ISSN 2250-3153

Image de-noising using Markov Random Field in Wavelet Domain

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Abstract Removing noise from original image is still a challenging problem for researchers. There have been several published algorithm and each approach has its assumptions, advantages and disadvantages. Markov Random Field is n-dimensional random process defined on a on a discrete lattice. Markov Random Field is a new branch of probability theory that promises to be important both in theory and application of probability. This paper is an attempt to present the basic idea of the subject and its application in image denoising to the wider audience. In this paper, a novel approach for image denoising is introduced using ICM (Iterated Conditional Modes) approach of Markov Random Fields model.

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Index Terms- ICM (Iterated Conditional Modes), Image denoising, Markov Random Field, Wavelet.

I. INTRODUCTION

Many problems in Image processing can be cast in the framework of state estimation, in which we have state variables whose values are not directly accessible and variables whose values are available. Variables of the latter kind are also referred to as observations in this context. Usually there exists a statistical relationship between the state variables and the observations such that we can infer estimates of the states from the observations. In many cases prior knowledge about the states is also available (usually in form of a probability distribution on the state variables) and we can use that knowledge to refine the state estimate.

In a variety of interesting problems, however, neither the statistical relationship between the state variables and the observations nor the prior distribution are perfectly known and hence are modeled as parameterized distributions with unknown parameters. These parameters are then also subjected to estimation.

In the domain of physics and probability [1], a Markov Random Field (often abbreviated as MRF), Markov network or undirected graphical model is a set of random variables having a Markov property described by an undirected graph [2]. A Markov Random Field is similar to a Bayesian network in its representation of dependencies; the differences being that Bayesian networks are directed and acyclic, whereas Markov networks are undirected and may be cyclic. Thus, a Markov network can represent certain dependencies that a Bayesian network cannot (such as cyclic dependencies).

II. RANDOM MARKOV FIELD THEORY

Markov Random Fields (MRF) are a natural extension to the concept of Markov Chains [3]. A MRF is described by a undirected graph. The vertices in a MRF stand for random variables and the edge impose statistical constrains on these random variables. Specifically, based on the standard MRF theory, the indexed set of random variables.

$$H = \{ h[i,j : 0 \le i \le M-1, \quad 0 \le j \le L-1\}]$$

is assumed to satisfy the following two conditions:

$$p(h[i,j]) > 0$$

$$p(h[i,j] \mid H \setminus h[i,j]) = p(h[i,j] \mid N[i,j])$$

Where H \h[i,j] is the entire set of random variables H without the element h[i,j] and N[i, j] represents the set of h[i,j]'s neighboring vertices. It is well known which consequences this setup has on the joint distribution of the random variables in H. Before we can elaborate on these however, we need to introduce the concept of a cilque [4][5][6]. A subset of H is called a clique if it is a singleton or if every pair of elements h[i,j] in that subset is neighbors in the corresponding graph. The lattice shaped MRF considered in this paper is depicted in Figure 1.

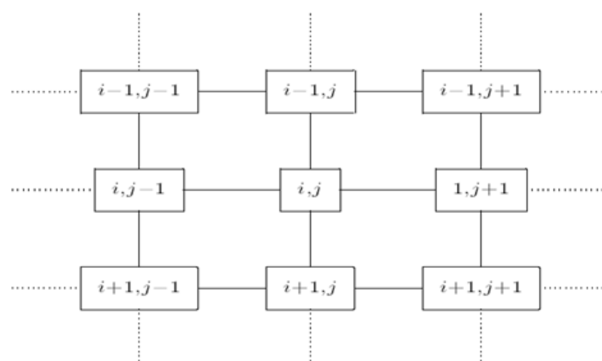


Figure 1: Lattice shaped MRF

We easily identify a single clique for each vertex h[i,j] and also identify cliques of the form {h[i,j], h[i,j-1]} or {h[i,j], h[i-1,j]} for each pair of adjacent vertices. According to the Hammersley-Clifford theorem [3] an MRF has equivalent Gibbs distribution is given by

$$p(H) \sim \exp\left(- \frac{\sum_{b \in B} V_b\left(\bar{b}\right)}{K} \right)$$

Where K is the temperature parameter chosen to be unity in this paper. The argument of the exponential function includes a sum of clique potentials Vb(b) over all the possible cliques B, with b denoting a vector composed of the set of vertices h[i,j] within the clique b. The clique potentials Vb(b) are simply defined to be non-negative functions of their arguments. In this paper we take the potential of pairwise cliques as the square of adjacent differences:

$$\mathrm{Vb}(b) = \alpha_{[i_b,\, j_b],[m_b,\, n_b]} \,|\, (h[ib,\, jb] - \mu[\,jb]) - (h[mb, nb] - \mu[nb])\,|^2$$

Where, [ib, jb] and [m] are the coordinates of the vertices in the one pair clique b and a b, nb[ib, jb], [mb,nb], $\mu[jb]$ and μ [n] are parameters. The potentials f single cliques that are associated with a random variable h [I,j] with index I = 0 form a Gaussian distribution b.

$$\mathrm{Vb}(b) = \alpha_{[\,j_b]} \,|\, h[ib,\, jb] - \mu[\,jb]\,|\, 2$$

With the parameters $\mu[jb]$ and $\alpha_{[\,j_b]}$. The other potentials are assumed to be zero. So we have

$$p(\mathbf{H}\,|\,\theta) = \mathrm{Z}(\theta)\text{-}1 \prod_{\mathrm{b}\in \mathrm{B}_1} \exp(-\alpha_{[\,j_b]} \,|\, h[ib,\, jb] - \mu[\,jb]\,|^2$$

$$\prod_{b\in B_2} \exp(-\alpha_{[i_b,\, j_b],[m_b,\, n_b]} \,|\, (h[ib,\, jb] - \mu[\,jb]) - (h[mb, nb] - \mu[nb])\,|^2)$$

Where, the vector θ contain all the model parameters i.e. the $\alpha[i_b, j_b],[m_b, n_b]$, the $\alpha[\,j_b]$ and the $\mu[\,jb]$. The set B1 comprises all single cliques that correspond to random variables h[i,j] with index i=0 and the set B2 contains all the pairwise cliques. Z(θ) is normalization constant and is also referred to as the partition function in this context.

III. OPTIMAZATION

An optimization problem is one that involves finding the extreme of a quantity or function. Such problems often arise as a result of a source of uncertainty that precludes the possibility of an exact solution. Optimization in an MRF problem involves finding the maximum of the joint probability over the graph, usually with some of the variables given by some observed data. Equivalently, as can be seen from the equations above, this can be done by minimizing the total energy, which in turn requires the simultaneous minimization of all the clique potentials are plentiful. Many of them are also applicable to optimization problems other than MRF. For example, gradient descent methods are well-known techniques for finding local minima, while the closely-related method of simulated annealing attempts to find a global minimum.

An example of a technique invented specifically for MRF optimization is Iterated Conditional Modes (ICM)[7]. This simple algorithm proceeds first by choosing an initial configuration for the variables. Then, it iterates over each node in the graph and calculates the value that minimizes the energy given the current values for all the variables in its neighborhood. At the end of iteration, the new values for each variable become the current values, and the vext iteration begins. The algorithm is guaranteed to converge, and may be terminated according to a chosen criterion of convergence.

IV. MRF APPLICATION TO IMAGE DENOISING

Problems in computer vision usually involve noise, and so exact solutions are most often impossible. Additionally, the latent variables of interest often have the Markov property. For example, the pixel values in an image usually depend most strongly on those in the immediate vicinity, and have only weak correlations with those further away. Therefore, vision problems are well suited to the MRF optimization technique. Image denoising is one of the computer vision problem to which MRF has been applied. Having constructed an MRF, the clique potentials must be defined [7][8]. This encodes the relationship between variables, and so this is where we get to specify what we want from the solution. Finding an appropriate energy function and selecting the parameters that give an acceptable solution requires insight, as well as trial and error. However, there are many often-used, standard energy functions for different types of problem.

V. PROPOSED ALGORITHM

Following algorithm was used while denoising images using the MRF technique.

1. Choose an initial condition for the variables
2. Iterate over each node of the graph
3. Calculate the value that minimizes the energy given the current values for the variables in neighborhood.
4. After every iteration, the new value for each variable becomes the current value and the next iteration begins.
5. Calculate Vmax using the following formula :

$$V_{\max} = rc\left(\frac{256^2}{2n} + 4 * w * \max P\right)$$

Where, Vmax: a larger value than potential of any pixel
R: row count of image
C: column count of image
N: noise variance
W: weights and maxP: maximum potential of the neighboring pixels

6. Initial local potential value with the highest potential value for each pixel at each iteration and minimum value below which no pixel will descend.
7. Calculate the component due to known image data (from noisy image)

$$Vdata = \frac{(pInt - \mathrm{Im}\, gPix)^2}{2n}$$

Where,
Vdata: component due to known image data (from noisy image)
pInt: intensity value
ImgPix: image pixel value

8. Calculate component due to difference btw neighboring pixel values

$$Vdata = \min((\,pInt - \mathrm{Im}\, gPix)^2, diffM\,)$$

Vdiff: component due to difference between neighboring

pixels
diffM: maximum contribution to the potential of the difference between two neighboring pixel values.

9. The current potential value for a pixel is calculated as :

$$V_{current} = V_{data} + diffW * V_{diff}$$

diffW: weighting attached to the component of the potential due to the difference between two neighboring pixel values.

This is a simple algorithm to be implemented on the noisy image. But, there are some other information that has to be kept in mind while evaluating this algorithm. The value of Vlocal is initialized for each pixel of input image will be processes for all the algorithm and testing for too many cases, we have concluded the following values best suited for optimum results:

i. Minimum value (step) should be kept -1. diffM should be 200.
ii. diffW should be 0.02 and a particular image should be processed for 10iterations.
iii. A pixel value will be changed if and only if Vcurrent<Vloca, otherwise that pixel value is left unchanged.
iv. And when the pixel value is changed, Vlocal is set to Vcurrent for next intensity processing. Also keep alternating the image and output image. This way, we can attain the best possible solution.

VI. RESULT

The performance of RMF method is illustrated with a quantitative and qualitative performance measure. The qualitative measure is the visual quality of the resulting image. The Peak-signal-to-noise (PSNR) is used as the quantitative measure. Different images, like natural, medical, aerial and under water, are used with four different noise, Gaussian, salt and pepper, speckle and Poisson. Fig (1), (4) and (7) show aerial, medical and underwater images respectively. Fig(2), (5) and (8) show original images with Gaussian , Poisson and speckle noise with PSNR values 30.9688 dB, 27.8729 dB and 27.247dB . And fig. (3), (6) and (9) are the denoised images with PSNR 38.5907dB, 35.324dB and 32.2061dB. (4) and (7) show aerial, medical and underwater images respectively. Fig(2), (5) and (8) show original images with Gaussian , Poisson and speckle noise with PSNR values 30.9688 dB, 27.8729 dB and 27.247dB . And fig. (3), (6) and (9) are the denoised images with PSNR 38.5907dB, 35.324dB and 32.2061dB.

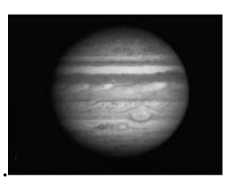
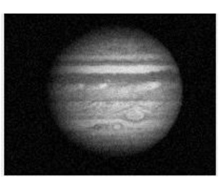


FIGURE 2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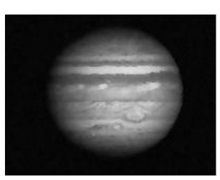
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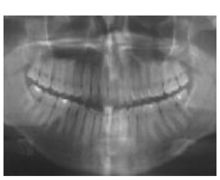
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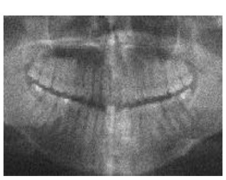
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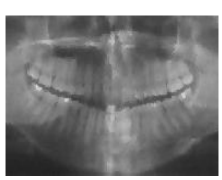
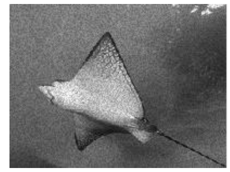


FIGURE 7


FIGURE 8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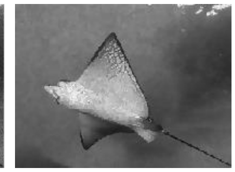
FIGURE 10

VII. CONCLUSION

To improve the denoising performance and reduce the computational complexity, a denoising method based on MRF models is wavelet domain is proposed in this paper. Experiment result demonstrate that this method has a good denoising performance, while the image is having Gaussian noise it gives the best output for aerial images, similarly, image with Poisson noise gives best suited output for medical images whereas image with Speckle noise gives best output for underwater images.

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