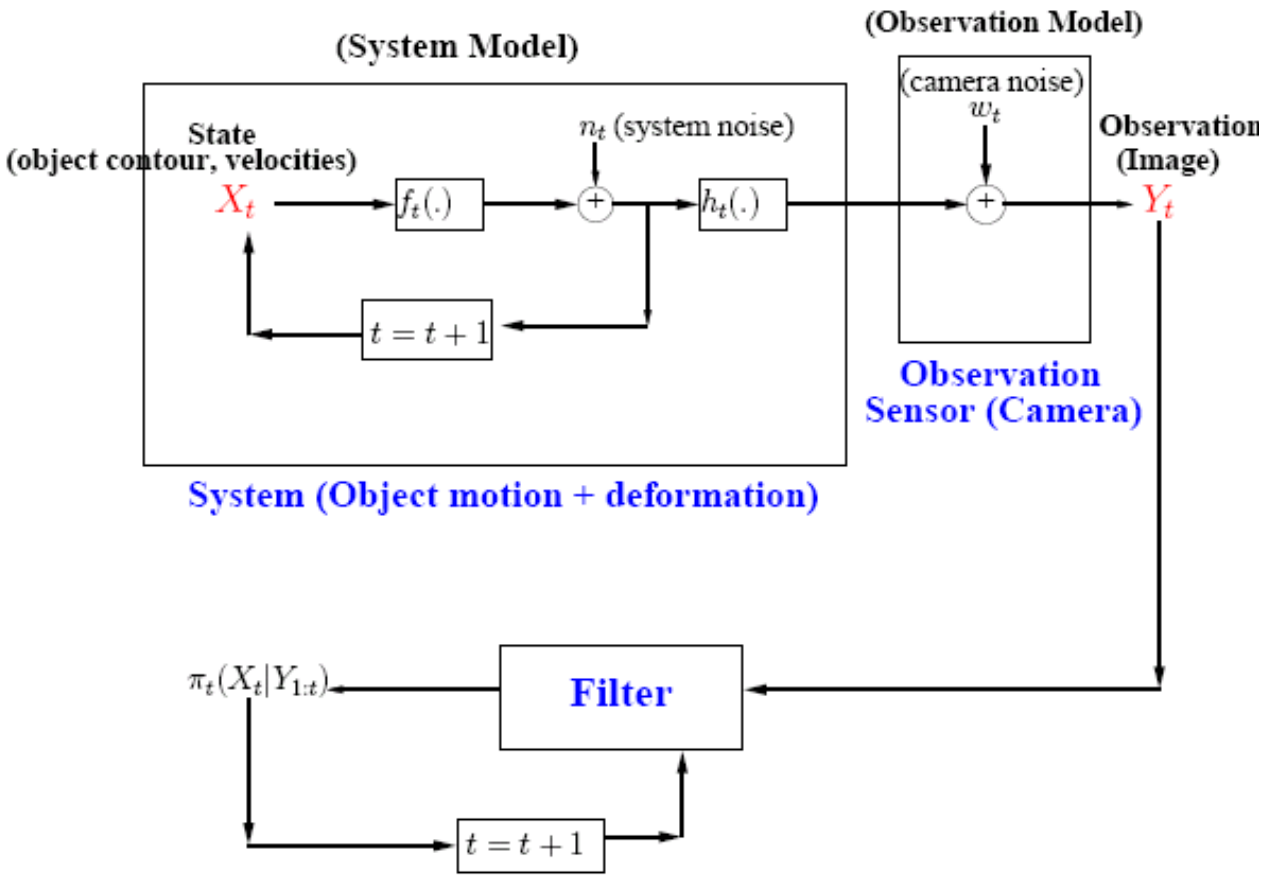
Outline

- The Tracking Problem
- Main Issues & Limitations of Existing Work

- Our Key Ideas
- Affine PF-MT & Deform PF-MT

- Summary & Open Issues

Tracking Framework



Definitions

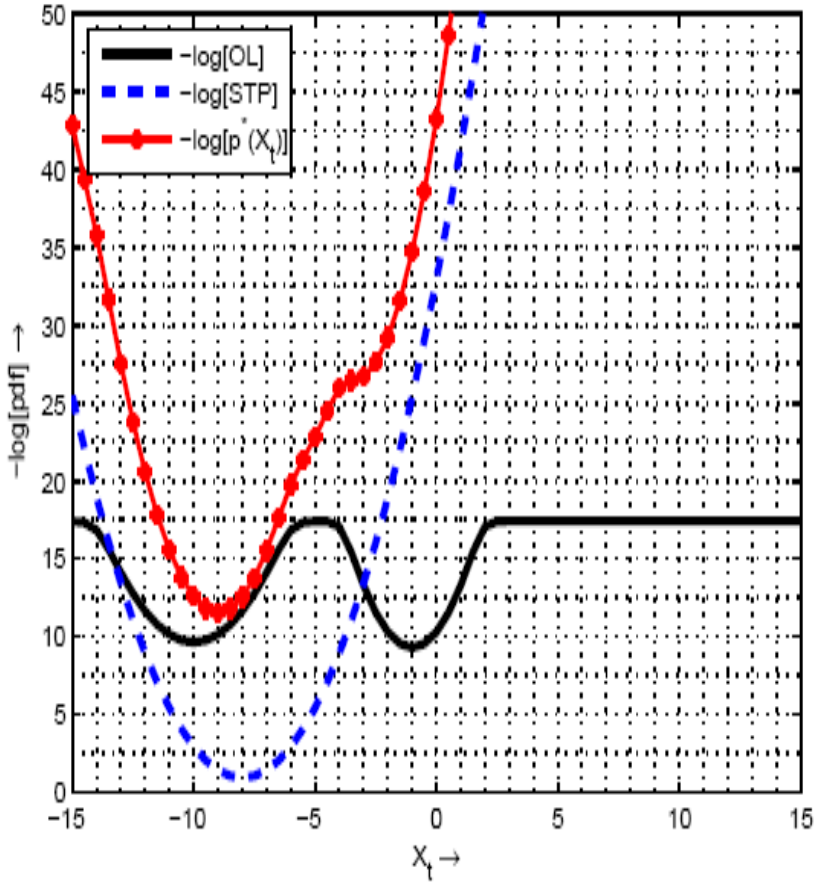
- State transition prior (STP): $p(X_t \mid X_{t-1})$
  - PDF of X_t conditioned on a value of X_{t-1}
- Observation Likelihood (OL): $p(Y_t \mid X_t)$
  - Probability of Y_t taking a certain value conditioned on a value of X_t
  - "OL multimodal": OL has multiple local maxima (modes) as a function of X_t

Main Issues

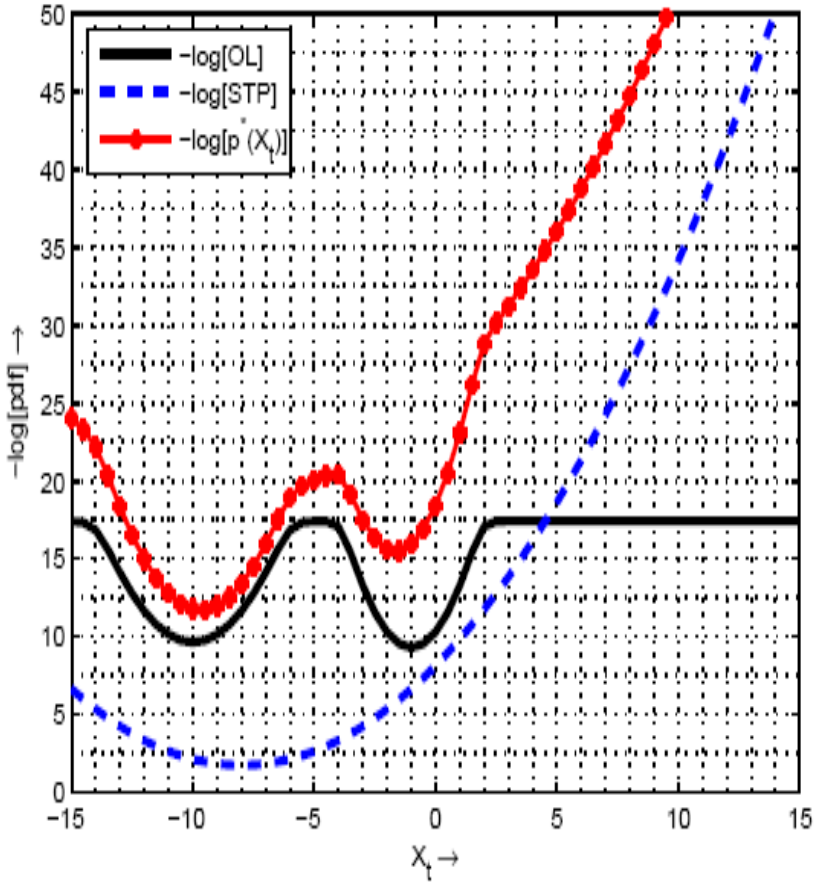
Main Issues

- Observation Likelihood (OL) is often multimodal
  - e.g. clutter, occlusions, low contrast images
  - If STP narrow enough, posterior is unimodal: adapt KF
  - If STP broad (fast deforming sequence): require a Particle Filter (PF)
- Deforming contours: Large dim state space (LDSS)
  - If constrained motion, e.g. rigid/affine: easy to use PF
  - LDSS: PF expensive (requires impractically large N)

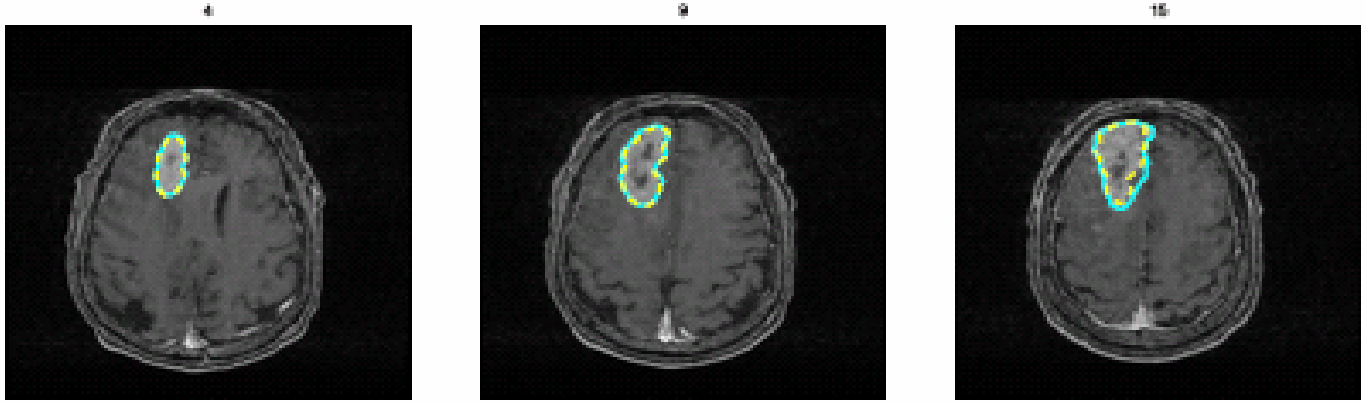
Narrow prior: Unimodal posterior



Broad prior: Multimodal posterior

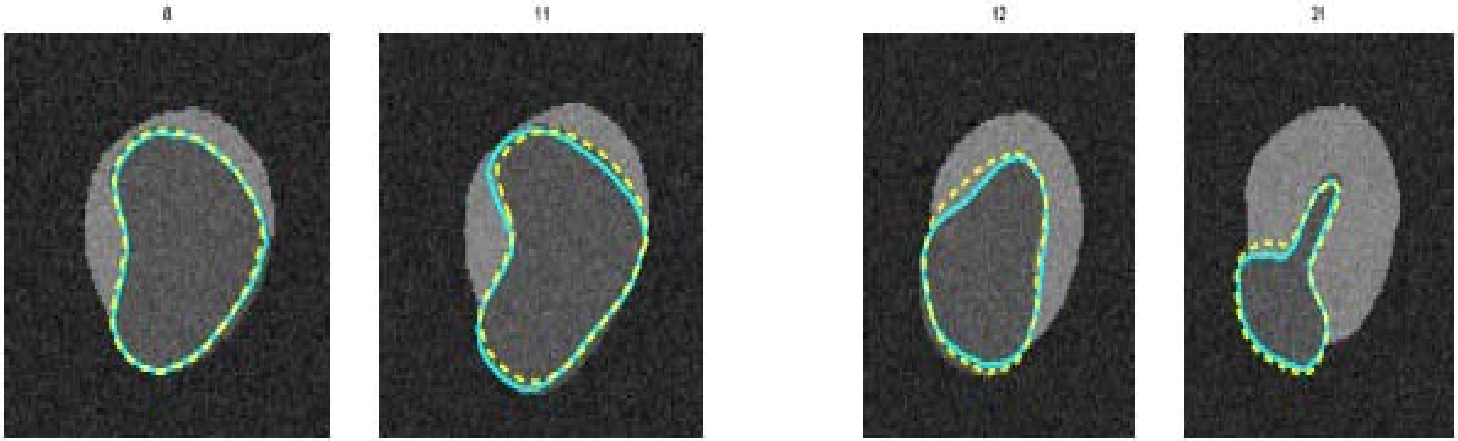


Low contrast + deforming contours (large deformation per frame)

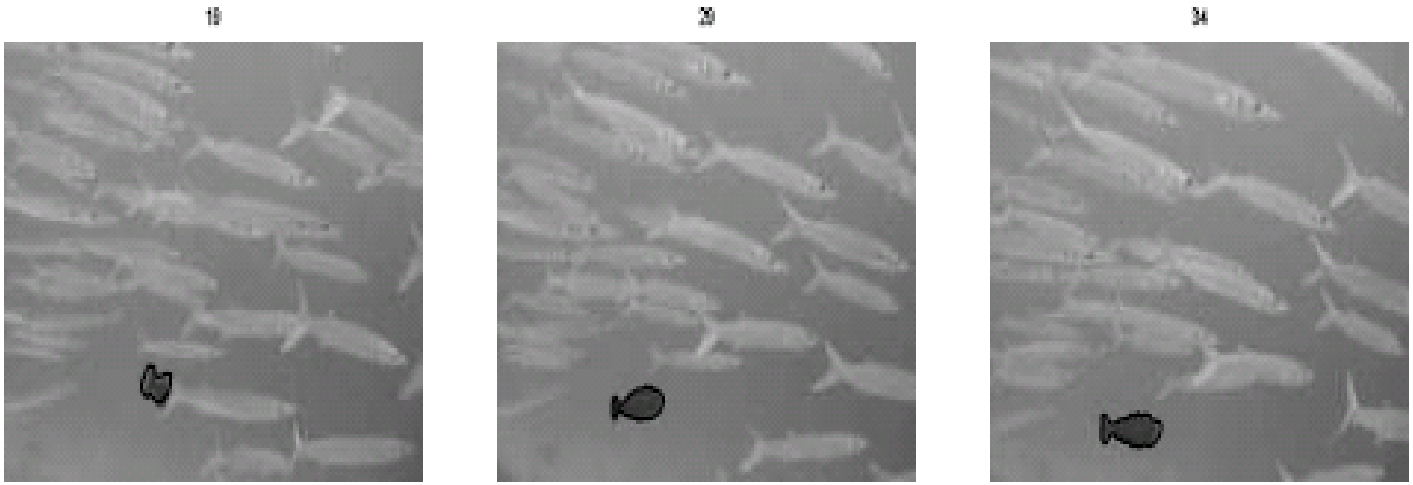


Low contrast + Frequent viewpoint changes (small non-affine deformation per frame)

Overlapping clutter (light grey object) + deformation



Separate clutter (multiple fishes) + deformation



Multimodal OL

- As a function of affine deformation
  - Background clutter due to separate objects
  - Background clutter due to concentric contours
- As a function of non-affine deformation
  - Low contrast (weak edges: multiple edge responses)
  - Overlapping background clutter
  - Partial occlusions
  - Outlier noise

Deforming contours

- Actual deformations: biological images
  - Humans: surveillance, sports videos,...
  - Animals
  - Medical sequences: ROIs in brain or heart
- Changing region of partial occlusions
  - Automatic vehicle navigation
  - Robot navigation
- Frequently changing camera viewpoint
  - Tracking using a UAV

Existing Work: Limitations

- Different trackers & diff contour representations
- Condensation [IB, ECCV'96]
  - Used a particle filter to track multimodal posteriors, but
  - Tracked only on a small (6) dimensional space of affine deformations
- Approx. linear observers + level set repr. [JYS,'04]
  - Handled large dimensional deformation, but
  - Did not handle multimodal posteriors
  - Uncoupled observers for global & local deformation

Proposed Solution [Rathi et al, CVPR'05]

- Use level set representation of contour
- Replace the linear observer by a particle filter
  - Can handle multimodal posteriors & defines an asymptotically optimal coupled observer
  - Problem: Deforming contours large dimensional: PF expensive
  - Solution: Imp sample only on a smaller "effective basis" space. Track posterior mode on the "residual space"

Particle Filter (PF) [Gordon et al,'93]

- A sequential Monte Carlo technique to approx Bayes' recursion for computing the posterior $\pi_t(X_{1:t}) = p(X_{1:t}|Y_{1:t})$

- Does this sequentially at each time, t, using Sequential Importance Sampling along with a Resampling step (to throw away particles with very small importance weights)

Monte Carlo, Importance Sampling

- Goal: compute $E_p[\gamma(X)] = \int_x \gamma(x)\, p(x)\, dx$

(compute expected value of any function of X, when $X \sim p$)

- Monte Carlo: Sample $X^i \sim p$

$E_p[\gamma(X)] = \int_x \gamma(x)\, p(x)\, dx \approx (1/N)\sum_i \gamma(X^i)$

- Imp Sample: If cannot compute or sample from p:
  Choose a q, sample $X^i \sim q$

$E_p[\gamma(X)] = E_q[\gamma(x)\, p(x)/q(x)] \approx (1/N)\sum_i w^i \gamma(X^i)$,

- Bayesian Imp Sample: uses same idea to approx numerator & denominator of a posterior expectation

Particle Filter

Goal: To approx $p(X_{1:t} \mid Y_{1:t})$

- Choose Imp Sampling density s.t. it factorizes as

  $q_{t,Y_{1:t}}(X_{1:t}) = q_{t-1,Y_{1:t-1}}(X_{1:t-1})\ \ q_{X_{t-1},Y_t}(X_t)$

  Allows for recursive computation of weight

- At each t, for each particle i,
  - Importance Sample: $X_t^i \sim q_{X_{t-1}^i,Y_t}(X_t)$
  - Weight:

    $w_t^i \propto w_{t-1}^i\ p(Y_t \mid X_t^i)\ p(X_t^i \mid X_{t-1}^i) / q_{X_{t-1}^i,Y_t}(X_t^i)$
  - Resample to eliminate low weight particles

The Problem is…

- Brute force particle filtering on space of deforming contours (very large dimensional space): very expensive
  - "effective particle size" reduces with dimension: need more particles for the same tracking accuracy

Key Ideas of Our Work

Key Idea 1: "LDSS" [Vaswani et al, ICASSP'06]

- Even though space of contour deformation is very large dimensional,
  - At any given time, most of the deformation occurs in a small # of dims (effective basis) while the deformation in the rest of the dims (residual space) is small
    - Different from dimension reduction (PCA) assumption
  - Effective basis dim can change with time

Key Idea 2:"Unimodality" [Vaswani,ICASSP'07]

- If residual deformation small enough (its STP narrow enough) compared to distance b/w OL modes, can show that the "residual posterior" is unimodal
  - "residual posterior": posterior of residual deformation conditioned on effective basis states
- Ensure this by choosing enough dims as part of effective basis

Key Idea 3: "IS-MT" [Vaswani, ICASSP'07]

- If residual deformation still smaller, the residual posterior is unimodal & also narrow
- If an importance sampling (IS) density is unimodal & narrow, any sample from it is close to its mode with high probability
  - A valid approx is to just use its mode as the sample: Mode Tracking (MT) approx of IS or IS-MT
- Resulting algorithm is called PF-MT

Affine PF-MT

Affine PF-MT [Rathi et al, CVPR'05, PAMI, Aug'07]

- Contour represented using level set method
- Use Importance Sampling to track on the 6-dim space of affine deformations (effective basis)
- For each affine deformed contour particle, track the unique mode of the posterior of non-affine deformation (residual space): Mode Tracking (MT)
- Very efficient: Imp sampling dim was only K=6, small N sufficed for given accuracy

Affine PF-MT assumes

- Non-affine deformation per frame small enough, s.t. its residual posterior is unimodal & “narrow enough” to replace IS by MT
  - Much weaker than assuming the same thing for the full posterior

- This is satisfied whenever either
  - Small non-affine deformation per frame

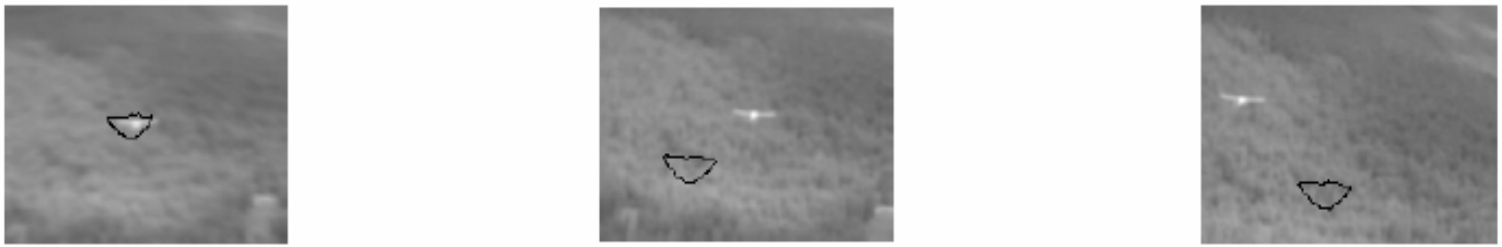
  or

  - OL modes (contour modes in image) separated only by translation or scale or other affine deformation

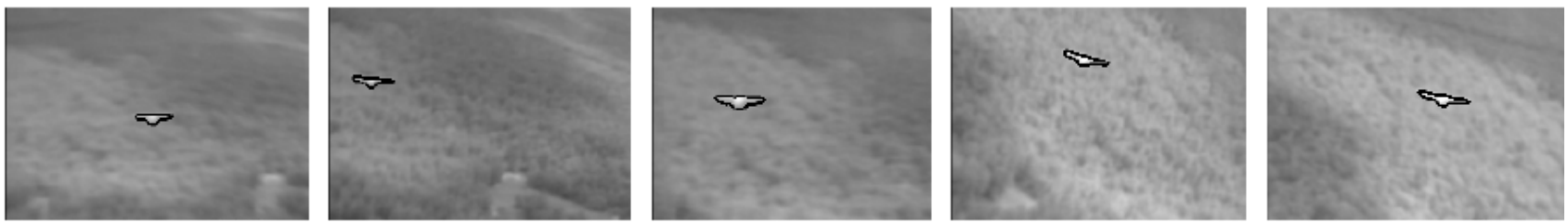
Low contrast, viewpoint changes

- Deformation due to perspective camera effects (changing viewpoints), e.g. UAV tracking a plane

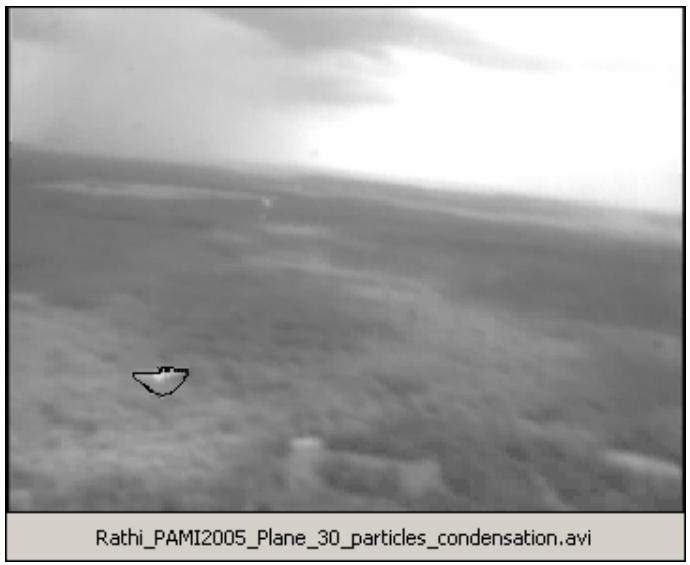
Condensation fails

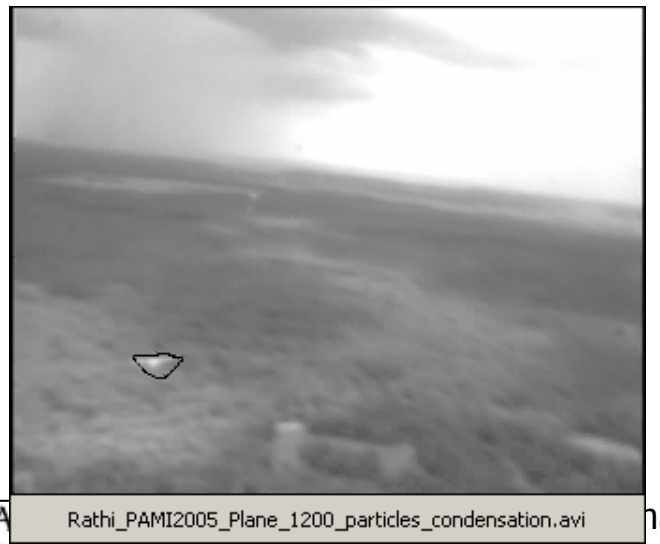


Affine PF-MT works



Condensation
(30 & 1200 particles)





Affine PF-MT
(30 particles)

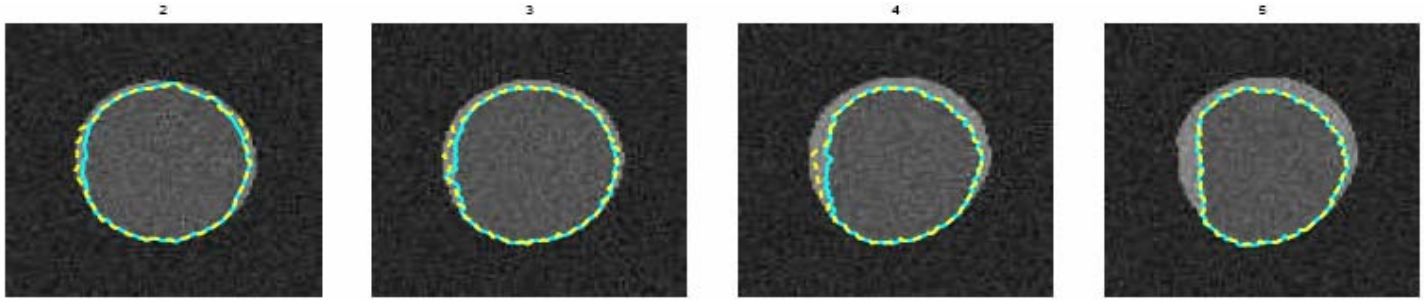
Condensation only tracks affine deformation

Assumption fails when…

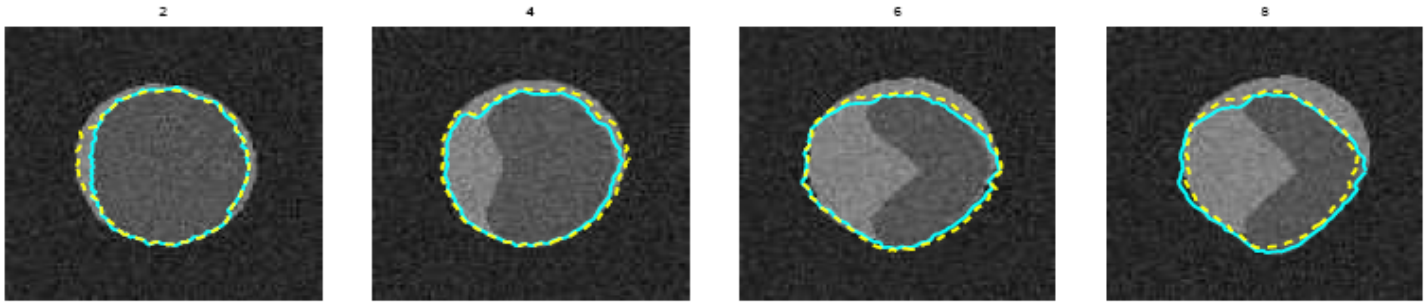
- Large non-affine deformation per frame (fast deforming sequence) & OL multimodal as a function of non-affine deformation (low contrast images, overlapping clutter or partial occlusions)

- Results in multimodal residual posterior of non-affine deformation

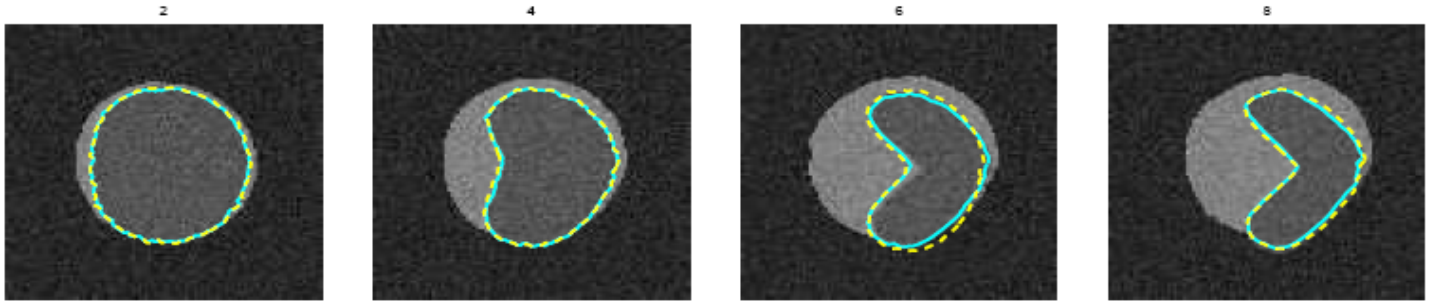
Small non-affine deformation per frame: Affine PF-MT works



Large non-affine deformation per frame: Affine PF-MT fails



Deform PF-MT works



Deform PF-MT

Deform PF-MT [Vaswani et al, CDC'06]

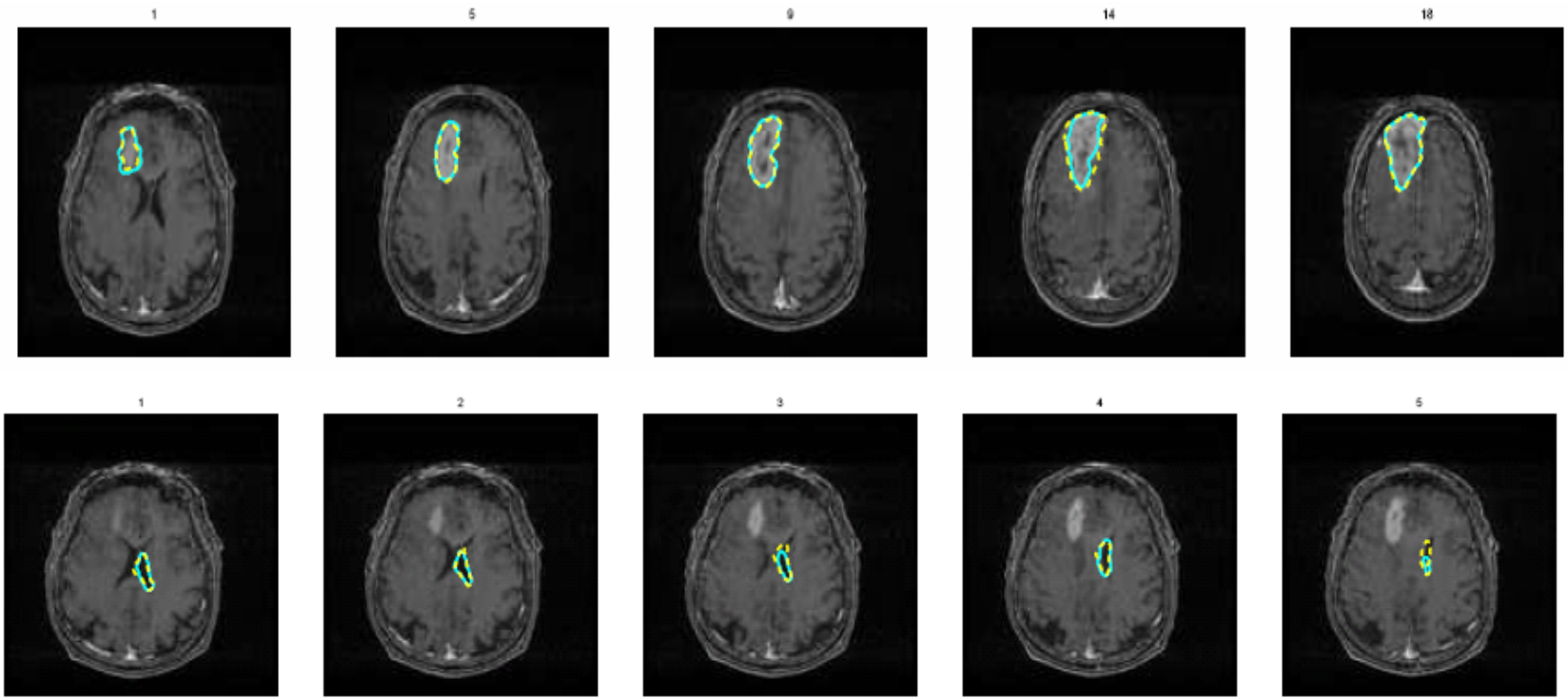
- For multimodal posterior of non-affine deformation, need an importance sampling step in PF that also samples on space of local deformations
  - This is a very large dim space: regular PF inefficient
- Again use PF-MT but with deformation at a subsampled set of K contour points (basis points) & translation as the effective basis
- K = # of basis points: fixed or time varying

Multiple Issues

- Imp. Sample + Level Set Rep of contour: CFL?
  - Interpolate & compute extension velocity efficiently
  - Using multiple iterations to deform a contour: slow
- How to parameterize contour deformation?
  - As as a function of arclength: Expensive to implement using level sets, Cannot handle topology change
  - As function of radial/tangent angle: Fails if 2 contour points far along arclength are close along angle
- Estimate/Change effective basis dimension?
  - Use spatial freq response of deformation “signal”

Low contrast images, large def per frame: Brain MRI (Tumor, Ventricle)

- Multiple nearby modes due to low contrast

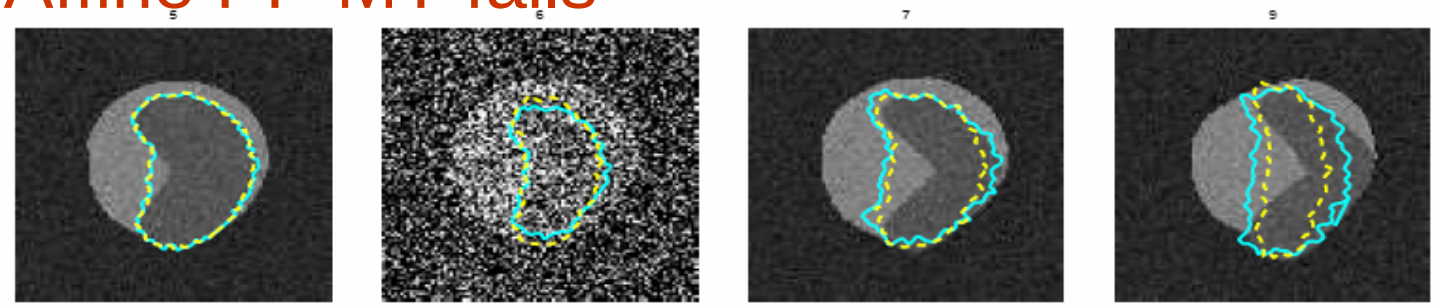


(b) Attempt to track the right ventricle (black region in the center) using Algorithm 2. Notice the low contrast imagery.

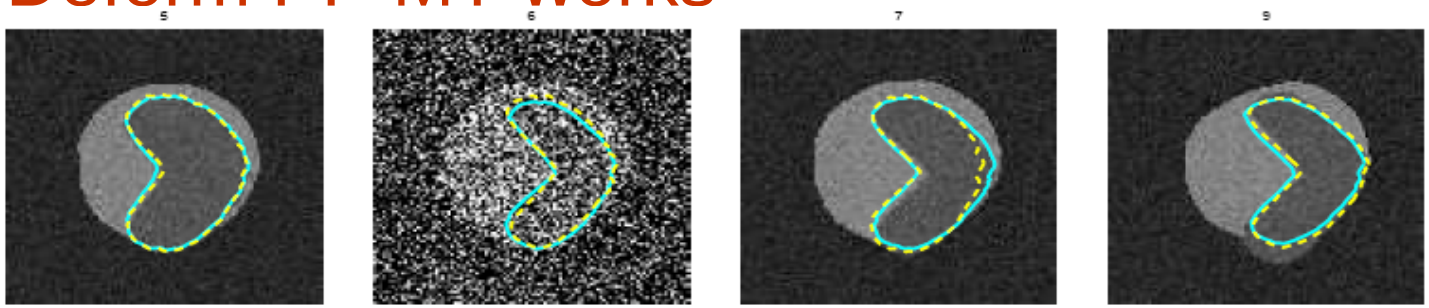
Outlier: multiple nearby modes

- Every even frame: outlier frame
- Multiple nearby modes separated by non-affine deformation

Affine PF-MT fails



Deform PF-MT works



Relation to Other Work

- PF-MT
  - Extension of PF-Doucet [Doucet'98]
  - Approx to Rao-Blackwellized PF [Chen-Liu'00]
- PF for tracking Heart LV [Sun et al, MICCAI'04]
  - PF-MT with PCA effective basis + retaining MAP particle
- Approx linear observer + level sets [JYS, CDC'04]
  - PF-MT with zero dimensional effective basis
- Condensation [IB, ECCV'96]
  - PF-MT with zero dimensional residual space
- Stochastic Active Contours [JPK, VLSM'04]
  - Annealing for segmentation

Summary & Open Issues

- Affine PF-MT
  - Use when small non-affine deformation per frame
- Deform PF-MT & Smoother: Fixed or changing K
  - Human body contour tracking
  - Heart LV, Brain ROIs, Lung ROIs

- Observation models, tracking intensity variations
- PF smoother: better estimate for offline problems

- Level Set Rep. + Imp Sampling: speedup, CFL
- Extensions to surface tracking

Collaborators

- Affine & Deform PF-MT
  - Yogesh Rathi, Anthony Yezzi & Allen Tannenbaum at Georgia Tech

- System Identification
  - Ongoing work with grad student, Wei Lu

Other applications of PF-MT

- Spatially varying illumination change of moving objects
  - Moving into lighted room, face tracking [Kale et al, ICASSP'07]
  - Vehicle tracking through changing illuminations
- Change in spatially varying physical quantities using sensor networks
  - Tracking temperature change [Vaswani, ICASSP'07]
- Deformations of shapes of landmark points using the nonstationary shape activity model

Illumination Tracking: PF-MT [Kale et al'07]

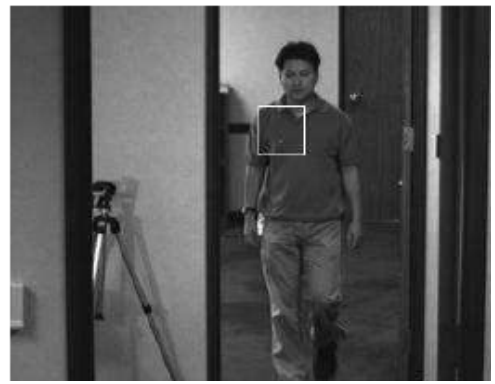
- State = Motion (3 dim) + Illumination (7dim)

- PF on motion (3 dim) & MT on illumination
  - Illumination change very slow
  - OL usually unimodal as a function of illumination
  - If OL multimodal (e.g. occlusions), modes usually far apart compared to illumination change variance

Face tracking results

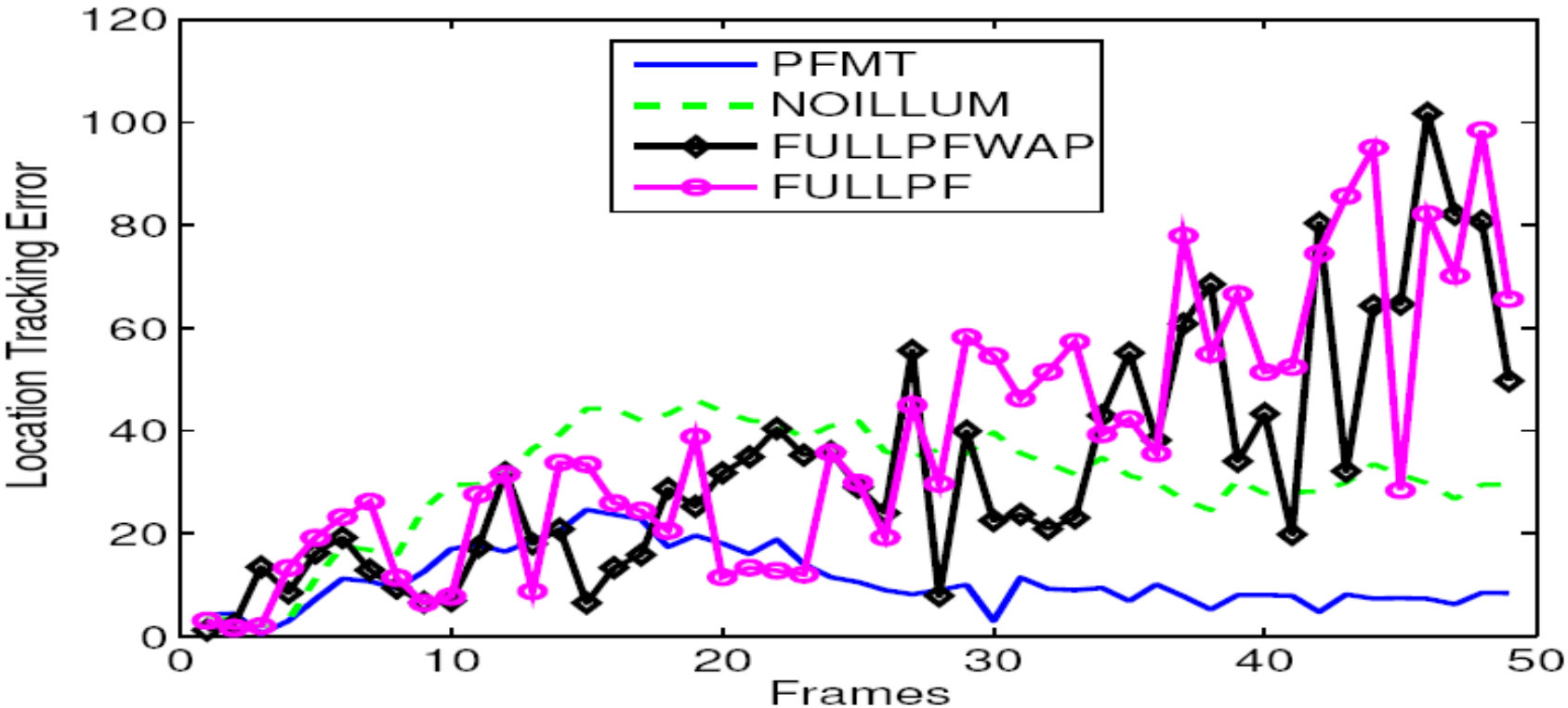
PF-MT

3 dim PF (no illum)



10-dim Auxiliary PF

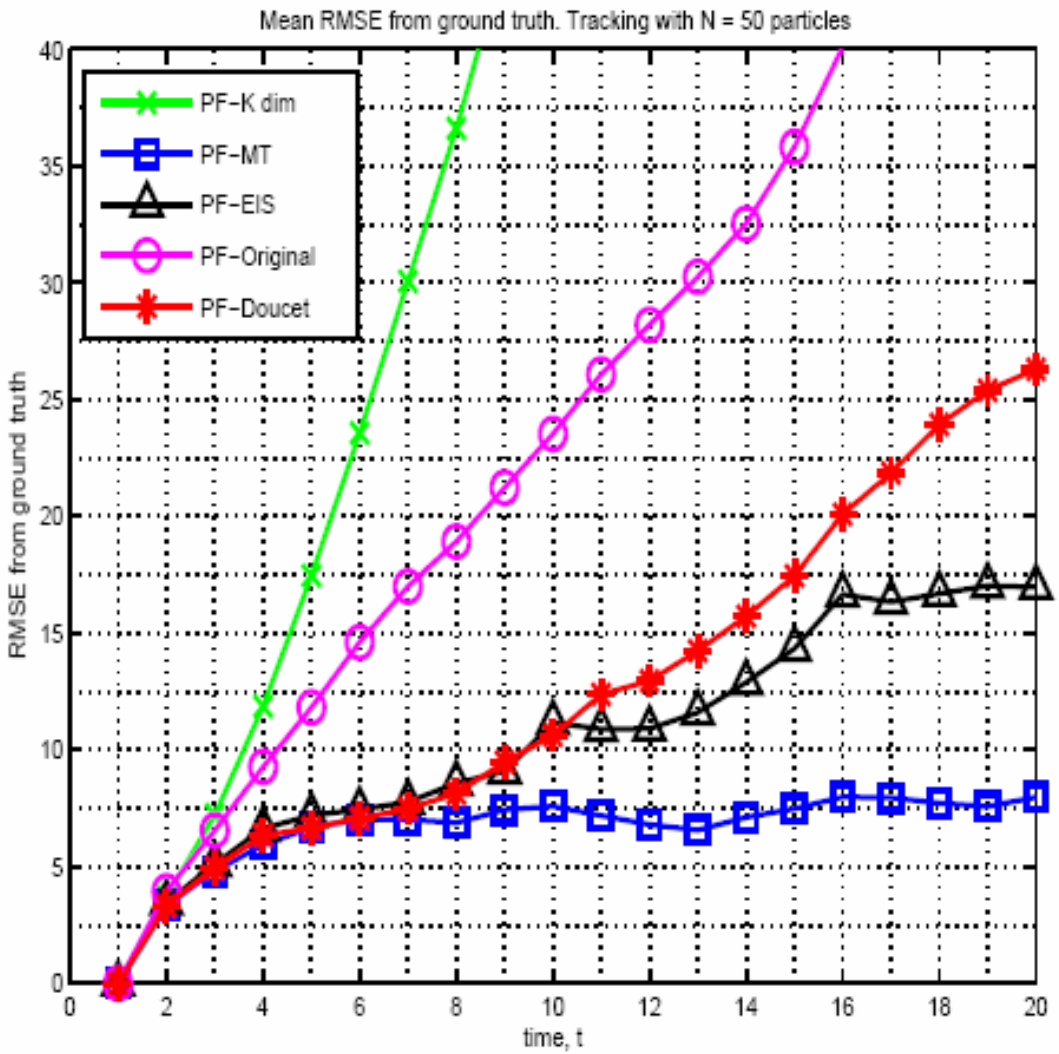
Error from ground truth



Comparing with 10 dim regular PFs (original, Auxiliary) & with PF- K dim (not track illumination at all)

Sensor nets: Temperature tracking

- Dim(X_t) =10
- K = 1, i.e. Δ_s=10, Δ_r =1, & OL multimodal
- N = 50 particles
- Plotting RMSE from ground truth
- PF-MT better than all full PFs (PF-EIS, PF-D) & PF-K dim (dim reduced PF)

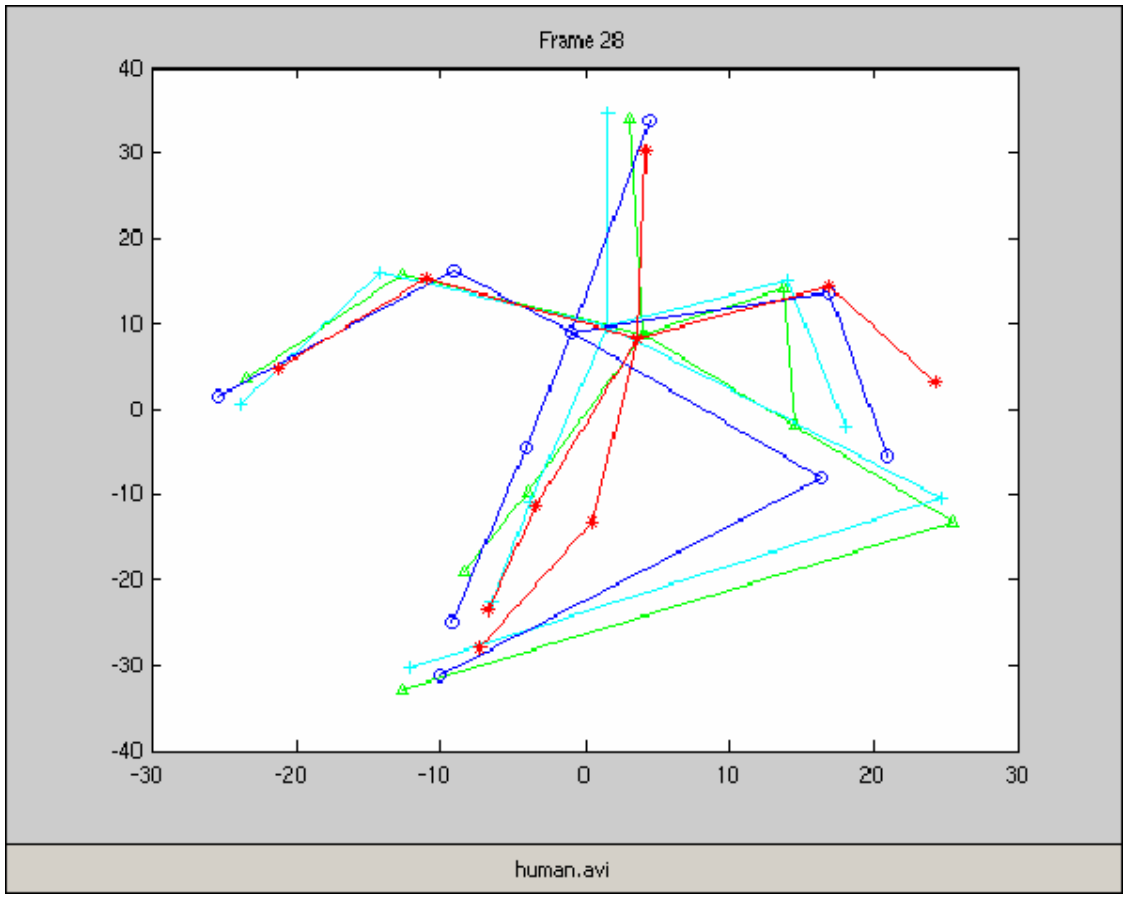


Landmark Shape Tracking

- Tracking deformations of shapes of landmark points using nonstationary SA (NSSA) model

- NSSA better models larger & nonstationary shape changes than existing methods (ASMs)
  - Existing ASM work uses piecewise ASMs to track long sequences, e.g separate ASM for systolic & diastolic heart motion, or hierarchical ASMs
  - Cannot model transitions b/w pieces very well
  - Cannot detect change while tracking

Landmark Shape Tracking



Landmark Shape Tracking

- Compared modeling error of our method (NSSA) with Active Shape Models for CMU MOCAP dataset (human action sequences)

- For all sequences, modeling error of our method much smaller than ASM

Modeling Error Comparison

- Defined 10 dimensional PCA space for ASM and for shape velocity (our method)

- Defined AR model for ASM & for shape velocity. Total modeling error

  Crawl: ASM: 0.00870, Shape Velocity: 0.00030

  Sit: ASM: 0.00760, Shape Velocity: 0.00005

  Interview: ASM: 0.00450, Shape Velocity: 0.00020