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Fast and Efficient Method for Image Denoising

Dr. Anna Saro Vijendran, Bobby Lukose
Director& Head, PhD Scholar

Abstract*— This paper presents a fast and efficient Rao-Blackwellized Particle Filter (RBPF) for real noisy image restoration. The proposed method first estimates the noise level from the noisy image. Then RBPF with Maximum Likelihood Estimation method is used for noise removal. The Maximum likelihood Estimation method is used for noise distribution process. Rao-Blackwellized particle filtering is a combination of a particle filter (PF) and a bank of Kalman filters. 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. The performance of the method is improved by parallel pixel processing. This algorithm, which exhibits good performance both in denoising and in restoration, can be easily and effectively parallelized. Experimental results carried out with real noisy satellite images. The RBPF is very effective in eliminating noise. RBPF is compared with other standard filters. In terms of noise removal and performance RBPF outperforms for naturally degraded satellite images.

Index Terms—**Maximum Likelihood, Mean Square Error, Normalized Absolute Error, Rao-Blackwellized Filter.**

I. INTRODUCTION

Noise is introduced into images during acquisition and transmission. Imaging noise produces random perturbations of intensity values that degrade the visual quality of images and reduce the reliability of computer vision algorithms. There has been much work on modeling and removing these variations. Removal of noise is a difficult one that preserves the actual scene information in the measured intensity signal. Since there does not exist sufficient information in an image to extract the original scene data, noise reduction cannot be performed with high accuracy. To reduce the noise from images, various Denoising 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. 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, 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 [24]. 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. The NL means filter achieves the best results in term of small detail preserving since noise contains less image information. The disadvantage is slow in terms of computation time. The NL-mean algorithm assumes fixed size with respect to the local filtering window and the window is centered at the origin pixel. Then based on the similarity between the center patch and the candidate patches it performs filtering [10], [19]. The sigma filter identifies noise from noisy gray scale images by utilizing the standard deviation measure [17]. And the mean shift filter does not require prior knowledge of the number of clusters, and does not constrain the shape of the clusters. The main advantage of this method is computational efficiency, but it is constrained by the amount of information present at the considered window. 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. In the particle filter, the posterior probability density is approximated as a set of particles [8] [9], [20]. Image restoration process involves two steps, (i) a learning stage where the image structure is modeled, and (ii) a reconstruction step. The aim of this paper 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. This 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.

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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 work described in image restoration using particle filters by improving the scale of texture with MRF [6] is an improvement of the paper [20] 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. 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 [13]. The work described in the paper [7] is an improvement of the paper [6] which deals with the learning stage of the image. It overcomes the issues of paper [6]. In this five levels of noises are added to the original image. Then reduce the noise and improve the quality of the image using Rao-Blackwellized Particle Filter. The remainder of this paper is organized as follows: Section II provides a literature review of existing Particle Filter, Rao-Blackwellized Particle Filter, Maximum Likelihood Estimation methods and Parallel Pixel Processing (PPP), Section III describes the proposed Method Rao-Blackwellized Particle Filtering with MLE and PPP, the Gaussian noise model and estimation and experimental results and discussions are presented in section IV. Finally, conclusions are drawn in section V.

II. RELATED WORK

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 [9]. 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 [1]. In the mid 1990s, several PF algorithms were proposed independently under the names of Monte Carlo filters [8], [12], 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. 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 [15] 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. 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 Akashi and Kumamoto [1], [23] fixed parameter estimation and Dirichlet process models. Efficient Monte Carlo particle filter RBPF [14] 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 continuous states are assumed to be Gaussian distributed. Also this algorithm exploits some of the analytical structure of the model. In this we know the values of the discrete states; it is possible to compute the distribution of the continuous states exactly. Rao-

Blackwellized particle filter is used to estimate a posterior. The Sampling Importance Resampling (SIR) filter is used for updating a set of samples representing the posterior. In the work [18] presented an alternative approach for dealing with the effects of imaging noise on vision algorithms. Rather than attempt to remove the noise from an image, it aim to directly account on intensity similarity measurement, which is one of the most fundamental and important operations in computer vision. Similarity between intensity observations is used to guide a broad range of algorithms including segmentation, object recognition, and optical flow. Estimation of parameters is a fundamental problem in data analysis. The paper [5] is about maximum likelihood estimation, which is a method that finds the most likely value for the parameter based on the data set collected. A handful of estimation methods existed before maximum likelihood, such as least squares, method of moments and Bayesian estimation [21], [22].

A basic knowledge of statistics, probability theory and calculus is assumed. Maximum Likelihood captures the intensity dependent noise distribution and then based on these probability distributions; derive a probabilistic measure of the similarity between two observed intensities. This metric represents the likelihood that two intensity observations with respect to the probabilistic noise distributions. The likelihood that two observations have the same noise-free value depends upon these noise characteristics, such that the similarity is high when the two intensities are both well within the noise distributions of certain true intensities, and becomes significantly lower otherwise. In conventional metrics which have a fixed structure that is intended to measure distance between observations rather than their similarity. These distance measures do not represent the likelihood that two intensity observations. Alter *et al*. [5] established an intensity similarity measure for low-light conditions, which uses Maximum Likelihood (ML) estimation to define the similarity between two intensity observations. It more accurately measures similarity than other basic metrics, it is accurately estimating the *true* intensity signal, which is difficult to achieve from only two observations. An optimized version of the Chan's method is introduced, the algorithm has been parallelized both using Fast Flow [2], a framework for parallel programming over multicore platforms, and GPU programming for improving the efficiency of the filter in order to be really compatible with real-time applications. The key vision of Fast Flow is that ease-of-development and runtime efficiency can both be achieved by raising the abstraction level of the design phase, thus providing developers with a set of parallel programming patterns, such as farm, divide & conquer, pipeline, map, reduce patterns, and supports their arbitrary nesting and composition. The parallel version has been semi-automatically derived by the sequential algorithm thanks to Fast Flow and its software acceleration technique [3], [4]. The possibility of pipelining made it possible to further accelerate the denoising of stream of images. Despite the very limited development effort required, the parallel version guarantees close to optimal speedup and scalability on standard cache-coherent multi-core workstations.

III. PROPOSED METHOD

A. Rao-Blackwellized Particle Filtering

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 [10]. 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 [16]. 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.

B. 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. The Image model is given by

$$I_n(x,y) = I(x,y) + n(x,y) \quad (1)$$

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.

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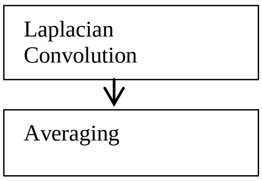

Fig.1 Block diagram of "Fast Estimation" [16].

C. Noise Estimation Steps

Step1.To suppress the image structures by the Laplacian operator

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

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

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

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

D. Markov Linear Gaussian Model

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

$$z_t \sim P(z_t | z_{t-1}) \quad (3)$$
$$x_t = A(z_t)x_{t-1} + B(z_t)w_t + F(z_t)u_t \quad (4)$$
$$y_t = C(z_t)x_t + D(z_t)v_t + G(z_t)u_t \quad (5)$$

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

$$P(x_t | z_t, x_{t-1}) = N(A(z_t)x_{t-1} + F(z_t)u_t, B(z_t)B(z_t)^T) \quad (6)$$

$$P(y_t | x_t, z_t) = N(C(z_t)x_t + G(z_t)u_t, D(z_t)D(z_t)^T) \quad (7)$$

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.

E. 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.

$$P(x_{0:t}, z_{0:t} | y_{1:t}) = P(x_{0:t-1}, z_{0:t-1} | y_{1:t-1}) \times \frac{P(y_t|x_t,z_t)P(x_t,z_t|x_{t-1},z_{t-1})}{P(y_t|y_{1:t-1})} \quad (8)$$

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

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

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

$$\hat{P}_N(z_{0:t}|y_{1:t}) = \sum_{i=1}^{N} w_t^{(i)} \delta_{z_{0:t}^{(i)}}(z_{1:t}) \quad (10)$$

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

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

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:

$$\mu_{t|t-1}^{(i)} = A(z_t^{(i)})\mu_{(t-1|t-1)}^{(i)} + F(z_t^{(i)})u_t \quad (12)$$

$$\Sigma_{t|t-1}^{(i)} = A(z_t^{(i)})\Sigma_{t-1|t-1}^{(i)} A(z_t^{(i)})^T + B(z_t^{(i)})B(z_t^{(i)})^T \quad (13)$$

$$S_t^{(i)} = C(z_t^{(i)})\Sigma_{t|t-1}^{(i)} C(z_t^{(i)})^T + D(z_t^{(i)})D(z_t^{(i)})^T \quad (14)$$

$$y_{t|t-1}^{(i)} = C(z_t^{(i)})\mu_{(t|t-1)}^{(i)} + G(z_t^{(i)})u_t \quad (15)$$

$$\mu_{t|t}^{(i)} = \mu_{t|t-1}^{(i)} + \Sigma_{t|t-1}^{(i)} C(z_t^{(i)})^T S_t^{-1(i)} (y_t - y_{t|t-1}^{(i)}) \quad (16)$$

$$\Sigma_{t|t}^{(i)} = \Sigma_{t|t-1}^{(i)} - \Sigma_{t|t-1}^{(i)} C(z_t^{(i)})^T S_t^{-1(i)} C(z_t^{(i)}) \Sigma_{t|t-1}^{(i)} \quad (17)$$

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 (9), we find that the importance weights for z_t are given by the predictive density.

$$\mathrm{P}(y_t|y_{1:t-1}, z_{1:t}) = N(y_t; y_{t|t-1}, S_t) \quad (18)$$

F. 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 $\hat{z}_t^{(i)} \sim P_r(z_t|z_{t-1}^{(i)})$

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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

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

Updating step

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

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

G. Maximum Likelihood Estimation (MLE)

The measured intensity of a pixel can be considered as a random variable that takes a value I in the space of observations Ω. Given an observed I, the probability that it resulted from a true intensity I' of scene radiance is given by the conditional probability density $P(I|I')$. Alter *et al.* [5] presents a similarity measure based on ML estimation. From two observations, it first estimates the true intensity I^*, and then derives similarity as the product of conditional probabilities:

$$I^* = \underset{I'}{argmax}\, p(I_1|I')p(I_2|I') \quad (19)$$

$$S_{ML}(I_1, I_2) = p(I_1|I^*)p(I_2|I^*) \quad (20)$$

The ML similarity S_{ML} is defined as the likelihood of two intensity observations resulting from the single true intensity I^* that gives the greatest likelihood.

H. Parallel Pixel Processing

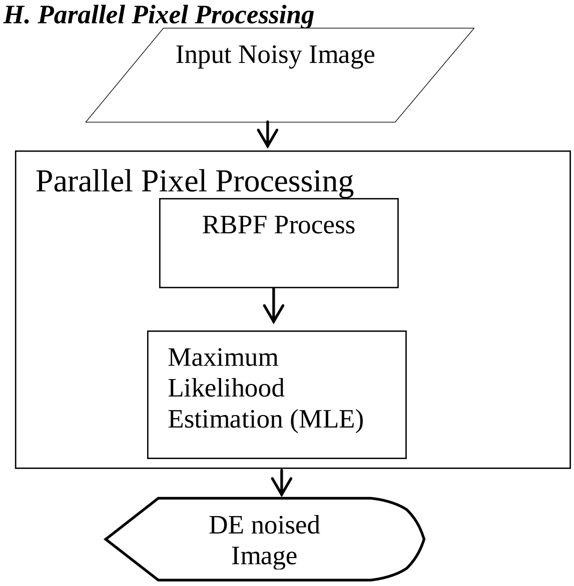

Fig. 2 Block diagram of Proposed Method

The major factor of speed of the proposed algorithm is due to a number of optimizations performed on of basic algorithm, such as reduction of expensive mathematic operations, better memory management and noisy pixel manipulation. Fast Flow-based high-level parallelization of the algorithm that is able to exploit parallelism. In this filters can be parallelized in a data-parallel fashion.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed algorithm is tested using 256 X 256 8-bits/pixel standard gray scale images. The dataset satellite images have taken from internet. The performance of the proposed algorithm is tested with different noisy images. These noisy images are denoised by four algorithms such as particle filter, MRF particle filter, RBPF and the proposed approach RBPF with MLE and PPP. The performance measured by the parameters PSNR, MSE and NAE. The Denoising performance of the proposed algorithm and other standard methods are tested different satellite images. All the filters are implemented in Mat Lab 10. The algorithm was evaluated according to two main metrics:

1) Noise identification and restoration quality, and

2) Execution time.

Denoising and restoration performance was measured by the peak signal-to-noise ratio (PSNR) and the mean absolute error (MAE) and Normalized Absolute Error (NAE) is defined follows:

$$PSNR = 10 \log_{10} \frac{255^2}{MSE} \quad (21)$$

$$MSE = \frac{1}{\|\Omega\|} \sum_{x \in \Omega} \left(U(x) - \hat{U}(x)\right)^2 \quad (22)$$

$$NAE = sum\left(sum(ABS(error))\right) / sum(sum(origImg)) \quad (23)$$

$$Error = origImg - distImg$$

A. Tables and Figures

Table 1: PSNR Values for the Denoised Satellite Images of Different Estimated Gaussian Noise Levels

Images	Noise Level	PF	MRF	RBPF	RBPF+ MLE+P PP
Image1	8.128	33.326	36.859	41.252	43.585
Image2	3.071	35.913	38.902	42.894	45.027
Image3	10.709	32.331	35.869	41.339	42.682
Image4	16.437	32.080	35.756	40.679	42.689
Image5	5.718	34.323	37.555	42.153	44.011

Table 2: MSE Values for the Denoised Satellite Images of Different Estimated Gaussian Noise Levels

Images	Noise Level	PF	MRF	RBPF	RBPF+ MLE+P PP
Image1	8.128	2.320	1.563	0.911	0.719

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Image2	3.071	1.603	1.164	0.746	0.575
Image3	10.709	2.682	1.800	0.909	0.818
Image4	16.437	2.780	1.827	0.983	0.817
Image5	5.7178	2.055	1.435	0.819	0.679

Table 3: NAE Values for the Denoised Satellite Images of Different Estimated Gaussian Noise Levels

Images	Noise Level	PF	MRF	RBPF	RBPF+ MLE+ PPP
Image1	8.128	0.052	0.035	0.021	0.016
Image 2	3.071	0.031	0.022	0.014	0.011
Image 3	10.70 9	0.054	0.035	0.018	0.016
Image 4	16.43 6	0.060	0.039	0.021	0.018
Image 5	5.718	0.046	0.032	0.019	0.015

Table 4: Comparison of Computation Time in Seconds between Rao-Blackwellized Particle Filter and Rao-Blackwellized Particle Filter with MLE and PPP

Images	Noise Level	RBPF	RBPF+MLE+PPP
Image1	8.128	548.827	68.932
Image 2	3.071	566.924	33.073
Image 3	10.709	563.290	78.131
Image 4	16.437	589.147	73.792
Image 5	5.718	590.940	82.359

Computation Time: The CPU time of the proposed method is compared to PF and MRF is given in the table.4. For all satellite images are corrupted with different noise levels and applied to the various de-noising methods. All the methods are implemented in MATLAB 10 on a PC equipped with INTEL (R) Pentium (R) Dual CPU, 1.73 GHz and 896 MB of RAM memory. In all cases the proposed method takes as an average of 490 seconds lower than RBPF to restore the original image. The proposed method improved the overall quality of restoration and execution time faster when compared to RBPF.

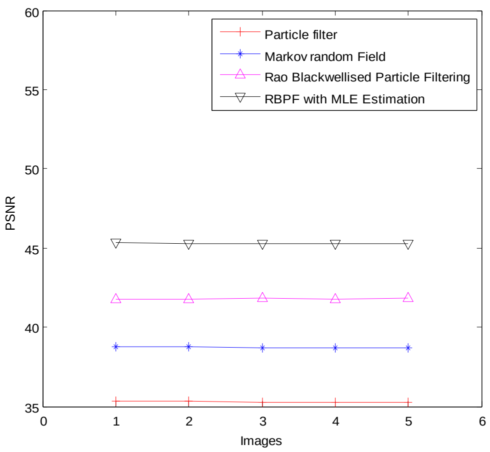

Fig.3. (a) PSNR of particle filter, MRF particle filter, RBPF & RBPF with MLE for 5 satellite images at various estimated noise levels

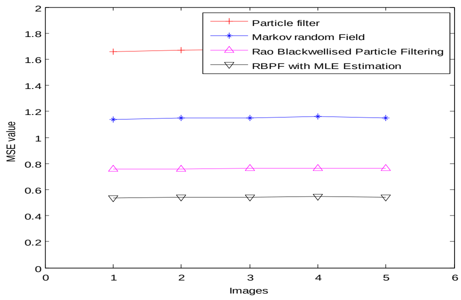

Fig.3. (b) MSE of the particle filter, MRF particle filter, RBPF and RBPF with MLE for 5 satellite images at various estimated noise levels

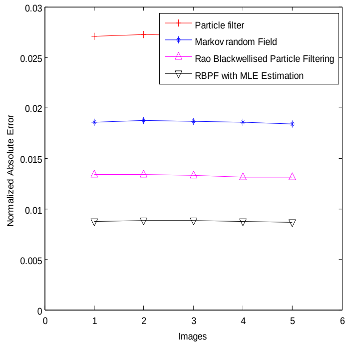

Fig.3. (c) NAE of the particle filter, MRF particle filter, RBPF and RBPF with MLE for 5 satellite images at various estimated noise levels

Fig.4. (a) Result of Denoised image1 using PF (PSNR 33.3263, MSE 33.3263 and NAE 0.0521)

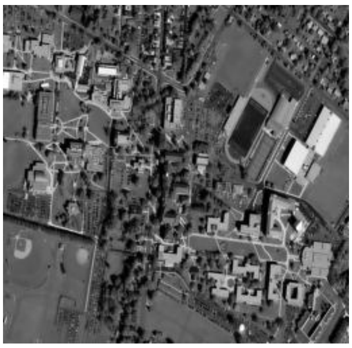

Fig 4. (b) Result of Denoised image1 using MRF-PF (PSNR 36.8585, MSE 1.5627 and NAE 0.0351)

Fig 4. (c) Result of Denoised image1 using RBPF (PSNR 41.2522, MSE 0.9109 and NAE 0.0207)

Fig 4. (d) Result of Denoised image1 RBPF+MLE (PSNR 43.5853, MSE 0.7186 and NAE 0.0161)

B. Discussion

Simulations are carried out to verify the noise removing capability of the RBPF with MLE and PPP and the results are compared with several existing filters. Experiments are conducted on satellite gray scale test images corrupted by Gaussian noise. The performances in terms of PSNR, MSE and NAE for all the methods are given in Table 1, Table 2, and Table 3. The same are plotted in Fig.3.a, Fig.3.b and Fig.3.c. The visual quality of the results is presented in Fig.4. In all graphs the x-axis values are represented as image1, image2, image3 etc., which denotes satellite images. The PSNR results of restored satellite images for the particle filter, the MRF particle filter, RBPF and RBPF with MLE are included in Table 1. The MSE results of restored satellite images for the particle filter, MRF particle filter, RBPF and RBPF with MLE are included in Table 2. The NAE results of restored satellite images for the particle filter, the MRF particle filter, RBPF, and RBPF with MLE are included in Table 3. As seen the results of all above said tables the RBPF with MLE method produces very good results. The visual quality results are presented in Fig.4. Restored image using particle filter, using MRF particle filters RBPF and using RBPF with MLE for the satellite image1 at Estimated noise $\sigma =$ 8.1278 as shown in Fig.4.(a), (b), (c)and (d) respectively. The visual quality and quantitative results clearly show the RBPF with MLE perform much better than a particle filter, MRF particle filter and RBPF in terms of PSNR, MSE and NAE.

V. CONCLUSION

In this paper, a fast and efficient algorithm is presented to restore Gaussian noise corrupted digital images. This method computes a highly accurate proposal distribution based on the maximum likelihood observations and to increase the performance by performing the process in parallel for all pixels. This approach has been implemented and evaluated on real noisy satellite images. Experimental results show that the proposed algorithm has less Mean Square Error, less Normalized absolute Error and higher Peak Signal Ratio than other methods. The RBPF with MLE outperforms the PF, MRF and RBPF in noise removal both objectively and visually. As a result, the overall quality of the restored image is significantly improved. The proposed method works well for satellite images. Good importance distributions and efficient.Rao-Blackwellized particle filters lead to more accurate estimates than standard PFs. Limitation for the Rao-Blackwellized 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.

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AUTHOR'S PROFILE

Dr. Anna Saro Vijendran received Ph.D. Degree in Computer Science from Mother Teresa Women's' University, Tamil Nadu, India, in 2009. She has 20 years of experience in teaching. She is currently working as the Director, MCA in SNR Sons College, Coimbatore, Tamil Nadu, India. She has presented and published many papers in International and National conferences. She has authored and co-authored more than 30 refereed papers. Her professional interests are Image Processing, Image fusion, Data mining and Artificial Neural Networks.

Mrs. Bobby Lukose received her Master degree in Computer Applications from Manonmaniam Sundaranar University of Tamil Nadu in the year 1997 and also received MPhil degree in Computer Science from Bharathiar University of Tamil Nadu in the year 2008. Currently she is working as Associate Professor, PG and Research Department of Computer Science at Hindustan College of arts and Science, Coimbatore. She has more than 15 years of experience in teaching. She is also doing PhD in Computer science at SNR Sons College, Coimbatore, under the supervision of Dr. Anna Saro Vijendran Director & Head, Department of Computer Applications, S.N.R Sons College. Her research interests include Image Processing and Data mining. She is the academic community member of ICGST Journal of Graphics, Vision and Image Processing.