IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727
PP 33-36
www.iosrjournals.org

Enhancement Of Image Resolution Using Rg Algorithm And Bayesian Inla Approximation

M. Hemalatha
Assistant Professor Urumu Dhanalakshmi College Kattur, Trichy

Abstract: *Super-resolution (SR) is a technique to enhance the resolution of an image without changing the camera resolution, through using software algorithms. In this context, this paper proposes a fully automatic SR algorithm, using a recent nonparametric Bayesian inference method based on numerical integration, known in the statistical literature as integrated nested Laplace approximation (INLA). By applying such inference method to the SR problem, this paper shows that all the equations needed to implement this technique can be written in closed form. Moreover, the results of several simulations show that the proposed algorithm performs better than other SR algorithms recently proposed.*
Keywords: *Bayesian inference, Closed form, Integrated Nested Laplace Approximation (INLA), Nonparametric, Super-resolution (SR)*

I. Introduction

The main objective of this paper is to merge a sequence of Low Resolution (LR) images in a single High Resolution (HR) or Super Resolution (SR) Image. The motivation to study SR is that for many applications demanding HR images, such as remote sensing, surveillance, medical imaging, and the extraction of still images from a video, to increase the resolution through improved image acquisition sensors is not feasible because of the additional cost. Thus, the use of image processing techniques to improve the image resolution plays an important role in many applications.

The RG algorithm is used to enhance HR images from overlapping, offset, LR images.

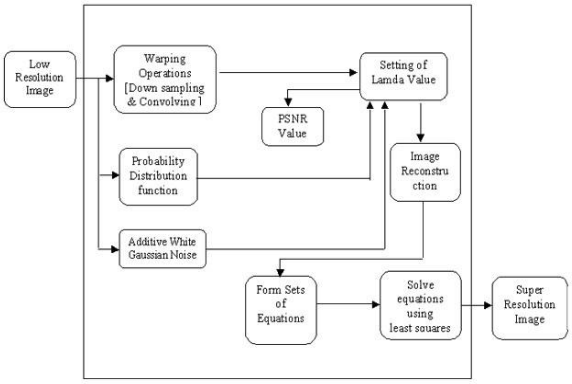
It is utilized for High Resolution applications. RG with recent Non-Parametric Bayesian Inference based on INLA. (Integrated Nested Laplace Approximation). It is used for Image Reconstruction. INLA-first time used in image processing.

II. MCMC Method (Markov Chain Monte Carlo Method)

SR reconstruction is an example of an ill-posed inverse problem, since multiple solutions exist for a given set of observation images. In a certain way, the well-known MCMC (the Markov chain Monte Carlo) method and the INLA (integrated nested Laplace approximation) inference algorithm are similar: both are methods of statistical inference in Bayesian frameworks.

However, while MCMC can be applied to any model of the priori, posteriori or likelihood probability distribution function, the INLA only can be applied to latent Gaussian models, where the covariance matrix is governed by a few parameters and the latent field is a Gaussian Markov random field (GMRF) with a sparse precision matrix Q. Thus, in the general case of Bayesian statistical inference, the MCMC should be used. The limitations are

- Images Edges are not sharper
- Output images are noisier.
- PSNR value is not good.
- Does not produce superior images.
- Motion was not restricted
- Unlimited shifts and rotations must be used
- It needs correct registration points..



III. Proposed System

A new and powerful nonparametric inference method, not used so far has been proposed in the image-processing field and has been successfully exploited and applied to the problem of SR image reconstruction.
We propose software algorithm for enhancing image resolution by matching inaccurate sub – pixel. In 2001, Fryer John and Kerry McIntosh presented a TRIGOROUS GEOMETRIC (RG) algorithm. It is used to enhance a higher resolution image from several overlapping, and slightly offset, images of low-resolution image (Fryer, 2001). The Two methods are Observation model and Least – Square model.

The result is an approach that consistently achieves superior image reconstruction results when compared to other state-of-the-art methods. The interference method, referred to as INLA, is a new Bayesian statistical inference method, based on approximations of the probability density functions and numerical integration, in a nonparametric way.

3.1 Advantages

- RG is used for applications successful with HR
- It is not more sensitive to noisy input messages
- INLA – it achieves superior image reconstruction results
- INLA can generate sharper edge images.
- High PSNR value & Improved Image Quality.
- Superior image reconstruction results.

3.2 PROPOSED SYSTEM ARCHITECTURE

IV. Algorithms Used

4.1 BAYESIAN INLA ALGORITHM

Bayesian INLA provides fast and accurate Bayesian approximation to posterior marginals in latent Gaussian models (Rue et al., 2009). Latent Gaussian models are a wide class of hierarchical models in which the response variables y = (y1,……..,yn) are assumed to be conditionally independent given some latent parameters η = (η1,…….., ηn) and other parameters θ1. The second hierarchical level corresponds to specifying θ as a function of a GMRF x = (x1; : : : ; xn) with a precision matrix Q and hyper parameters θ2, and the third and last hierarchical stage corresponds to prior specications for the hyperparameters θ = (θ1; θ2) Formally,

$$\pi(\mathbf{y}|\boldsymbol{\eta},\boldsymbol{\theta}_1) = \prod_j \pi(y_j|\eta_j(x_j),\boldsymbol{\theta}_1),$$

$$\mathbf{x} \sim MVN(\mathbf{0}, \mathbf{Q}^{-1}(\boldsymbol{\theta}_2)),$$

and

$$\boldsymbol{\theta} \sim P(\boldsymbol{\theta}).$$

An interface in R, called INLA, implements a wide variety of likelihoods, link functions (θ) and GMRFs, including the Poisson likelihood model for each observed value of yj (not necessarily the same for every yj) with a logarithmic additive link function and random walk of first order as a GMRF.
The algorithm starts by selecting a small set of λ values, based on the distribution p (λ|Y). First, the mode is located, and then some equally spaced points are spread over the domain. For each point λ in such grid two vectors are calculated, namely p (λk | Y) and p (xi | λk,Y). Then, the numerical integration Σk p (xi | λk ,Y) p

(λk |Y) $\Delta\lambda k$ is calculated, in a nonparametric way. Last, *p(xi |Y)* is re-scaled, by dividing each element of such vector by the sum of all elements, so that the sum of probabilities becomes equal to one.

STEPS:

Step 1: select a set of $\lambda = (\lambda 1, \ldots, \lambda\alpha)$;
Step 2: for k = 1 to α do;
Step 3: calculate $p(\lambda k |Y)$ as $\tilde{p}(\lambda|Y) \propto \left.\frac{p(X,\lambda,Y)}{\tilde{p}_G(X|\lambda,Y)}\right|_{X=\overline{X}}$
Step 4: calculate $p(\overline{xi} | \lambda k, Y)$ as a function of xi;
Step 5: end for;
Step 6: calculate $p(\overline{xi} | Y) = \Sigma k\, p(xi | \overline{\lambda k}, Y)\, p(\overline{\lambda} k |Y)\Delta\lambda k$;
Step 7: re-scale $p(\overline{xi} | Y)$;

Thus, the INLA SR algorithm here proposed:

Step 1: define the grid as $\lambda = (0.0005, 0.0010, \ldots, 0.01)$;
Step 2: for i = 1 to 20 do;
Step 3: calculate the vector $\mathbf{X}(i) = X(\lambda(i))$;
Step 4: calculate the vector $\mathbf{P}(i) = p(\mathbf{X}(i)|Y)$;
Step 5: end for;
Step 6: re-scale $\mathbf{P}(i)$, by dividing each element of the vector by the sum of all elements;
Step 7: calculate the HR image $X = \sum_{i=1}^{20} \mathbf{X}(i)\mathbf{P}(i)$.

4.2 TRIGOROUS GEOMETRIC (RG) ALGORITHM

The most important step of this algorithm is how to form the sets of equations in step 3. In the equations formation, the geometric relationships between coarse and fine pixels must be used. To develop the relationships, each pixel in the coarse images must be "mapped" onto the fine pixels coordinate system, thus determining which fine or unknown pixels are affected by each individual coarse pixel.

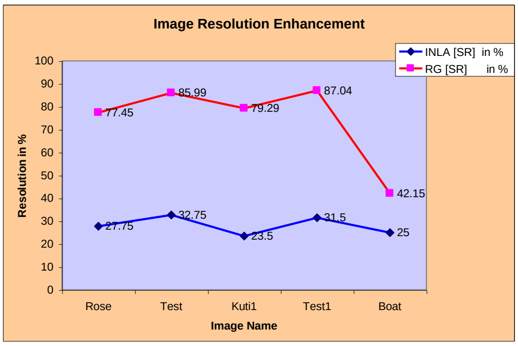
STEPS:

Step 1: Collect several low-resolution images, and select an enhancement ratio.
Step 2: Select an image as reference arbitrarily, and determine pixel offsets of each other image from the reference image.
Step 3: From sets of equations using the offsets as coefficients, the enhancement ratio, and the gray values of the low-resolution images as observations.
Step 4: Solve the sets of equations for higher resolution pixels using least squares.
Step 5: Display the resultant higher resolution image.

V. Evaluation Of A Reconstructed Sr Image

S.NO	TEST IMAGE	IMAGE TYPE	INLA [SR] in %	RG [SR] in %
1.	Rose	jpg	27.75	77.45
2.	Test	jpg	32.75	85.99
3.	Kuti1	jpg	23.5	79.29
4.	Test1	jpg	31.50	87.04
5.	Boat	bmp	25	42.15

5.1 PERFORMANCE EVALUATION



VI. Conclusion And Future WORK

A major advantage is a new and powerful nonparametric inference method, in the image-processing field, has been successfully exploited and applied to the problem of SR image reconstruction. The result is an approach that consistently achieves superior image reconstruction results when compared to other state-of-the-art methods. The interference method, referred to as INLA, is a new Bayesian statistical inference method, based on approximations of the probability density functions and numerical integration, in a nonparametric way. By applying INLA to the SR problem, this project showed that one could write all the equations necessary to implement the proposed technique in closed form. The INLA can be very useful in situations where the LR images are very noisy, particularly where the noise is Gaussian, because it can obtain HR images with sharper edges and less noise. The RG is the one that can generate super resolution images.

The same technique might be extended as a future implementation for enhancing resolution of video clips in a particular field such as medicine, crime detection etc.

References

[1] N. P. Galatsanos, V. Z. Mesarovic, R. Molina, and A. K. Katsaggelos, "Hierarchical Bayesian image restoration from partially-known blurs," *IEEE Trans. Image Process*., vol. 9, no. 10, pp. 1784–1797, Oct. 2000.

[2] M. Tipping and C. Bishop, "Bayesian image super-resolution," in *Advances in Neural Information Processing Systems,* Cambridge, MA: MIT Press, pp. 1303–1310, 2003.

[3] T. Pham, L. Van Vliet, and K. Schutte, "Robust fusion of irregularly sampled data using adaptive normalized convolution," *EURASIP J. Appl.Signal Process*., vol. 2006, pp. 1–12, Jan. 2006.

[4] M. Vetterli, "Superresolution images reconstructed from aliased images," in *Proceedings of SPIE/IS&T Visual Communications and Image Processing Conference, T. Ebrahimi and T. Sikora, Eds*., vol. 5150 of Proceedings of SPIE, Switzerland, 2003.

[5] P. Vandewalle, S. Süsstrunk, and M. Vetterli, "A frequency domain approach to registration of aliased images with application to superresolution," *EURASIP J. Appl. Signal Process*, vol. 2006, pp. 1–14, Mar. 2006.

[6] M. Irani and S. Peleg, "Motion analysis for image enhancement: Resolution, occlusion, and transparency," *J. Visual Commun. Image Represent*., vol. 4, no. 4, pp. 324–335, 1993.

[7] A. Patti, M. Sezan, and A. M. Tekalp, "Superresolution video reconstruction with arbitrary sampling lattices and nonzero aperture time," *IEEE Trans. Image Process*., vol. 6, no. 8, pp. 1064–1076, Aug. 1997.

[8] B. Tom and A. Katsaggelos, "An iterative algorithm for improving the resolution of video sequences," *Proc. SPIE Int. Soc. Opt. Eng*., vol. 2727, no. 3, pp. 1430–1438, 1996.