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Video Object Detection using Particle Filters

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Abstract

Wepropose an object detection method using particle filters. Our approach estimates the probability of object presence in the current image given the history of observations up to current time. To do so, object presence is modeled by a two-state Markov chain,and the problem is translated into sequential Bayesian estimation which can be solved by particle filters. The observation density, required by the particle filter is based on selected discriminative Aar-like features that were introduced by Viola and Jones [6] for object detection in static images. We illustrate the approach on the problem of face detection. Experiments on real video sequences show the feasibility of the approach. This paper will explain why should we prefer the particle filters than any other method require to detect and recognize the object and also it gives the basic information about the kalman filters[5] the disadvantages of it and how they are removed in the particle filters[3].it will also give the basic steps of particle filters. Generally recognition of the objects in video can offers significant benefits to video retrieval including automatic annotation and content based queries based on the object characteristic. Detecting particular object in video is an important step toward semantic understanding of visual imagery.

***Keywords*-object recognition, kalman filter, particle filter, sequential importance sampling and resampling,pdf**

1. INTRODUCTION

Object detection in images has received considerable attention in the past decades, probably because reliable object detection systems are required as a front-end in numerous applications. Object detection deals with determining if an instance of a given class of objects (for examples cars, faces, etc.) is present or not in an image. Successful object detection systems are based on the learning of object appearance using large collections of exemplars. It has been dominated by approaches that separate processing into distinct stages of feature extraction and matching. In the first stage, discrete primitives, or features are detected. In the second stage, stored models are matched against those features.. The model-based recognition paradigm of the 1980's similarly followed this approach[1]. These methods focus largely on the problem of efficiently searching for correspondences between features that have been extracted from an image, and features of a stored model.

One of the important examples of the recognition is target tracking that is to track an object in video target tracking is an important element of surveillance, guidance or obstacles avoidance systems whose role is to determine the number, position and movement of the targets the fundamental building block of a tracking systems is a filter for recursive target applications. Visual object tracking is a difficult problem, but in recent years, particle filter-based object trackers have proven to be very effective. Conceptually, a particle filter-based tracker maintains a probability distribution over the state (location, scale, etc.) of the object being tracked.

2. WHY SHOULD PARTICLE FILTER

Because, like Kalman filters, they're a great way to track the state of a dynamic system for which you have a Bayesian model. That means that if youhave a model of how the system changes in time, possibly in response to inputs, and a model of what observations you should see in particular states, you can use particle filters to track your belief state .

Applications that we've seen in class before, and that we'll talk about today, are Robot localization, SLAM, and robot fault diagnosis. So why should you use particle filters instead of Kalman filters? Well, the main reason is that for a lot of large or high-dimensional problems particle filters are tractable whereas Kalman filters are not. The key idea is that a lot of methods, like Kalman filters, try to make problems more tractable by using a simplified version of your full, complex model.

Then they can find an exact solution using that simplified model. But sometimes that exact solution is still computationally expensive to calculate, and sometimes a simplified model just isn't good enough. Thus we needs omething like particle filters, which use the full, complex model, but just find approximate solution

3. PARTICLE FILTER

The basic idea of particle filters is that any pdf can be represented as a set of samples (particles). If your pdf looks like the two-humped line in the figure, you can represent that just by drawing a whole lot of samples from it, so that the density of your samples in one area of the state space represents the probability of that region. Each particle has one set of values for the state variables. This method can represent any arbitrary distribution, making it good for non-Gaussian, multi-modal pdfs. So we draw particles (with replacement)from the set of weighted particles according to their importance weights(probabilities). High-weighted particles can be chosen a lot of times, whereaslow-weighted particles are likely not to be chosen at all. The result looks likethe third figure, in which the particles go back to being unweighted, and the density of the particles properly represents the pdf.

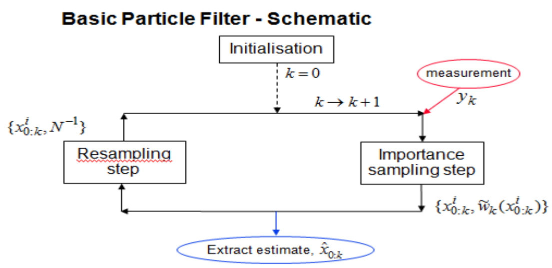

Figure.1 steps of particle filtering

4. WHY RESAMPLE?

If you just keep your old particles around forever without resembling them, what happens is that your particles drift around according to your motion model (transition probabilities for the next time step), but other than their weights, they are unaffected by your observations. Highly unlikely particles will be kept around and transitioned to more unlikely states, and you might only have say, one particle in the area of high probability of your posterior. So what you end up with is one particle with a way higher likelihood than any of the other particles, and a whole lot of particles with almost-nil probability. This is what we call 'particle depletion', because you in effect have only one particle. And one particle doesn't represent a pdf very well.

If you don't havea lot of particles in the areas of your pdf with high probability, you won'trepresent the pdf very well [4]. The density of your particles should be high inhigh-probability areas, and low in low-probability areas. And so you have tore sample the particles, so that they continue to represent the pdf accurately and keep track of many high-probability hypotheses, instead of tracking lots ofuseless, low-probability hypotheses.

Particle filtering has two main advantages over importance sampling [9]. First, it can be used for an unbounded number of variables. Second, the particles better cover the hypothesis space. Whereas importance sampling will involve some particles that have very low probability, with only a few of the particles covering most of the probability mass.

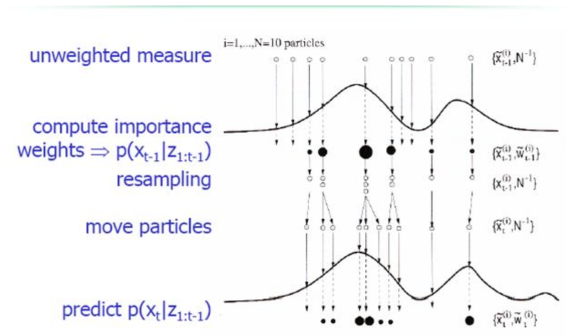

Figure. 2 pdf representation for particle

5. PROBLEM FORMULATION

If $\mathbf{x_n}$ is a hidden state vector and y_n be a measurement in time n. The particle filter algorithm builds an approximation of a maximum posterior estimate of the filtering distribution'$\mathbf{s(x_n \mid y_{1:n})}$,where $\mathbf{y_{1:n}=(y_1 \ldots y_n)}$ is the history of the observation .This distribution is represented by the set of pairs $\mathbf{\{x_n^{(1)}:y_n^{(1)}\}_{l=1}^{Np}}$
Where$\mathbf{x_n^{(l)}\ \alpha\ p(y_n|x_n^{(l)})}$.

Using Bayes rule the filtering distribution can be calculated using two steps

Prediction step:

$$P(x_n|y_{1:n-1})\text{-} \int p(x_n|x_{n-1})p(x_{n-1}.y_{n-1})dx_{n-1} \qquad (1)$$

Update step:

$$P(x_n|y_{1:n})\alpha p(y_n|x_n)p(x_n|y_{1:n-1}) \qquad (2)$$

Therefore ,starting with a weighted set of a samples $\{x_0^{(l)};\Pi_0^{(l)})^{Nl}{}_{t-1}$,the new sample set $\{x_n^{(l)};\Pi_n^{(l)}\}_{t=1}^{Np}$is generated according to the distribution ,that may depend on the previous set $\{x^{(l)}_{n-1}\ ;\Pi^{(l)}_{n-1}\}_{l=1}^{Np}$ and the new measurement ,i=1,….,Np. The new weights are calculated using the following formula:

$$\Pi_n^{(l)}=\left(\frac{P(yn.xn(l))p(xn(l)|x(n-1)(l))}{q(xn(l)|x(l)n-1,y)}\right) \qquad \textbf{(3)}$$

Where $q(x_n^{(l)|}x_{n-1},y_n)$ is the proposal distribution

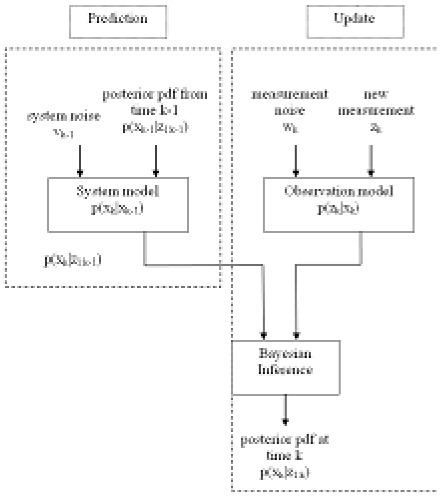

Figure.3.steps of particle filter

6. OBJECT PRESENCE

Let us model the event 'object is present ' and 'object is not present' by a discrete random variable E with E=0 when the object is not visible and E=1 when the object is visible as explained by Jacek in[2] .classically the detection is done in a given z_k at the time step k by comparing the probability that the object is present given the input signal i.e $P(E=1|z_k)$with the probability that the object is absent $P(E=0|z_k)$ .this is equivalent to comparing the likelihood ratio

$$L(z_k)=\frac{p(zk|E=1)}{p(zk|E=0)} \quad \textbf{(4)}$$

Information from several frames do so, we can model the presence of the object using a markov chain with two values :E=0and E=1 .The position and the size of the object can be included in a unknown random vector x_k.The probability of the object presence given frame z_k is the marginal of the joint probability of the presence and the object position and size given the observation .

i.e.$\mathbf{P(E_k=1|z_{1:k})=\int p(E_k=1,x_k|z_{1:k})dx_k}$ (5)

Bayesian sequential estimation allow to find $p(E_k,x_k\, z_{1:k})$recursively.The random variable E€{0,1} is modeled by an 2 state Markov chain ,whose transitions are specified by a 2×2 transitional probability matrix (TPM)

$$\Pi=\begin{matrix} 1-Pa & Pa \\ Pd & 1-Pd \end{matrix}$$

Where

$\mathbf{P_a=pr\{E_k=0|E_{k-1}=1\}}$ **(6)**

$\mathbf{P_d=pr\{E_k=1|E_{k-1}=0\}}$ (7)

Are the profanities of the object appearance and disappears respectively. Finally the presence of the object is estimated and the probability of the object presence(E=1|z 1:k) is computed in the PF is

$$\mathbf{P}=\frac{1}{N}\sum_{n=1}^{N}\partial(E_k^n,1) \quad (8)$$

Where ∂(i,j) is the kronecker delta .The estimate of the state vector of the object is then

$x_{k|k}=\frac{1}{N}\sum_{n=1}^{N}X_{t,k}^{n}\,\partial(E_k^n,1)$.......(9)Where $\mathbf{Ni}=\sum_{n=1}^{N}\partial(E_k^n,1)$

If **P> 0.5** the face will be decided to be present and a white box will be drawn using the estimated state vector.

7. APPLICATION

a] visual tracking(human body parts)
b] Prediction of time series
c] surveillance

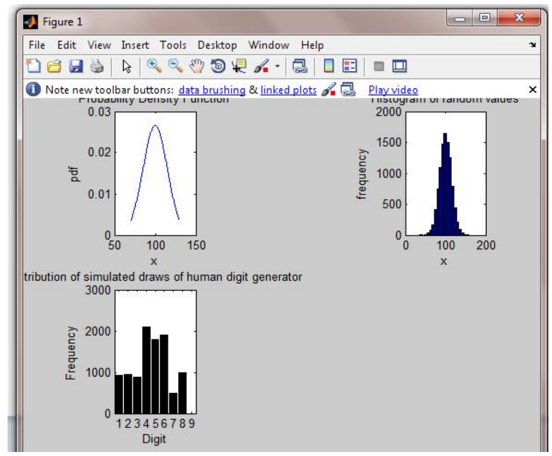

Figure. 4 mat lab window showing pdf and sampling

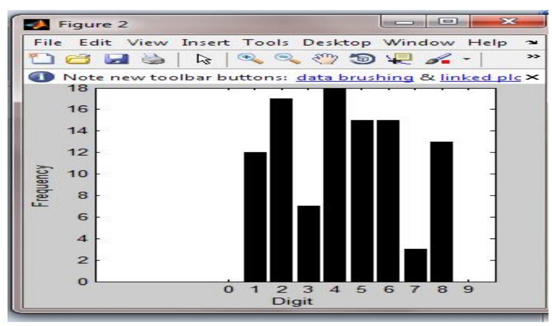

Figure.5 resample window

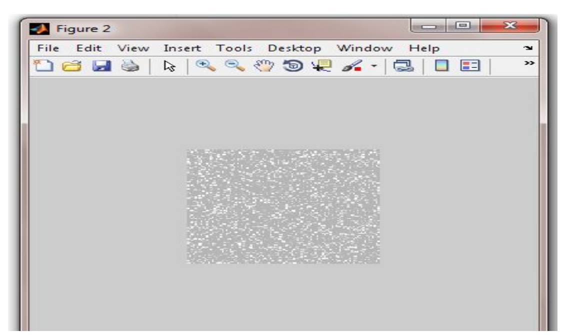

Figure.6 particle generated from pdf

8. CONCLUSION

We have presented an algorithm based on PF's for detecting objects in video. The observation density required by the PF is based on a set of rectangular features selected by an ad boost procedure as introduced in [6]. The approach allows estimating the probability of face presence in the current frame given the history of all observed frames. This allows accumulating the likelihood of object presence over several frames. The resulting system is therefore less sensitive to false detections, while being able to detect faces in difficult cases. In future automatic initialization of reference window can be used to detect an object; similarly multiobject tracking can be done.

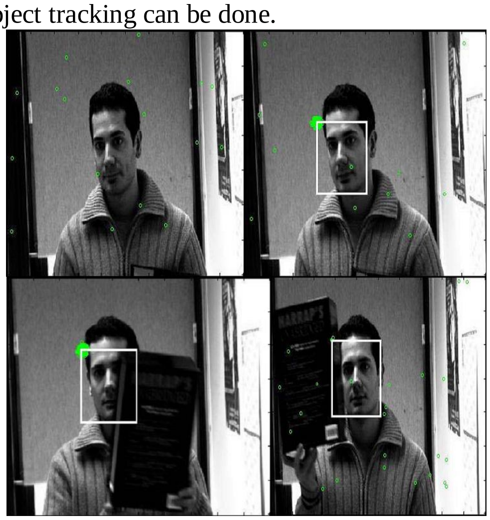

Figure 7.Face detection results. Small circles show the *x* and *y* component of particles (i.e. theupper left corner of the region) with *Enk* = 1. Once *P* >0.5 the face is decided to be present and awhite box is drawed using the estimated state vector.

REFERENCES

1. Y. Nakashima ,N. Babaguchi ,J. Fan, **Detecting Intended human objects in Human captured videos**. 978-1-4744-7030-3/10 IEEE.
2. Jack Czyz. **Object detection in video via particle filtering** proceeding of 18th International conference on pattern recognition(ICPR06)0-7695-0/06,IEEE.
3. B.Ristio,SArulampalam,N. Gordon. **Beyond kalman filtering :Particle filter for tracking applications** .Arten house 2004.
4. Young Min Kim **object tracking in video sequence** CS 229 IEEE final project report.
5. CMPE 264:Image analysis and computer vision ,hai tao,**Object tracking and kalman filtering** ,dept of computer engg,university of California.
6. Viola and jones.rapid object detection using a boosted cascade of simple features.In IEEE conference on computer Vision and Pattern Recognition
7. M. Jaward ,L.Mihaylava **,Multiple Object tracking using particle filters** ,IEEEAC paper #1280,IEEE2006
8. S.Fazli,H. moradi,H.Bouzari,Particle **filter based object tracking with sift and color features** ,2009 IEEE second international conference on machine vision.
9. Krishna V.Tangirala and Kamlesh R.Namuduri,OBJECT TRACKING IN VIDEO USING PARTICLE FILTERING,Dept of computer engg. Wichita State university,USA