Object Tracking using Particle Filter

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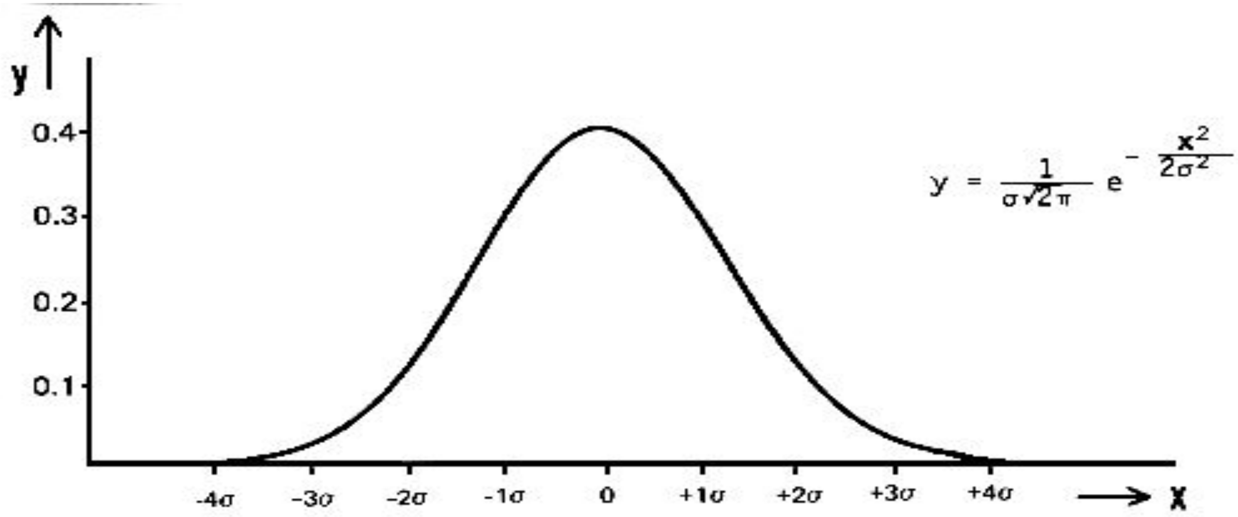
Overview

- Background Information
- Basic Particle Filter Theory
- Rao Blackwellised Particle Filter
- Color Based Probabilistic Tracking

Object Tracking

Tracking objects in video involves the modeling of non-linear and non-gaussian systems.

- Non-Linear
- Non-Gaussian



Background

- In order to model accurately the underlying dynamics of a physical system, it is important to include elements of non-linearity and non-gaussianity in many application areas.
- Particle Filters can be used to achieve this.
- They are sequential Monte Carlo methods based on point mass representations of probability densities, which are applied to any state model.

The Particle Filter

- Particle Filter is concerned with the problem of tracking single and multiple objects.
- Particle Filter is a hypothesis tracker, that approximates the filtered posterior distribution by a set of weighted particles.
- It weights particles based on a likelihood score and then propagates these particles according to a motion model.

Mathematical Background

- Particle Filtering estimates the state of the system, x t, as time t as the Posterior distribution:

$$P(\, x_t \mid y_{0\text{-}t} \,)$$

- Let,

$$\text{Est}\,(t) = P(\, x_t \mid y_{0\text{-}t} \,)$$

- Est(1) can be initialized using prior knowledge

Mathematical Background

- Particle filtering assumes a Markov Model for system state estimation.
- Markov model states that past and future states are conditionally independent given current state.
- Thus, observations are dependent only on current state.

Mathematical Background

- $Est(t) = P(x_t \mid y_{0-t})$

$= p(y_t \mid x_{t}, y_{0-t-1}).P(x_t \mid y_{0-t-1})$

(Using Baye's Theorem)

$= p(y_t \mid x_t). P(x_t \mid y_{0-t-1})$

(Using Markov model)

$= p(y_t \mid x_t). P(x_t \mid x_{t-1}).P(x_{t-1} \mid y_{0-t-1})$

$= p(y_t \mid x_t). P(x_t \mid x_{t-1}).Est(t-1)$

Mathematical Background

- Final Result:

  $Est(t) = p(y_t \mid x_t).\ P(x_t \mid x_{t-1}).Est(t-1)$

  Where:

  - $p(y_t \mid x_t)$: Observation Model
  - $P(x_t \mid x_{t-1}).Est(t-1)$: Proposal distribution

Mathematical Background

- To implement Particle Filter we need
  - State Motion model: $P(x_t | x_{t-1})$
  - Observation Model: $p(y_t | x_t)$:
  - Initial State: Est(1)

Mathematical Background

- We sample from the proposal and not the posterior for estimation.
- To take into account that we will be sampling from wrong distribution, the samples have to be likelihood weighed by ratio of posterior and proposal distribution:

  W t = Posterior i.e.Est (t) / proposal Distribution

  $= p(y_t \mid x_t)$
- Thus, weight of particle should be changed depending on observation for current frame.

Basic Particle Filter Theory

- A discrete set of samples or particles represents the object-state and evolves over time driven by the means of "survival of the fittest". Nonlinear motion models can be used to predict object-states.

Basic Particle Filter Theory (Cont.)

- Particle Filter is concerned with the estimation of the distribution of a stochastic process at any time instant, given some partial information up to that time.
- The basic model usually consists of a Markov chain X and a possibly nonlinear observation Y with observational noise V independent of the signal X.

Basic Particle Filter Theory (Cont.)

- System Dynamics ie.Motion Model:

  $p(x_t | x_{0:t-1})$
- Observation Model:

  $p(y_t | x_t)$
- Posterior Distribution:

  $p(x_t | y_{o..t})$
- Proposal Distribution is the Motion Model
- Weight, w_t = Posterior / Proposal = observation

Basic Particle Filter Theory (Cont.)

- Given N particles (samples) $\{x^{(i)}_{0:t-1}, z^{(i)}_{0:t-1}\}^{N}_{i=1}$ at time t-1, approximately distributed according to the distribution $P(dx^{(i)}_{0:t-1}, z^{(i)}_{0:t-1} | y_{1:t-1})$, particle filters enable us to compute N particles $\{x^{(i)}_{0:t}, z^{(i)}_{0:t}\}^{N}_{i=1}$ approximately distributed according to the posterior distribution $P(dx^{(i)}_{0:t}, z^{(i)}_{0:t} | y_{1:t})$

Basic Particle Filter Theory (Cont.)

- The basic Particle Filter algorithm consists of 2 steps:
  - Sequential importance sampling step
  - Selection step

Particle Filter Algorithm

- Sequential importance sampling
  - Uses Sequential Monte Carlo simulation.
    - For each particle at time t, we sample from the transition priors
    - For each particle we then evaluate and normalize the importance weights.

Particle Filter Algorithm

- Selection Step
  - Multiply or discard particles with respect to high or low importance weights $w^{(i)}_t$ to obtain N particles.
  - This selection step is what allows us to track moving objects efficiently.

Rao-Blackwellised Particle Filter

- RBPF is an extension on PF.
- It uses PF to compute the distribution of discrete state with Kalman Filter to compute the distribution of continuous state.
- For each sample of the discrete states, the mean and covariance of the continuous state are updated using the exact computations.
- We have implemented the particle filter algorithm and not the RBPF.

RBPF Approach

- RBPF models the states as <C_t,D_t>
  - C_t is the continuous state representation
  - D_t is the discrete state representation
- The aim of this approach is to predict the discrete state $D_{t.}$
- However, for our object tracking application, the above approach was unsuitable.

Implementation

- We have implemented the Particle Filter algorithm in Matlab.
- Our approach towards this project:
  - Reading research papers on PF given to us by Dr.Latecki.
  - Trying to implement PF-RBPF algorithm written by Nando de Freitas.

Implementation

- Color Based Probabilistic Tracking
  - These trackers rely on the deterministic search of a window, whose color content matches a reference histogram color model.
  - Uses principle of color histogram distance.
- This color based tracking is very flexible and can be extended in many ways.

Color Based Probabilistic Tracking

- The combination of tools used to accomplish a given tracking task depends on whether one tries to track:
  - Objects of a given nature eg.cars,faces
  - Objects of a given nature with a specific attribute eg.moving cars, face of specific person
  - Objects of unknown nature, but of specific interest to us eg.moving objects.

Color Based Probabilistic Tracking

- Reference Color Window
  - The target object to be tracked forms the reference color window.
  - Its histogram is calculated, which is used to compute the histogram distance while performing a deterministic search for a matching window.

Color Based Probabilistic Tracking

- State Space
  - We have modeled the states, as its location in each frame of the video.
  - The state space is represented in the spatial domain as:
    - X = (x , y)
  - We have initialized the state space for the first frame manually.

Color Based Probabilistic Tracking

- System Dynamics
  - A second-order auto-regressive dynamics is chosen on the parameters used to represent our state space i.e (x,y).
  - The dynamics is given as:
    - $X_{t+1} = Ax_t + Bx_{t-1}$
    - Matrices A and B could be learned from a set of sequences where correct tracks have been obtained.
    - We have used an ad-hoc model for our implementation.

Color Based Probabilistic Tracking

- Observation y_t
  - The observation y_t is proportional to the histogram distance between the color window of the predicted location in the frame and the reference color window.
  - $Y_t \; \alpha \; Dist(q, q_x)$,
    Where
    - q = reference color histogram.
    - qx = color histogram of predicted location.

Color Based Probabilistic Tracking

- Particle Filter Iteration

  Steps:

  - Initialize xt for first frame
  - Generate a particle set of N particles $\{x^m_t\}_{m=1..N}$
  - Prediction for each particle using second order auto-regressive dynamics.
  - Compute histogram distance
  - Weigh each particle based on histogram distance
  - Select the location of target as a particle with minimum histogram distance.
  - Sampling the particles for next iteration.

Color Based Probabilistic Tracking

- An step by step look at our code, highlighting the concepts applied:
  - Initialization of state space for the first frame and calculating the reference histogram:
    - reference = imread('reference.jpg');
    - [ref_count,ref_bin] = imhist(reference);
    - x1= 45; y1= 45;
  - Describing the N particles within a specified window:
    - for i = 1:N
    -     x(1,i,1) = x1 + 50 * rand(1) - 50 *rand(1);
    -     x(2,i,1) = y1 + 50 * rand(1) - 50 *rand(1);
    -     end

Color Based Probabilistic Tracking

- For each particle, we apply the second order dynamics equation to predict new states:
  - if (j==2) x(:,i,j) = A * x(:,i,j-1);
  - else x(:,i,j)=rand(n_x)*x(:,i,j-1)+rand(n_x)*x(:,i,j-2);
- The color window is defined and the histogram is calculated:
  - rect = [(x(1,i,j)-15),(x(2,i,j)-15),30,30];
  - [count,binnumber] = imhist(imcrop(I(:,:,:,j),rect));

Color Based Probabilistic Tracking

- Calculate the histogram distance:
  - for k = 1:255
  - d(I , j) = d(i, j) + (double (count (k)) - double(ref_count(k))) ^ 2;
  - end
- Calculating the normalized weight for each particle:
  - w(:,j) = w(:,j)./sum(w(:,j));
  - w(:,j) = one(:,1) - w(:,j);

Color Based Probabilistic Tracking

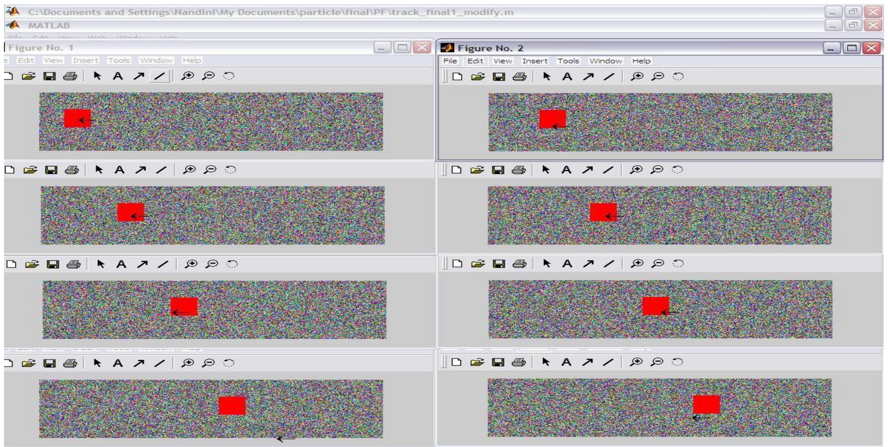
- Re-sampling step, where the new particle set is chosen:
  - for i = 1:N
  - x(1,i,j) = state(1,j) + 50 * rand(1) - 50 *rand(1);
  - x(2,i,j) = state(2,j) + 50 * rand(1) - 50 *rand(1);
  - end

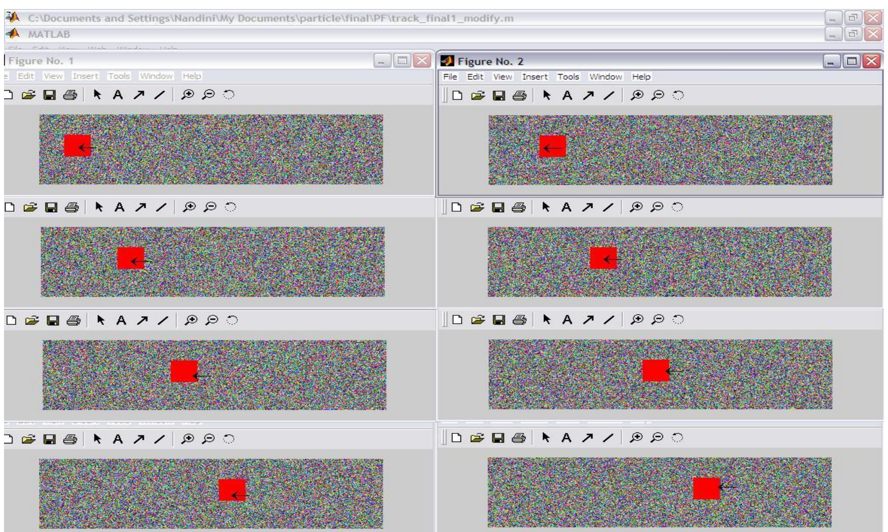
Color Based Probabilistic Tracking

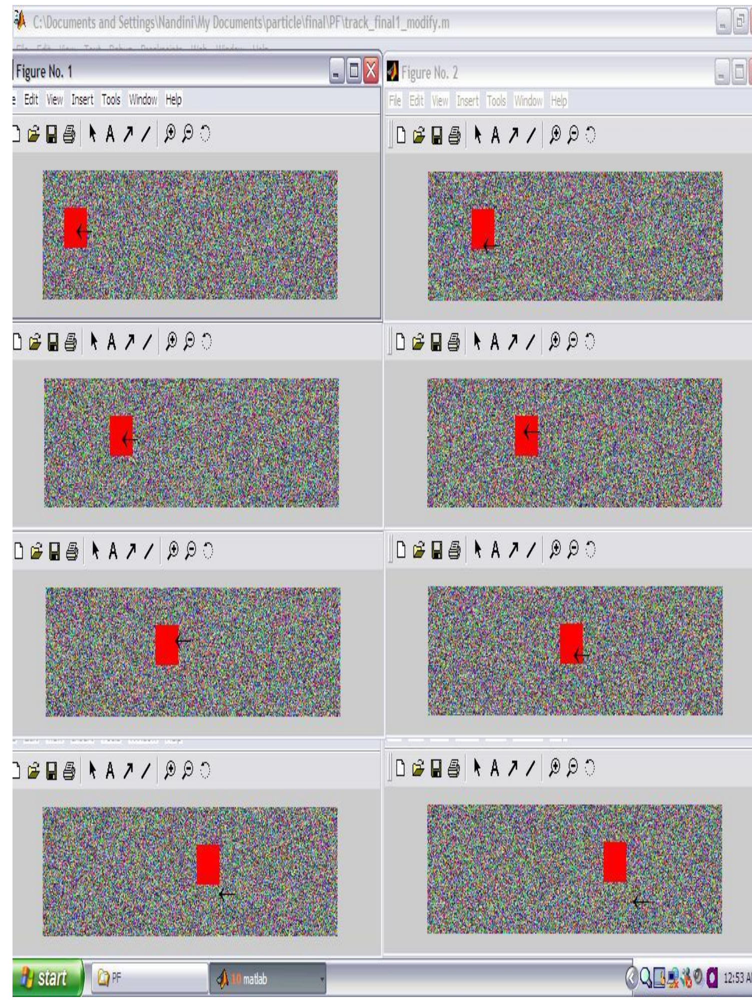
- Functions Used:

  - Track_final1.m : PF tracking code
  - multinomialR.m : Resampling function.

Color Based Probabilistic Tracking: Results







Applications

- Video Surveillance
- Gesture HCI
- Reality and Visual Effects
- Medical Imaging
- State estimation of Rovers in outer-space.

Future Work

- Automatic initialization of reference window.
- Multi part color window.
- Multi-object tracking.

References

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Thank You