Efficient JPEG Reconstruction using Bayesian MAP and BFMT

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ABSTRACT - JPEG reconstruction can be considered as decompression and denoising. Standard decompression of JPEG images produces disturbing checkboard pattern and also artifacts along edges. Such problems can be reduced using Bayesian maximum a posteriori probability by (ADMM) alternating direction method of multipliers iterative optimization algorithm. In this type of problem, the prior knowledge about an image is usually given by L1 norm of learned frame prior. Bilateral filter is local and non linear which gives denoised image without smoothing edges by considering both gray level similarities and geometric closeness of neighbourhood pixels. The extension of bilateral filter such as multiresolution bilateral filter results in loss of some image details thereby resulting in cartoon like appearance. To solve this issues, for denoising, bilateral filter and its method noise thresholding (BFMT) using wavelets is proposed. This method has inferior performance compared to existing methods like bilateral filter, multiresolution bilateral filter, wavelet thresholding, NL means and kernal based methods. Quality of reconstruction by this approach is shown both visually and interms of SNR.

Key Words: JPEG, MAP, bilateral filter, wavelet thresholding, method noise.

I. INTRODUCTION

The standard way to store image data is by compression. Image compression can be lossy or lossless. The lossy compression using JPEG standard [1] has become a standard way to store image data. It is based on the quantization of discrete cosine transform (DCT) coefficients. The compression process results loss of information which is artifacts along strong edges and also visually disturbing checkboard pattern. So the JPEG decompression is considered as image reconstruction problem, since the adoption of the JPEG standard in 1992, the image processing community has worked in order to find the efficient methods for restoring the original data. Many JPEG decompression methods, from simple filters to more elaborate methods based on more rigorous statistical formulations for suppressing the checkboard pattern and smoothing along strong edges are used. The latter uses the maximum a posterior probability (MAP) principle as an approximation solution. The JPEG restoration, the log-likelihood is quantization constraint set (QCS), which is defined as the interval of DCT coefficients, rounding of which stored as integer coefficients in JPEG file [2]. The alternative is to approximate this QCS by a multivariate Gaussian function which makes optimization simplified and also convergence is speeded up [7]. Compared to QCS the Gaussian approximation of QCS, resulting function has no constraints thus makes optimization of the posterior probability simplified and speeds up convergence [6]. Bayesian approach with learned priors found its use in many image processing compressed sensing and machine learning applications. The difficulty we encounter in this is non smooth functions resulted in this are not easy to optimize by standard methods. This problem made spreading of various first order techniques for optimization of non smooth functions [10], these are fast and simple to implement. The most popular one is alternating direction method of multipliers (ADMM) [11]. It is also known as split-Bregman method, and the accelerated Arrow-Hurwicz algorithm.

The Gaussian approximation of quantization noise used in this gives efficient improved results, it has various advantages. The convergence is improved due to strong convex of the likelihood. It also improves reconstruction quality both visually and in terms of signal to noise ratio (SNR). Application of ADMM on the combination of Gaussian approximation of QCS is used based on our experience with ADMM in other problems. ADMM has asymptotical convergence properties, the behaviour of this is concentrated mainly for small number of iterations, which are relevant in most of the practical applications, this justifies the use of ADMM instead of accelerated primal-dual methods which convergence is improved by using strong convexity of the likelihood function. ADMM is competitive and sometimes even faster than for [13], this makes MAP based iterative methods practical as non-iterative methods.

The quality of reconstruction depends on mainly the choice of image prior probability distribution which is represented by the regularization function. Early many smooth priors are used like Huber function of spatial gradient [7] or quadratic function of gradient [2]. Later methods incorporated non differentiable sparse priors that provided state of art results for various image reconstruction problems [8] which includes the total variation, field of experts, total generalized variation(TGV), non local means, achieving good results at the cost of longer run times.

The total variation based JPEG decompression [3], uses the total variation as a regularization term and solving minimization problem by using primal dual algorithm. It is effective in reducing the noise without oversmoothing sharp boundaries but results shows block artifacts.

Adaptive non local means filter for image deblocking [9]. Non local means filter is anon linear edge preserving smoothing filter, and it can smooth blocking artifacts and preserve the edge details simultaneously. In this filter can be applied to image block and modify its pixel as the weighted sum of its neighbourhood pixels, whose weighted parameter are determined by similarity of image block neighbourhoods.

Later total generalized variation (TGV) proposed by same author [4] for variational image decompression, reconstruction and also zooming. The TGV functional generates total variation (TV) function by using higher order smoothness information. This avoids staircasing effect but it doesn't favour for natural images.

This can be done by using learned frame priors. They are self dual, efficient to compute and they preserve norm. Generally these are imposed when there is a need to reconstruct and stability of the reconstruction is an issue. Since these priors doesn't require inversion of matrices they seem to be a natural choice.

Bilateral filter [12] considers both spatial and intensity information, unlike conventional linear filter where only spatial information is considered. Researchers have devoted to the improvement of bilateral filtering algorithm[13]. Buades et al.proposes NL means filter, using similarity of local patches the pixel weights are determined.in [14], an empirical study of optimal bilateral filter parameter selection and proposed (MRBF) multi resolution bilateral filter. Bilateral filter on approximation subbands results loss in some image details, as after each level of wavelet reconstruction the gray levels becomes flatten which results in cartoon like appearance. This is due to the application of bilateral filter removes both noise as well as some details of image without edge information loss. To solve this issues, bilateral filtering and its method noise thresholding using wavelets is proposed for image denoising.

II. PROPOSED METHOD

In this approach, the decompression is based on Bayesian MAP. In Bayesian MAP, the posteriori probability of possible observations is estimated and then chooses highest probability image. According to this Bayesian, this posterior probability of possible solutions is proportional to the product of likelihood which is the error occurred in the compression process, and prior probability approximation. In this, instead of maximizing the probability, the negative log probability is minimized which becomes the product this two as sum of negative log likelihood and a regularization function.

The JPEG compression/decompression process is described by a sequence of operators

$$y = C^{-1} Q^{-1} [QCx] \quad (1)$$

where x and y are original and decompressed images respectively .The linear operators are Q and C. The Q is quantization operator and C is DCT operator. x and y are imaged as vectors, and the operators Q and C are matrices. C is block diagonal matrix obtained by square matrices of DCT.Q is diagonal matrix obtained by element wise operation of quantization coefficients by using quantization table which is stored in each JPEG file which means for 64 values for 8*8 blocks.

For given observation y, the probability distribution of possible solutions p(y/x) and a prior probability p(x). The bayesian MAP maximizes the posterior probability

$$p(x/y) \sim p(y/x)p(x) \qquad (2)$$

where from eq(2), P(x/y) the posterior probability, p(y/x) the likelihood probability, and p(x) is the prior probability. The prior used is learned frame prior which is obtained from the input image that is patches collected from input database [15]. This prior probability is represented by using regularization function. The optimum observation is estimated which is the likelihood probability by maximizing the posterior probability so that the estimated image is close to the original image. It is done by taking distribution of Gaussian, as the quantization is approximated as Gaussian. Joint pdf of Gaussian of possible observations gives product of two functions, which involves negative log likelihood and prior probability which is represented by regularization function. It becomes sum of log likelihood function which is the noise introduced during compression and regularization function eq(4) the sum of two functions is shown which is optimized by ADMM iterative algorithm.

For obtaining this optimized image using Bayesian MAP, it is done by ADMM algorithm as minimization of the two functions requires the iterative optimization algorithm which minimizes sum of two functions and obtains the optimized image. The sum of two log likelihood function and regularization function in Bayesian MAP is minimized by this ADMM algorithm eq(3).

$$\min_x f(x) + g(Gx) \quad (3)$$

The MAP solution for this model is a covex problem.

$$\arg\min_x \frac{1}{2\sigma_q^2} ||\tilde{y} - QCx||^2 + \tau||\emptyset^T x|| \quad (4)$$

$\tilde{y}$ from eq(4) is the quantization coefficients stored in JPEG format.$\tilde{y}$ = QCy. As quantization error is taken as Gaussian approximation. The Gaussian approximation function with variance σ_q^2 is taken as 12, where variance is unit quantization noise.

$$QCy = QCx + e, \quad e \sim N(0. I\sigma_q^2) \quad (5)$$

Where eq(6) τ is regularization operator which is used from image data base, thus to best fit observation to original image for full convergence. The regularization function is added to obtain the optimized image, as it minimizes the sum of absolute differences between estimated and target image. The regularization used is L1 to obtain optimized image using ADMM algorithm. The scalar parameter τ can be estimated from training data by the distribution fitted as

$$p(x) \propto \tau^N e^{-\tau|\emptyset^T x|} \quad (6)$$

Where the maximization of p(x) is done over all x satisfying the interval -0.5 < QCy - QCx ≤ 0.5, the quantization is taken uniform in this interval. N eq(7) is dimension of x. The maximum likelihood is obtained by setting derivative of above eq(6) distribution to 0, which gives the scalar parameter as

$$\tau = N/|\emptyset^T x| \quad (7)$$

The image is degraded by gaussian noise and then compressed by JPEG algorithm, which requires image denoising stage. When the image noise is stronger than quntization, the decompression alone is not sufficient to use. The required denoising is donen by using method noise thresholding as shown in fig(1).

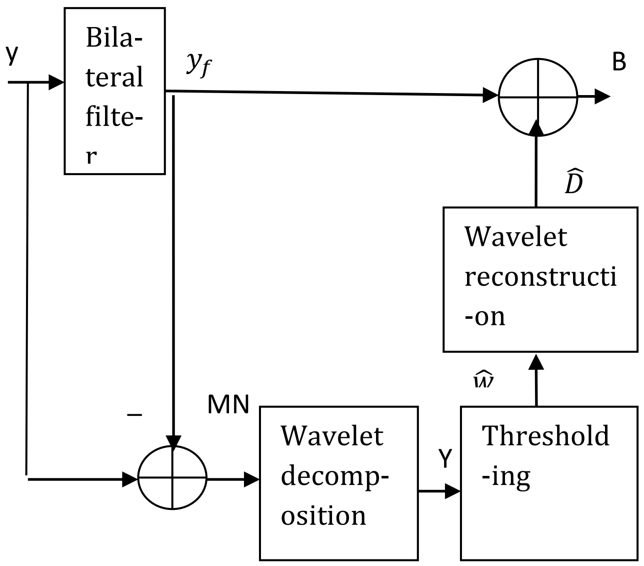

Figure-1: bilateral filter and method noise threshold denoising

The image denoising uses the combination of bilateral filter and its method noise thresholding using wavelets. Method noise is the noise removed by the algorithm, which is difference between original image and its denoised image. This method noise should look like a noise. Mathematically it is given by

$$MN = A - y_f \quad (8)$$

Where A is the original image and y_f is the output of denoising operator for given input image A.

The bilateral filter on noisy image averages noise and image details while preserving sharp boundaries well when the standard deviation of noise less than the edge contrast. To capture the removed part from noisy image by bilateral filter. The method noise is redefined as difference between noisy image and its denoised image. The eqn. (8) is rewritten as

$$MN = y - y_f \quad (9)$$

Where y = A+ Z is a noisy image obtained by corrupting the image A with white Gaussian noise Z and y_f is output of bilateral filter for input image y.

The bilateral filter has removed noise and image details by averaging the pixels, the method noise consist of noise and image details along with some edges. The combination of image details D and white Gaussian noise of method noise is written as

$$MN = D + N \quad (10)$$

The detail image D is estimated, which has original image features and edge boundaries that are removed by bilateral filter, and is added with bilateral filtered image y_f for better denoised image with details. Eqn (10) in wavelet domain is represented as

$$Y = W + N_w \quad (11)$$

Where Y is noisy wavelet coefficient which is method noise, W is true wavelet coefficient which is detail image and N_w is Gaussian noise. In wavelet domain the aim is to estimate true wavelet coefficient W from Y by thresholding with proper value so that MSE is minimized and retains the original image and sharp boundaries well in denoised image. The estimate of image detail $\hat{D}$ is obtained from the estimate of true wavelet coefficient $\hat{W}$ and its wavelet reconstruction. The summation of $\hat{D}$ and bilateral filtered image y_f gives denoised image B. The denoised image has more image details and edges compared to Gaussian filtered image y_f.

The BayesShrink gives better MSE than SureShrink, it is used in this method to threshold method noise wavelet coefficients. BayesShrink is an adaptive data driven thresholding by soft thresholding by means of deriving the threshold in a Bayesian approach with assumption of generalized Gaussian distribution. For a given subband the threshold obtained by minimizing Bayesian risk is given by

$$T=\frac{\sigma^2}{\sigma_w} \qquad (12)$$

Where σ^2 is noise variance estimated from subband by median estimator (3) given as

$$\hat{\sigma}=\frac{\text{Median}(|Y_{i,j}|)}{0.6745},\ Y_{i,j}\in\{HH_1\} \qquad (13)$$

σ_w^2 is variance of wavelet coefficient in that subband, the estimate of it is computed using

$$\hat{\sigma}_w^2=\max(\hat{\sigma}_y^2-\hat{\sigma}^2, 0) \qquad (14)$$

Where $\hat{\sigma}_y^2=\frac{1}{MN}\sum_{i,j=1}^{M,N} Y^2_{i,j}$ (15)

III.RESULTS AND DISCUSSION

Experiments were carried out on the image of size 256*256 as shown in fig(2). The Decompression done by Bayesian approach is shown in fig(3), and denoised image by bilateral filter and its method noise thresholding using wavelets improved image reconstruction as shown in fig (4). The table 1 shows results of JPEG decompression by Bayesian approach in terms of PSNR, MSE, NMSE. The denoised image is shown in terms of improved SNR in table 2, where the denoising process on image corrupted by white Gaussian noise with zero mean and standard deviation of 10 is considered. The denoising algorithm should not change the noise free images, so that even for some kind of regularity for image is assumed, the method noise should be very small. The method noise should look like a noise for very good denoising methods.

Figure 2: original image

Figure 3: Decompressed image

Figure 4: Denoised image

TABLE 1:

Parameter	Bayesian approach
PSNR	27.50
MSE	7.22
NMSE	0.001

TABLE 2:

parameter	Bilateral	Method noise threshold
PSNR	28	32
MSE	2.6	0.9

IV. CONCLUSION

The fast solution of this transform matrix algorithm of compression and JPEG decompression based on MAP formulation with prior information by ADMM has been presented. The denoising is done by bilateral filter and its method noise thresholding using wavelets. The performance is compared with bilateral filter method. With less computational complexity, this method shows superior performance to that of bilateral filter. The combination of Gaussian approximation with QCS and the priors used for image decompression also improves SNR, this counter intuitive fact probably results from the partial inadequancy of priors preferring smooth functions in our situation, where high frequencies are damages by JPEG compression Gaussian approximation favors solutions closer to original JPEG decompression, which prevents the algorithm to make result too smooth, as a result the reconstruction is improved and shown in terms of SNR. It can be extended to resolution enhancement of compressed videos. The denoising performance can be improves by employing shift invariant transform for method noise decomposition with computing better threshold value and thresholding techniques.

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