ISSN 2278-3091

International Journal of Advanced Trends in Computer Science and Engineering, Vol.2 , No.1, Pages : 21-25 (2013)
Special Issue of ICACSE 2013 - Held on 7-8 January, 2013 in Lords Institute of Engineering and Technology, Hyderabad

Removal of Gaussian Noise Using Rao-Blackwellised Particle Filters

Dr. Anna SaroVijendran[1],Bobby Lukose[2]
[1]Director & Head, Department of Computer Applications, India, saroviji@rediffmail.com
[2]Assistant Professor, Department of Computer Science, India, bobbylukose74@gmail.com

Abstract: In this paper, we propose an efficient Monte Carlo particle filter for restoring images using probabilistic dynamic model. The evolution of the discrete and continuous states are described by the probabilistic dynamic model. Usually, the continuous states are assumed to be Gaussian distributed. This algorithm exploits some of the analytical structure of the model. Using this algorithm the values of the discrete states are found, and possible to compute the distribution of the continuous states exactly. The importance of the Rao-Blackwellized particle filter is to improve the learning stage by estimating a posterior. The proposed work is to identify the discrete state of operation using the continuous measurements corrupted by Gaussian noise. This algorithm also finds some of the analytical structure of the model. The Rao-Blackwellized particle filter is the combination of particle filter (PF) and states with a bank of Kalman filters.

Keywords: Adaptive Resampling,Gaussian mixture,Kalman filter, Rao-BlackwellizedParticle Filter,.

INTRODUCTION

A digital image could get corrupted easily due to various types of noise during transmission and acquisition. A noise is any unwanted signal/pixel that may be added or subtracted during transmission. These unwanted signals/pixels decrease the image quality. The sources of noise in digital images arise during image acquisition and/or transmission with unavoidable short noise of an ideal photon detector.

Noise Models

Most types of noise are modeled as known probability density functions. Noise model is decided based on an understanding of the physics of the sources of noise. Parameters can be estimated based on histogram on a small flat area of an image.

- Gaussian: poor illumination
- Rayleigh: range image
- Gamma, Exp: laser imaging
- Impulse: faulty switch during imaging,
- Uniform is least used.

Image de-noising is a common procedure in digital image processing aiming at the suppression of different types of noises without losing much detail contained in an image. This procedure is traditionally performed in the spatial-domain or transform-domain by filtering. To reduce the noise from images, various images de-noising filters are used. Image denoising still remains a challenge for researchers because noise removal introduces artifacts, blurring of the images, and the noise remaining in the image edges. The purpose of image restoration is to restore a degraded image to its original content and quality.

The proposed work is to identify the discrete state of operation using the continuous measurements corrupted by Gaussian noise. This algorithm also finds some of the analytical structure of the model. For this to compute the distribution of the continuous states exactly. combining a particle filter (PF) which is used to compute the distribution of the discrete states with a bank of Kalman filters which is used to compute the distribution of the continuous states. That is, approximate the posterior distribution with a recursive, stochastic mixture of Gaussians.The importance of the Rao-Blackwellized particle filter is to improve the learning stage by estimating a posterior. One of the most common particle filtering algorithms is the Sampling Importance Resampling (SIR) filter. This is done by updating a set of samples representing the posterior.

RELATED WORK

The images are corrupted by noise, some of the quantities are unobservable. To address these constraints, we need to adopt probabilistic dynamic models. These models describe the evolution of the discrete and continuous states. The continuous states are assumed to be Gaussian distributed. In this paper, we propose a substantially more efficient Monte Carlo particle filter for improving the learning stage.The state of the art method is the Monte Carlo particle filter proposed in [2],[4],[6]. This method computes recursively in time, a stochastic point-mass approximation of the posterior distribution of the states given the observations.

Recently Murphy, Doucet and colleagues[12], [14] introduced Rao-Blackwellized particle filters as an effective means to solve the simultaneous localization and mapping (SLAM) problem. The main problem of the Rao-Blackwellized approaches are their complexity, measured in terms of the number of particles required to build an accurate map. Therefore reducing this quantity is one of the major challenges of this family of algorithms.

Additionally, the resampling step can eliminate the correct particle. This effect is also known as the particle depletion problem [7],[9]. A proposal distribution that

ISSN 2278-3091

International Journal of Advanced Trends in Computer Science and Engineering, Vol.2 , No.1, Pages : 21-25 (2013)
Special Issue of ICACSE 2013 - Held on 7-8 January, 2013 in Lords Institute of Engineering and Technology, Hyderabad

allows to draw particles in a highly accurate manner, as well as an adaptive resampling technique, which maintains a reasonable variety of particles and this way reduces the risk of particle depletion. The proposal distribution is computed by evaluating the likelihood around a particle-dependent. In this way generating the new particle, allowing to estimate the evolution of the system to be a more accurate modelin [1], [5], [11]. This model has two effects. The estimation error accumulated over time is lower and less particles are required to represent the posterior.

The estimation algorithms are Extended Kalmanfilters (EKFs), maximum likelihood techniques and Rao-Blackwellized particle filters. In a work by Murphy [12]Rao-Blackwellized particle filters (RBPF) have been introduced. The framework has been subsequently extended by Montemerlo [14] for that reduces the number of required particles.

Several methods for computing improved proposal distributions and for reducing the risk of particle depletion have been proposed [13]. It has several advantages compared to EKF since it better covers the nonlinearities and is faster to compute. In the particle filter, the posterior probability density is approximated as a set of particles. When the particles are properly placed, weighted and propagated, posteriors can be estimated sequentially over time. The density of particles represents the probability of posterior function. In this the set of candidate pixels not fixed and changes per pixel location according to local pixel properties. The disadvantage is even with a large number of particles, there are no particles in the vicinity of the correct state. This is called the particle deprivation problem.

The paper image restoration using particle filters by improving the scale of texture with MRF [3] deals with capturing the geometric structure of the image. It is the important process in image restoration. Such a process involves two steps, (i) a learning stage where the image structure is modeled, and (ii) a reconstruction step. Our aim is to introduce a strategy that allows a best possible selection of the pixels contributing to the reconstruction process driven by the observed image geometry. Using this to retrieve similar pixels. The issues are (i) the selection of the trajectory, (ii) and the evaluation of the trajectory appropriateness. To overcome the issues optimizing the selection of candidate pixels within a walk as well as the overall performance of the method image structure at local scale is considered as a learning stage. It computes a probability density function that describes the spatial relation between similar image patches in a local scale. Here to improve the scale of texture by using MRF.

PROPOSED METHOD

Rao-Blackwellised Particle Filtering

It is an efficient Monte Carlo particle filter for restoring images. This algorithm finds the analytical structure of the model. To compute the distribution of the continuous states exactly by knowing the values of the discrete states. A particle filter (PF) which is used to compute the distribution of the discrete states and a bank of Kalman filters which is used to compute the distribution of the continuous states. Therefore, combine a particle filter (PF) with a bank of Kalman filters is known as *Rao-Blackwellisation*, because it is related to the Rao-Blackwell formula [8], [15]. That is, we approximate the posterior distribution with a recursive, stochastic mixture of Gaussians. The RBPF makes less estimation mistakes. The distribution of the discrete states is computed by RBPF. The Rao-Blackwellized particle filter is to improve the learning stage by estimating a posterior. Here Sampling Importance Resampling (SIR) filter is used for updating a set of samples.

In the particle filtering, we use a weighted set of particles to approximate the posterior. This approximation can be updated recursively [4]. The Gaussian density can be computed analytically by using marginal posterior density[10]. This density satisfies the alternative recursion. The particle filter starts at a time with an unweighted measure. For each particle we compute the importance weights using the information at time t. A resampling step selects only the correct particles to obtain the unweighted measure. This yields an approximation of that is "concentrated" on the most likely hypothesis. Now use a weighted set of samples to represent the marginal posterior distribution. The marginal density is a Gaussian mixture that can be computed efficiently with a stochastic bank of Kalman filters. A Rao-Blackwellised filter that combines this marginalisation and sampling.

Markov Linear Gaussian Model

In this paper adopt the following jump Markov linear Gaussian model:

$$z_t \sim P(z_t \mid z_{t-1}) \quad (1)$$

$$x_t = A(z_t)x_{t-1} + B(z_t)w_t + F(z_t)u_t \quad (2)$$

$$y_t = C(z_t)x_t + D(z_t)w_t + G(z_t)u_t \quad (3)$$

Where $y_t \in R^{n}{}_{y}$denotes the observations, $x_t \in R^{n}{}_{z}$denotes the unknown Gaussian states, $u_t \in U$ is a known control signal, $z_t \in \{ 1,\ldots,n_z\}$denotes the unknown discrete states. The noise processes are *i.i.d*Gaussian:$w_{t \sim N(0,1) \text{ and }} v_{t \sim N(0,1).}$

The continuous densities are calculated using the following equation

$$P(x_t|z_t,x_{t-1}) = N(A(z_t)x_{t-1} + F(z_t)u_{t}\,,\, B(z_t)B(z_t)^T) \quad (4)$$

ISSN 2278-3091

International Journal of Advanced Trends in Computer Science and Engineering, Vol.2 , No.1, Pages : 21-25 (2013)
Special Issue of ICACSE 2013 - Held on 7-8 January, 2013 in Lords Institute of Engineering and Technology, Hyderabad

$$P(x_t|z_t,x_{t-1}) = N(C(z_t)x_t + G(z_t)u_t , D(z_t)D(z_t)^T) \quad (5)$$

Where the parameters A,B,C,D,E,F,$P(z_t|z_{t-1})$ are known matrices with $D(z_t)D(z_t)^T > 0$ for any z_t. Finally, the initial states are $x_0 \sim N(\mu_0, \sum_0)$ and $z_0 \sim P(z_0)$. The unknown Gaussian states x_t is calculated using the kalman filter algorithm by substituting the value of z_t.

Kalman Filter Algorithm

The aim is to compute the marginal posterior distribution of the discrete states $P(z_{0:t} | y_{1:t})$. This distribution can be derived from the posterior distribution by standard marginalisation. The posterior density satisfies the following recursion.

$$P(x_{0:t}, z_{0:t} | y_{1:t}) = P(x_{0:t-1}, z_{0:t-1} | y_{1:t-1}) \frac{P(y_t|x_t,z_t)P(x_t,z_t | x_{t-1},z_{t-1})}{P(yt|y_{1:t-1})} \quad (6)$$

This recursion involves intractable integrals. The density is Gaussian and it can be computed analytically using the marginal posterior density.

$$P(z_{0:t} | y_{1:t}) = P(z_{0:t-1} | y_{1:t-1}) \times \frac{P(y_t|y_{1:t-1},z_{0:t})P(z_t | z_{t-1})}{P(yt|y_{1:t-1})} \quad (7)$$

The continuous probability distributions and discrete distributionsadmit densities. To represent the marginal posterior distribution using a weighted set of samples.

$$\hat{P}_N(z_{0:t}|y_{1:t}) = \sum_{i=1}^{N} \omega_t^{(i)} \delta_{z0:t}(i)(z_{1:t}) \quad (8)$$

The marginal density $x_{0:t}$ is a Gaussian mixture that can be computed efficiently with a stochastic bank of Kalman filters.

$$\hat{P}_N(x_{0:t}|y_{1:t}) = \sum_{i=1}^{N} \omega_t^{(i)} p(x_{0:t} | y_{1:t} , z^{(i)}_{0:t}) \quad (9)$$

A Rao-Blackwellised filter that combines this marginalisation and sampling of z_t.

The RBPF is similar to the PF, but we only sample the discrete states. Then for each sample of the discrete states, we update the mean and covariance of the continuous states using exact computations. In particular, we sample $z_t^{(i)}$ and then propagates the mean $\mu^{(i)}$ and covariance $\sum^{(i)}_t$ of x_t with a Kalman filter as follows:

$$\mu^{(i)}_{t|t-1} = A(z_t^{(i)})\mu^{(i)}_{t-1|t-1} + F(z_t^{(i)})u_t$$

$$\sum^{(i)}_{t|t-1} = A(z_t^{(i)}) \sum^{(i)}_{t-1|t-1} A(z_t^{(i)})^T + B(z_t^{(i)}) B(z_t^{(i)})^T$$

$$S_t^{(i)} = C(z_t^{(i)}) \sum^{(i)}_{t-1|t-1} C(z_t^{(i)})^T + D(z_t^{(i)}) D(z_t^{(i)})^T$$

$$y^{(i)}_{t|t-1} = C(z_t^{(i)})\mu^{(i)}_{t|t-1} + G(z_t^{(i)})u_t$$

$$\mu^{(i)}_{t|t} = \mu^{(i)}_{t|t-1} + \sum^{(i)}_{t|t-1} C(z_t^{(i)})^T S_t^{-1(i)} (y_t - y^{(i)}_{t|t-1})$$

$$\sum^{(i)}_{t|t} = \sum^{(i)}_{t|t-1} - \sum^{(i)}_{t|t-1} C(z_t^{(i)})^T S_t^{-1(i)} C(z_t^{(i)}) \sum^{(i)}_{t|t-1}$$

Where $\mu_{t|t-1} \triangleq E(x_t | y_{1:t-1})$, $\mu_{t|t} \triangleq E(x_t | y_{1:t})$, $y_{t|t-1} \triangleq E(y_t | y_{1:t-1})$, $\sum_{t|t-1} \triangleq cov(x_t | y_{1:t-1})$, $\sum_{t|t} \triangleq cov(x_t | y_{1:t})$ and $S_t \triangleq cov(y_t | y_{1:t-1})$. Hence, using the prior proposal for z_t and applying equation (7), we find that the importance weights for z_t are given by the predictive density

$$P(y_t | y_{1:t-1}, z_{1:t}) = N(y_t; y_{t|t-1}, S_t) \quad (10)$$

EXPERIMENTAL RESULTS AND DISCUSSION

The proposed algorithm is tested using 256 X 256 8-bits/pixel standardgray scaleimages. There are 50 imagestaken from the Berkely Segmentation Dataset & Benchmark database. The performance of theproposed algorithm is tested with different noise levels.Each time the test image is corrupted by different additive white Gaussian noise standard deviation ranging from 10 to 50 with an increment of 10. These noisy images are denoised by RBPF and the performancearemeasured by the parameters PSNR and MSE. All the filters are implemented inMatlab 10.

In Table 1and 2 provide a PSNR, MSE values of restored images for the RBPF. The PSNR values for the RBPF for five images at different Gaussian levels are displayed in Table1. The MSE values for the RBPF for five images at different Gaussian levels are displayed in Table 2. As seen the results of Table 1, 2 the RBPF method produces very good results. The visual quality results are presented in Fig. 2. A noise free image, Gaussian noise image, restored image using RBPF Gaussian noise σ = 10 as shown in Fig. 3. (a), (b) and (c) respectively. In all graphs the x-axis values are represented as 1,2,3,4 and 5 which denotes 1 for baboon, 2 for Barbara, 3 for Buiding, 4 for Cameraman and 5 for Lena. The visual quality and quantitative results clearly show the RBPF better than other existing methods in terms of PSNR and MSE.

Table 1: :PSNR Values For The Denoised Images At Different Guassian Noise Levels

Images	σ =10	σ =20	σ =30	σ =40	σ =50
Baboon	41.85	47.12	49.79	51.45	52.81
Barbara	42.85	47.97	50.58	51.96	52.81
Building	43.74	48.69	51.10	52.45	53.27
Cameraman	44.17	49.03	51.43	52.83	53.65
eena	43.21	48.28	50.81	52.21	53.10

Table 2: MSE Values For The Denoised Images At Different Guassian Noise Levels

Images	σ =10	σ =20	σ =30	σ =40	σ =50
Baboon	0.85	0.45	0.32	0.25	0.21
Barbara	0.75	0.39	0.28	0.23	0.20
Building	0.64	0.35	0.26	0.21	0.18
Cameraman	0.59	0.33	0.24	0.19	0.17
Leena	0.70	0.38	0.27	0.22	0.19

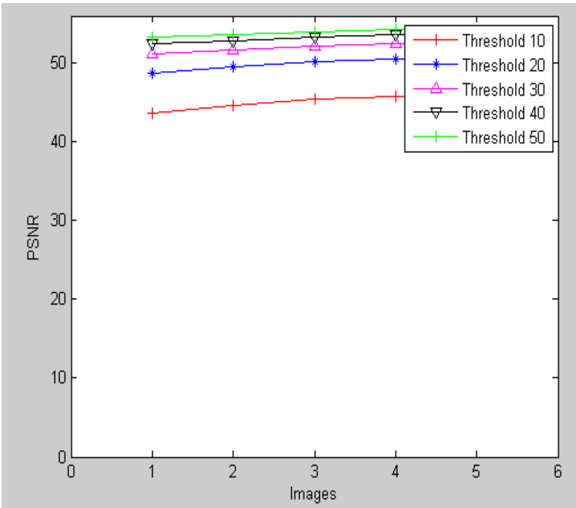

Fig. 1.(a) :PSNR of RBPF for 5 images at different Gaussian noise levels

Experiments are conducted on standard grayscale test images corrupted by additive Gaussian white noise at different levels. Fig1. (a) shows PSNR versus the noise standard deviation of the RBPF for 5 standard test images. In all graphs x-axis represents images and the y-axis represents PSNR values. In this the red line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 10, The blue line indicate the PSNR values of the RBPF for 5 images at Gaussian noise level 20, The pink line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 30, The black line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 40, The green line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 50.

Fig1. (b) shows MSE versus the noise standard deviation of the RBPF for 5 natural images. In this the red line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 10, The blue line indicate the PSNR values of the RBPF for 5 images at Gaussian noise level 20, The pink line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 30, The black line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 40, The green line indicates the PSNR values of the RBPF for 5 images at Gaussian noise level 50.

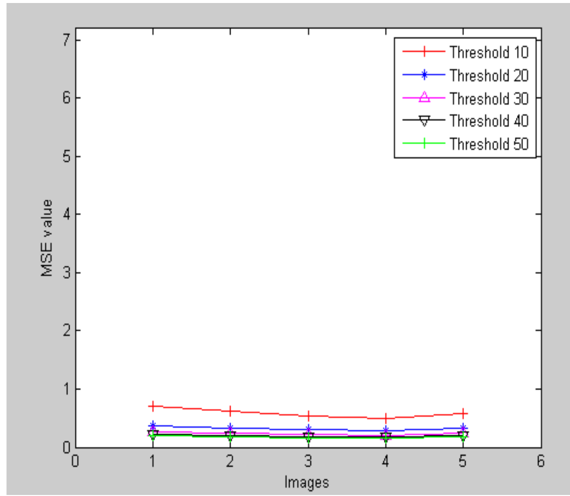

Fig. 1.(b) :MSE of RBPF for 5 images at different Gaussian noise levels

In fig. 2. (a) shows the input image, (b) shows the image with Gaussian noise of 10. Denoising using the RBPF are shown in ©. Denoising quality is given by PSNR and MSE w.r.t. the original image. The experimental results are shown as graphs in Fig.1. Performance of denoising algorithms is measured using quantitative performance measures such as PSNR, MSE as well as in terms of visual quality of the images.

Fig.2. (a) : Input Image

(b) Gaussian Noise Image

(c) RBPF

CONCLUSION

In this paper, an efficient algorithm is proposed for removing noise from corrupted image. RBPF approach computes a highly accurate proposal distribution based on the observation likelihood. This allows us to draw particles in a more accurate manner which seriously reduces the number of required samples. The approach has been implemented and evaluated with different data sets. To demonstrate the superior performance of the proposed method, extensive experiments have been conducted on several standard test images. The proposed RBPF performs better than other existing methods both in PSNR and visually. Promising experimental results demonstrate the potentials of our approach.

Limitation for the Rao-Blackwellized approaches is their complexity measured in terms of the number of particles required to build an accurate map and the performance of the system is reduced since each particle is iterated.

The future work is to increase the performance of theRao-Blackwellized particle filters and to improve proposal by limiting the number of particles and to reduce the risk of particle depletion in a highly accurate manner.

REFERENCES

[1] C. Andrieu, N.De Freitas, and A.Doucet. Sequential Bayesian estimation and model selection applied to neural networks. Technical Report CUED/FINFENG/TR 341, Cambridge University Engineering Department, May 1999.

[2] C.Andrieu, A.Doucet, and E.Punskaya. Sequential Monte Carlo methods for optimal filtering.

[3] Anna SaroVijendran and Bobby Lukose. Image Restoration using particle filters by improving the scale of texture with MRF. International Journal of Image Processing (IJIP), Volume (6), Issue (5), 2012.

[4] N. De Freitas, M. Niranjan, A. H. Gee, and A.Doucet. Sequential Monte Carlo methods to train neural network models. *Neural Computation*, 12 (4): 955–993,2000.

[5] Doucet. On sequential simulation-based methods for bayesian filtering. Technical report, Signal Processing Group, Dept. of Engineering, University of Cambridge, 1998.

[6] Doucet, N. De Freitas, and N. Gordan, editors. *Sequential Monte-Carlo Methods in Practice*. Springer Verlag, 2001.

[7] A.Doucet, S.Godsill, and C.Andrieu. On sequential Monte Carlo sampling methods for Bayesian filtering. *Statistics and Computing*, 10 (3): 197–208, 2000.

[8] D. Fox, S.Thrun, W.Burgard, and F.Dellaert. Particle filters for mobile robot localization

[9] U. Freseand G. Hirzinger. Simultaneous localization and mapping a discussion. In *Proc. of the IJCAI Workshop on Reasoning with Uncertainty in Robotics*, pages 17–26, Seattle, WA, USA, 2001.

[10] N. J. Gordon, D. J .Salmond, and A. F. M. Smith. Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEEE Proceedings-F*, 140 (2): 107–113, April 1993.

[11] F. Dellaert, D. Fox, W. Burgard, and S. Thrun. Monte Carlo localization for mobile robots. In *Proc. of the IEEE Int. Conf. on Robotics &Automation (ICRA)*, Leuven, Belgium, 1998.

[12] Doucet, J.F.G. De Freitas, K. Murphy, and S. Russel. Rao-Blackwellized particle filtering for dynamic Bayesian networks. In *Proc. Of the Conf. on Uncertainty in Artificial Intelligence (UAI)*, pages 176–183, Stanford, CA, USA, 2000.

[13] G. Grisetti, C. Stachniss, and W. Burgard. Improving grid-based slam with Rao-Blackwellized particle filters by adaptive proposals and selective resampling. In *Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA)*, pages 2443–2448, Barcelona, Spain, 2005.

[14] M. Montemerlo, S. Thrun D. Koller, and B. Wegbreit. FastSLAM 2.0: An improved particle filtering algorithm for simultaneous localization and mapping that provably converges. In *Proc. of the Int. Conf. on Artificial Intelligence (IJCAI)*, pages 1151–1156, Acapulco, Mexico, 2003.

[15] G. Casella and C. P. Robert. Rao-Blackwellisation of sampling schemes. *Biometrika*, 83 (1): 81–94, 1996.