International Journal of Advanced Computer Research (ISSN (print): 2249-7277 ISSN (online): 2277-7970)
Volume-3 Number-3 Issue-12 September-2013

An Improved Image Denoising Technique for Digital Mobile Camera Images

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Abstract

The particle filter is an effective image denoising technique. An important issue with the application of the particle filter is the selection of the filter parameters, which affect the results significantly. There are two main contributions of this paper. The first contribution is an estimation of the noise level. The second contribution is an improved particle filter (Rao-Blackwellized Particle Filter). The particle filter is combined with Kalman filter to form a new image denoising framework. The distribution of the discrete states is computed by using PF and the distribution of the continuous states are computed by using a bank of Kalman filters. An accurate proposal distribution is computed by using conditionally Gaussian state space models and Rao-Blackwellized particle filtering. This improved filter is very effective in eliminating noise in real noisy images. Experimental results carried out with real noisy digital mobile camera images and RBPF is compared with particle filter. In terms of noise removal RBPF outperforms for degraded mobile camera images.

Keywords

Denoising, Gaussian Noise, Particle Filter (PF), Rao-Blackwellized Particle Filter (RBPF).

1. Introduction

Photography can be expressed as drawing with light because it is about capturing light and recording it. The visual quality of captured images suffers from a loss of detail, especially in low-light and shadow regions. Denoising is still one of the most fundamental, widely studied, and largely unsolved problems in image processing. The purpose of denoising is to estimate the original image from noisy data. Many methods for image denoising have been suggested, and an outstanding review of them can be explained below.

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A traditional way to remove noise from image data is spatial filters. Spatial filters are a low pass filter. It can be classified into non-linear and linear filters. Linear filters, which consist of convolving the image with a constant matrix to obtain a linear combination of neighborhood values, have been used for noise elimination in the presence of additive noise. Linear filters destroy lines and other fine image details, also it produce a blurred and smoothed image with poor feature localization and incomplete noise suppression. Variety of nonlinear median type filters such as weighted median, rank conditioned rank selection has been developed to overcome this drawback. Edge-Preserving Smoothing Filters (Neighborhood filters) are Bilateral filters, sigma filter[1], mean sigma filter. They are used to solve the halo artifacts and noise. The extensions of Adaptive range and domain filters is Bilateral Filter which performs weighted averaging in both range and domain [2]. It smooth's noisy images while preserving edges using neighboring pixels. Bilateral filtering is a local, nonlinear, and a non iterative technique which considers both gray level and color similarities and geometric closeness of the neighboring pixels.

Neighborhood filters are performing a weighted sum of noisy pixels over a given neighborhood. Such approaches include the sigma filter, the bilateral filter and the NL-mean filter [3] and the fast version of the NL-mean filter [4]. These methods include the image structure in the weight definition the selection of filtering window is always fixed in shape and size. The main advantages of these methods are computational efficiency, but they are constrained by the amount of information present at the considered window. The Denoising algorithm should be able to extract the most important correlations of local structure of the entire image domain.

Gaussian kernels are the most common selection of such an approach. Sequential Monte Carlo is a well known technique evolving densities to the different hypotheses. 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 aim of the paper [5] 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. The issues are (i) the selection of the trajectory, (ii) and the evaluation of the trajectory appropriateness. Each walk is composed of a number of possible neighboring sites/pixels in the image which are determined according to the observed image structure. When the particles are properly placed, weighted and propagated, posteriors can be estimated sequentially over time.

The work described in image restoration using particle filters by improving the scale of texture with MRF [6] which deals with capturing the geometric structure of the image. It overcomes the issues such as optimizing the selection of candidate pixels within a walk and improved the overall performance of the method. Our aim is to preserve the local structure of the texture as much as possible. To achieve this to define a strategy to generate neighborhood candidate windows that takes into account the image content. After that to determine the most appropriate window for estimating the image intensity in a given position. MRF models have been used in image restoration, region segmentation, and texture synthesis. In image processing, texture may be defined in terms of spatial interactions between pixel gray levels within a digital image. The aim of texture analysis is to capture the visual characteristics of a texture by mathematically modeling these spatial interactions. Markov Random Fields (MRFs) are widely used probabilistic models for regularization [7]. The probability density function (PDF) defined by the MRF is the normalization constant. Sampling techniques, such as Markov chain Monte Carlo (MCMC) used in this model.

An efficient particle filtering Denoising algorithm should be able to extract the most important correlations of local structure of the entire image domain. Gaussian kernels are the most common selection of such an approach. Sequential Monte Carlo is a well known technique evolving densities to the different hypotheses [8]. State estimation in state-space models is widely used in a variety of computer science and engineering applications. The Kalman filter is used to linear Gaussian models and models with finite state spaces, respectively. Even when the state space is finite, it can be so large that the junction tree algorithms become too computationally expensive. This is for large discrete dynamic Bayesian networks DBNs. To solve these problems, sequential Monte Carlo methods, also known as particle filters (PFs), have been introduced Akashi and Kumamoto [9].

In the mid 1990s, several PF algorithms were proposed independently under the names of Monte Carlo filters [10], sequential importance sampling (SIS) with resampling (SIR), bootstrap filters, condensation trackers, dynamic mixture models, survival of the fittest etc. One of the major innovations during the 1990s was the inclusion of a resampling step to avoid degeneracy problems. In addition, improved particle filter algorithms were applied and tested in many domains by Doucette, de Freitas and Gordon for an up-to-date survey of the field. One of the major drawbacks of PF is that sampling in high-dimensional spaces can be inefficient. The state of the art method is the Monte Carlo particle filter proposed in [11]. This method computes recursively in time, a stochastic point-mass approximation of the posterior distribution of the states given the observations.

Recently the paper [12] 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 is their complexity, measured in terms of the number of particles required to build an accurate map. The resampling step can eliminate the correct particle. This effect is also known as the particle depletion problem. Therefore reducing this quantity is one of the major challenges of this family of algorithms.

The work [13] deals with two approaches to increase the performance of Rao-Blackwellized particle filters applied to SLAM with grid maps. A proposal distribution that allows drawing 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 estimating the evolution of the system to be a more accurate model. This model has two effects. The estimation error accumulated over time is lower and fewer particles are required to represent the posterior. The second approach, the adaptive resampling strategy allows to perform a resampling step only when needed, keeping a reasonable particle diversity. This reduces the particle depletion problem.

In non-linear non-Gaussian state-space models [14] do not have a closed form expression for these densities and it is usual to rely on Monte Carlo methods. Standard particle filters (PF) approximate the associated sequence of probability distributions with weighted empirical distribution associated with a set of random samples. Rao-Blackwellized particle filters (RBPF) exploit the available structure by approximating only the marginal through Monte Carlo methods. The Monte Carlo approximation being performed in a space of lower dimension, for common marginal proposals and sample sizes the asymptotic variance of the Rao-Blackwellized particle estimates never exceeds that of standard particle estimates. Marginalizing out some of the variables is an example of the technique called *Rao-Blackwellization*, because it is related to the Rao-Blackwell formula. Rao-Blackwellized particle filters (RBPF) have been applied in specific contexts such as mixtures of Gaussians[15] fixed parameter estimation and Dirichlet process models. Efficient Monte Carlo particle filter RBPF is proposed for restoring images. RBPF is used to improve the learning structure by efficient selection of particles. Implementation of probabilistic dynamic models describes the evolution of the discrete and continuous states.

The paper is organized as follows. Section 2 briefly discusses the the proposed Method Rao-Blackwellized Particle Filtering, the Gaussian noise model and Noise estimation. Section 3 presents experimental results and discussions. Section 4 gives the conclusion and finally, references are drawn.

2. Proposed Method

Rao-Blackwellized Particle Filtering

The Rao-Blackwellized particle filter is to improve the learning stage by estimating a posterior. It is an efficient Monte Carlo particle filter for restoring images. This algorithm finds the analytical structure of the model. The distribution of the continuous states is computed 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-Blackwellization, because it is related to the Rao-Blackwell formula [16]. 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. 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 [17][18]. The Gaussian density can be computed analytically by using marginal posterior density. This density satisfies the alternative recursion. The particle filter starts at a time with an unweight 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 unweight 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-Blackwellized filter that combines this marginalization and sampling.

Gaussian noise model and Noise Estimation

First step of Denoising is to estimate the standard deviation σ_n of the noise from the noisy image. Assume that the image is corrupted by additive zero mean white Gaussian noise[19][20]. The Image model is given by

$$I_n(x,y) = I(x,y) + n(x,y) \tag{1}$$

Where x and y are the vertical and horizontal coordinates of a pixel. And $I_n(x,y), I(x,y)$and $n(x,y)$are the noisy image, the original image and the additive Gaussian noise respectively.

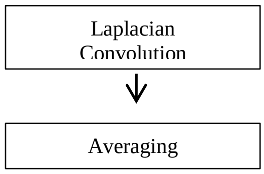

Figure 1: Block diagram of "Fast Estimation"

Noise Estimation Steps

Step1.To suppress the image structures by the Laplacian operator

$$N = \begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix} \tag{2}$$

Step2.Then computes the standard deviation of the noise using the formula

$$\sigma_n = \sqrt{\frac{\pi}{2}} \frac{1}{6(W-2)(H-2)} \sum_{Image\ I} |(I(x,y) * N)| \tag{3}$$

Where W and H are the width and height of the image respectively. This algorithm is fast because it has convolutions and averaging only.

Markov Linear Gaussian Model

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

$$z_t \sim P(z_t | z_{t-1}) \tag{4}$$

$$x_t = A(z_t)x_{t-1} + B(z_t)w_t + F(z_t)u_t \tag{5}$$

$$y_t = C(z_t)x_t + D(z_t)v_t + G(z_t)u_t \tag{6}$$

Where $y_t \in \mathrm{R}^{n_y}$ denotes the observations, $x_t \in \mathrm{R}^{n_z}$ denotes the unknown Gaussian states, $u_t \in U$ is a known control signal, $z_t \in \{1, \dots, n_z\}$ denotes the unknown discrete states. The noise processes are Gaussian: $w_t \sim N(0, I)$ and $v_t \sim N(0, I)$. The continuous densities are calculated using the following equation

$$P(x_t|z_t, x_{t-1}) = N(A(z_t)x_{t-1} + F(z_t)u_t, B(z_t)B(z_t)^T) \tag{7}$$

$$P(y_t|x_t, z_t) = N(C(z_t)x_t + G(z_t)u_t, D(z_t)D(z_t)^T) \tag{8}$$

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 $x_0 \sim N(\mu_0, \Sigma_0)$ and $z_0 \sim P(z_0)$. The unknown Gaussian states x_t are 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 marginalization. The posterior density satisfies the following recursion.

$$P(x_{0:t}, z_{0:t}\,|y_{1:t}) = P(x_{0:t-1}, z_{0:t-1}\,|y_{1:t-1}) \times \frac{P(y_t|x_t,z_t)P(x_t,z_t|x_{t-1},z_{t-1})}{P(y_t|y_{1:t-1})} \tag{9}$$

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

$$P(z_{0:t}\,|y_{1:t}) = P(z_{0:t-1}|y_{1:t-1}) \frac{P(y_t|y_{1:t-1},z_{0:t})P(z_t|z_{t-1})}{P(y_t|y_{1:t-1})} \tag{10}$$

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

$$\hat{P}\,N(z_{0:t}|y_{1:t}) = \sum_{i=1}^{N} w_t^{(i)} \delta_{z_{0:t}^{(i)}}(z_{1:t}) \tag{11}$$

The marginal density is a Gaussian mixture that can be computed efficiently with a stochastic bank of Kalman filters.

$$\hat{P}\,N(x_{0:t}|y_{1:t}) = \sum_{i=1}^{N} w_t^{(i)} P(x_{0:t}|y_{1:t}\,,\, z_{0:t}^{(i)}) \tag{12}$$

A Rao-Blackwellized filter that combines this marginalization 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 propagate the mean $\mu_t^{(i)}$ and covariance $\Sigma_t^{(i)}$ of x_t with a Kalman filter as follows:

$$\mu_{t|t-1}^{(i)} = A(z_t^{(i)})\mu_{(t-1|t-1)}^{(i)} + F(z_t^{(i)})u_t \tag{13}$$

$$\Sigma_{t|t-1}^{(i)} = A(z_t^{(i)})\Sigma_{t-1|t-1}^{(i)} A(z_t^{(i)})^T + B(z_t^{(i)})B(z_t^{(i)})^T \tag{14}$$

$$S_t^{(i)} = C(z_t^{(i)})\Sigma_{t|t-1}^{(i)} C(z_t^{(i)})^T + D(z_t^{(i)})D(z_t^{(i)})^T \tag{15}$$

$$y_{t|t-1}^{(i)} = C(z_t^{(i)})\mu_{(t|t-1)}^{(i)} + G(z_t^{(i)})u_t \tag{16}$$

$$\mu_{t|t}^{(i)} = \mu_{t|t-1}^{(i)} + \Sigma_{t|t-1}^{(i)} C(z_t^{(i)})^T S_t^{-1(i)}(y_t - y_{t|t-1}^{(i)}) \tag{17}$$

$$\Sigma_{t|t}^{(i)} = \Sigma_{t|t-1}^{(i)} - \Sigma_{t|t-1}^{(i)} C(z_t^{(i)})^T S_t^{-1(i)} C(z_t^{(i)})\Sigma_{t|t-1}^{(i)} \tag{18}$$

where $\mu_{t|t-1} \triangleq \mathrm{E}(x_t|y_{1:t-1})$, $\mu_{t|t} \triangleq \mathrm{E}(x_t|y_{1:t})$, $\mu_{t|t-1} \triangleq \mathrm{E}(x_t|y_{1:t-1})$, $\Sigma_{t|t-1} \triangleq cov\,(x_t|y_{1:t-1})$, $\Sigma_{t|t} \triangleq cov\,(x_t|y_{1:t})$ and $S_t \triangleq cov\,(y_t|y_{1:t-1})$. Hence, using the prior proposal for z_t and applying equation (1.9), we find that the importance weights for z_t are given by the predictive density.

$$\mathrm{P}(y_t|y_{1:t-1}, z_{1:t}) = N(y_t; y_{t|t-1}, S_t) \tag{19}$$

The RBPF Algorithm

Sequential importance sampling step,

1. For $i = 1, \dots, N$,

   Set $\hat{\mu}_{t|t-1}^{(i)} \triangleq \mu_{t|t-1}^{(i)}, \hat{\Sigma}_{t|t-1}^{(i)} \triangleq \Sigma_{t|t-1}^{(i)}$,
   Sample $\hat{z}_t^{(i)} \sim P_r(z_t|z_{t-1}^{(i)})$

2. For $i = 1, \dots, N$, evaluate and normalize the importance weights
   $w_t^{(i)} \alpha\, P(y_t|y_{1:t-1}\hat{z}_t^{(i)})$

Selection step

3. Multiply/Discard particles $\left\{\hat{\mu}_{t|t-1}^{(i)}, \hat{\Sigma}_{t|t-1}^{(i)}, \hat{z}_t^{(i)}\right\}_{i=1}^{N}$ With respect to high/low importance weights $w_t^{(i)}$ to obtain N particles $\left\{\mu_{t|t-1}^{(i)}, \Sigma_{t|t-1}^{(i)}, z_t^{(i)}\right\}_{i=1}^{N}$

Updating step

4. For $i = 1, \dots, N$, use one step of the Kalman recursion to compute the minimum statistics

$\left\{\mu_{t+1|t}^{(i)}, \Sigma_{t+1|t}^{(i)}, y_{t+1|t}^{(i)}, S_{t+1}^{(i)}, \right\}$ Given $\left\{z_t^{(i)}, \mu_{t|t-1}^{(i)}, \Sigma_{t|t-1}^{(i)}\right\}$.

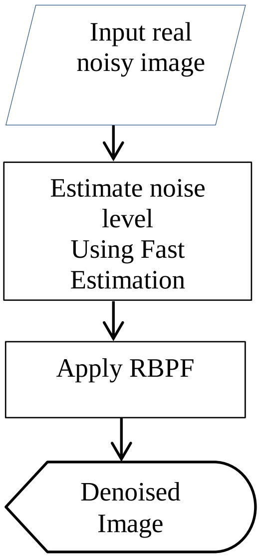

Figure 2: Block diagram of proposed method

3. Experimental Results and Discussion

The proposed algorithm is tested using 256 X 256 8-bits/pixel standard gray scale images. The images are taken by LG P500 Mobile Camera. The performance of the proposed algorithm is tested with different noisy images. These noisy images are DE noised by particle filter, and the proposed approach RBPF and the performance are measured by the parameter PSNR. All the filters are implemented in Mat Lab 10. A quantitative measure of comparison Peak Signal to Noise Ratio (PSNR) is used in this work.

$$PSNR = 10\log_{10}\frac{255^2}{MSE} \quad (20)$$

$$MSE = \frac{1}{\|\Omega\|}\sum_{x\in\Omega}\left(U(x) - \widehat{U}(x)\right)^2 \quad (21)$$

$$\text{NAE} = \text{sum}\left(sum\left(ABS(error)\right)\right) / sum\left(sum(origImg)\right) \quad (22)$$

$$Error = origImg - distImg$$

Tables and Figures

Table 1: PSNR Values for Denoised Mobile Camera Images of Different Estimated Gaussian Noise Levels

Images	Noise Level	(PF)	RBPF
image1	2.7688	36.7860	43.4523
image2	3.5799	35.7464	43.3326
image3	6.9420	33.7037	42.0282
image4	2.9977	35.5554	42.2365
image5	2.1333	36.6375	43.3472

Table 2: MSE Values for Denoised Mobile Camera Images of Different Estimated Gaussian Noise Levels

Images	Noise Level	PF	RBPF
image1	2.7688	1.3884	0.6851
image2	3.5799	1.6511	0.7023
image3	6.9420	2.1861	0.8305
image4	2.9977	1.7328	0.7920
image5	2.1333	1.4453	0.7320

Table 3: NAE Values for Denoised Mobile Camera Images of Different Estimated Gaussian Noise Levels

Images	Noise Level	PF	RBPF
image1	2.7688	0.0234	0.0117
image2	3.5799	0.0280	0.0120
image3	6.9420	0.0366	0.0140
image4	2.9977	0.0369	0.0173
image5	2.1333	0.0316	0. 0146

Figure 3: Result of Denoised image1 using PF (PSNR 36.7860)

Figure 4: Result of Denoised image1 using RBPF (PSNR 43.4523)

Discussion

Extensive experiments are conducted on digital mobile camera images corrupted by Gaussian noise. The performances in terms of PSNR, MSE and NAE for particle filter and RBPF methods are given in Table 1, Table 2 and Table 3. The visual quality of the results is presented in Figure 3 and 4. Restored image using particle filter and RBPF for a mobile camera image at Estimated noise σ =2.7688 as shown in Figure 3 and Figure 4 respectively. The visual quality and quantitative results clearly show the RBPF perform much better than particle filter in terms of PSNR, MSE and NAE.

4. Conclusion

In this paper, an improved particle filter algorithm RBPF is presented to restore Gaussian noise corrupted digital images. This method computes a highly accurate proposal distribution. This approach has been implemented and evaluated on real noisy mobile camera images. Experimental results show that the proposed algorithm has higher Peak Signal Ratio, less MSE and NAE than particle filter method. As a result, the overall quality of the restored image is significantly improved. The proposed method works well for mobile camera images. Rao-Blackwellized particle filters lead to more accurate estimates than standard PF. Limitation for the Rao-Blackwellized Particle Filter approaches is their complexity measured in terms of the number of particles required to Denoising. Therefore, reducing this quantity is one of the major challenges. Next is the performance of the system is reduced. RBPF will lead to a slower execution when compared to PF. Future work is to increase the performance of Rao-Blackwellized particle filters.

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