A Denoising Filter Design based on No-Reference Image Content Metric

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***Abstract*— DIGITAL images are subject to a wide variety of distortions during acquisition, processing, compression, storage, transmission and reproduction. Any of these may result in degradation of their visual quality. Hence, there has been an increasing need to develop quality measurement techniques that can predict perceived image/video quality automatically. These methods are useful in various image/video processing applications such as compression, communication, printing, display, analysis, registration, restoration, and enhancement. Subjective quality metrics are considered to give the most reliable results since, it is the end user who is judging the quality of the output in many applications. Subjective quality metrics are costly, time-consuming and impractical for real-time implementation and system integration. On the other hand, objective metrics like full-reference, reduced-reference, and no-reference metrics are most popular. This paper proposes an ideal no-reference measure that is useful for the parameter optimization problem and it takes care of both noise and blur on the reconstructed image into account. The experimental results have shown that the technique works well with images with various kinds of noise.**

Keywords-- Image Visual quality, Objective Metrics, No-Reference Metrics, Image noise, Parameter Optimization,Steering Kernel Regression Algorithm

I. INTRODUCTION

Humans have a remarkable capacity to perceive the content of an image or a scenario even when it is disturbed by noise, blur, and other factors. In other words human brain is able to register *true image content* even when the pixels are highly corrupted across the image. It is self-evident then that a computable, quantitative measure of image content would be highly desirable. This is a scalar Quantitative measure (Q) for a given true image content. This measure is properly correlated with the noise level, sharpness and intensity contrast of the structured regions of an image. For any given image, the nominal value of Q reacts in a natural way to the presence of noise and blur. That is, its value generally drops if the variance of noise rises, and/or if the image content becomes blur. With the definition of Q in hand, illustration is that it can be effectively used to maximize the performance [1] of some leading denoising algorithms.

In image and video processing, nearly all algorithms have various parameters which need to be set in order to yield good results. In practice, usually the choice of such parameters is made empirically with trial and error if no 'ground-truth' reference is available. Setting of parameters for denoising algorithms is huge task. Generally, larger the parameter is, smoother the image content becomes (small variance), while more useful detail and edges are flattened or blurred (larger bias). Similarly, parameter is smaller, it leads to more number of computations for restoring the images from noise. If the number iteration increases it also increases the computation time and complexity.

The proposed technique involves an ideal no-reference measure that is useful for the parameter optimization problem when algorithms need to take both noise and blur on the reconstructed image into account. However, most sharpness metrics can hardly distinguish image quality decay against high frequency behavior due to noise. However, the proposed metric value drops when the image is increasingly more blurred. The value of this measure also rises if the variance of noise is increased. For the metrics based on edge detection and edge width estimation, the performance stability can easily suffer from the presence of noise. Such problems are addressed precisely by the proposed metric Q.

II. RELATED WORK

First, let us briefly summarize the relevant existing literature in this area. Objective quality [2] and sharpness metrics [3], [4] have been developed recently and can generally be divided into three categories: full-reference, reduced-reference and no-reference. Full-reference metrics need a complete reference image, and what they calculate is basically the similarity between the target and reference images. Such measures of similarity include the classical mean-squared error (MSE) and the recently introduced Structural Similarity (SSIM) [2]. Reduced-reference metrics require the reference image to be partially available, which is usually in the form of a set of extracted features [2]. However, in most practical applications the reference image is unavailable. Therefore, in applications such as denoising, deblurring, super-resolution, and many other image reconstruction algorithms [2], the (full-reference) quality metrics MSE or SSIM cannot be directly used to optimize the parameters of algorithms.

Several (no-reference) approaches have been developed to address the parameter optimization problem. Generalized cross-validation (GCV) [5], [6] and the L-curve method [7], [8] have been widely used in choosing the regularization parameters for various restoration applications. More recently, methods based on Stein's unbiased risk estimate (SURE) were proposed for the denoising problem [9], [10], which provide a means for unbiased estimation of the MSE without requiring the reference image. Useful as they are, these methods are far from ideal. Namely, aside from their computational complexity, they address the parameter optimization problem without direct regard for the visual content of the reconstructed images. Instead, they compute or approximate quantities such as MSE (or the related cross-validation cost), which are not necessarily very good indicators of visual quality of the results. As a particular example, for instance, Ramani *et al.*'s Monte-Carlo SURE [10], which can be used for arbitrary denoising algorithms, is based on the idea of probing the denoising operator with additive noise and manipulating the response signal to estimate MSE. This approach is also only appropriate when the noise is assumed to be Gaussian, and generally requires an accurate estimation of the noise variance as well.

Some of the factors that decide the image quality are discussed below. By comparing them, the factors influencing the visual quality most is judged. Based on these factors, the Denoising Algorithms are designed with initially assumed parameters. The values of the parameters must also be optimized so that the finally restored image is of good quality.

A. Various Image quality factors

Sharpness determines the amount of detail an image can convey. System sharpness is affected by the lens (design and manufacturing quality, focal length, aperture, and distance from the image center) and sensor (pixel count and anti-aliasing filter). In the field, sharpness is affected by camera shake, focus accuracy and atmospheric disturbances. Lost sharpness can be restored by sharpening, but sharpening has limits. Over sharpening, can degrade image quality by causing 'halos' to appear near contrast boundaries.

Noise is a random variation of image density, visible as grains in film and pixel level variations in digital images. It arises from the effects of photonic nature of light and the thermal energy of heat inside image sensors. Typical noise reduction (NR) software reduces the visibility of noise by smoothing the image, excluding areas near contrast boundaries. This technique works well, but it can obscure fine, low contrast detail.

In addition to these, some more factors like accuracy of light exposure , Tone reproduction, Contrast, Color accuracy, Distortion also cause poor quality images.

In image restoration, as is the case for any estimation problem generally, it can be observed that selecting parameters amounts to a tradeoff between bias and variance in the final estimate. A canonical example is the regularization parameter in MAP-based restoration algorithms [5], [8]. Generally, the larger the parameter is, the more smooth the image content becomes (small variance), while more useful detail and edges are flattened or blurred (larger bias). In other words, an ideal no-reference measure that is useful for the parameter optimization problem should take both noise and blur on the reconstructed image into account [11]. However, most sharpness metrics [3], [12], [4], [13] can hardly distinguish image quality decay against high frequency behavior due to noise. For example, in [12] the method involved fails, if metric value drops when the image is more blurred. The value of this measure also rises if the variance of noise is increased. For the metrics based on edge detection and edge width estimation [4], the performance stability can easily suffer in the presence of noise. In order to address such problems, a proposed metric Q is designed.

On a related note, mentioned that some no-reference image quality metrics have been developed to detect noise and blur simultaneously. One example is the metric based on the image anisotropy [14] proposed by Gabarda and Crist ´obal [15]. They calculate the R´enyi entropy [16] pixel by pixel along different directions, and use the variance of the entropy to index visual quality. However, such metrics require uniform degradation across the whole image, and do not work well if the random noise or blur varies spatially, which is the case, in images denoised by spatially adaptive filters.

B. Existing System

Monte-Carlo SURE(Stein's unbiased risk estimate) is used to solve the problem of optimizing the parameters of a given denoising algorithm for restoration of a signal corrupted by white Gaussian noise. *Stein's unbiased risk estimate* (SURE) provides a means of assessing the true mean-squared error (MSE) purely from the measured data without need for any knowledge about the noise-free signal. Specifically, it presents a novel Monte-Carlo technique which enables the user to calculate SURE for an arbitrary denoising algorithm characterized by some specific parameter setting. This method is a black-box approach which solely uses the response of the denoising operator to additional input noise and does not ask for any information about its functional form.

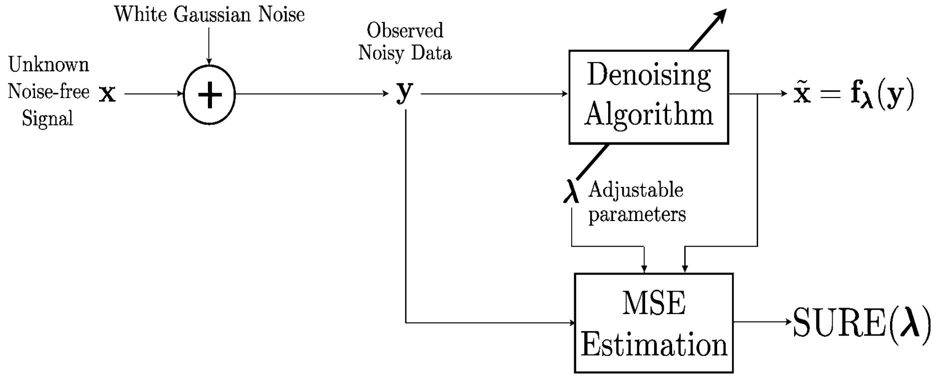


Figure 1. Existing System

Existing system computes or approximate quantities such as MSE or the related cross-validation cost and this does not result in good visual quality. Moreover, this approach is appropriate only when the noise is assumed to be Gaussian. It also requires an accurate estimation of the noise variance as well.

C. Proposed System

Mean Square Error computation by Monte Carlo SURE method is not a good visual indicator. Also, this approach is appropriate for only the images with Gaussian noise and this method also requires an accurate estimation of the noise variance as well. All these leads to a need for a new technique of denoising filter. Here we propose a No-Reference metric Q that is based on singular value decomposition of local image gradient matrix. This method provides a quantitative measure for the true image content (i.e., sharpness and contrast as manifested in visually salient geometric features such as edges), that too in the presence of various kinds of noises and other disturbances.

This proposed measure is used to automatically and effectively set the parameters of any 'black box' image denoising algorithms. Ample simulated and real data experiments support the proposed claims. Furthermore, experimental results have shown that this measure correlates well with subjective quality evaluations for both blur and noise distortions in the images. This measure is easy to compute and reacts reasonably to both blur and random noise. It also works well even when the noise is not Gaussian. The proposed system has been tested for images with Random, Gaussian, Speckle and Poisson types of noises.

III. OVERALL ARCHITECTURE OF THE PROPOSED SYSTEM

The input to the Overall system is a Noisy image. Initially the algorithm is applied to find the anisotropic regions /patches in the noisy image and this is followed by calculating the image content matric ie., Q. Then the Steering Kernel Regression algorithm is applied on this noisy image using the Q as initial parameter. Once the denoised output image is obtained , the Q value is recalculated on the output image and the old value is updated and the SKR algorithm is once again applied. This process is repeated for a maximum of 20 iterations and every time the Q values are tabulated and a performance graph is plotted. It is observed from the tabulations that the Q value increases and reaches a highest value at some iteration and then on decreases. And the denoised image quality is also perfect at this iteration which can be considered as the final denoised image.

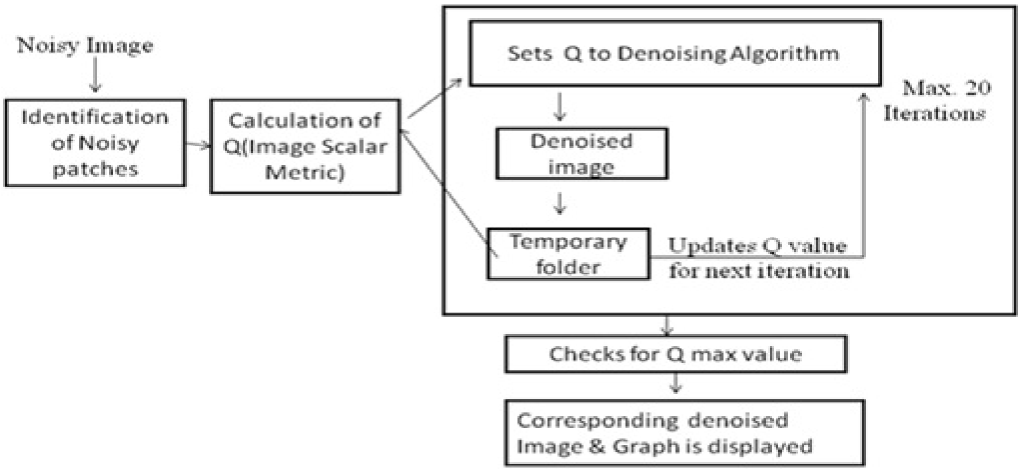


Figure 2. Proposed Overall Architecture

The entire proposed procedure is divided into three modules.

1.. Identification of Anisotropic Patches

2. Calculation of Image Content Metric Q

3. Optimizing Q using Steering Kernel Regression (SKR) Algorithm

1) Identification of Aniosotropic patches

Aim of this module is to calculate gradient matrix, covariance matrix and singular value decomposition (SVD) for the given image. Based on the SVD, coherence value is calculated. Coherence value is used to identify anisotropic patches by comparing this value with threshold value .These coherence and singular values are essential for framing the proposed image metric Q.

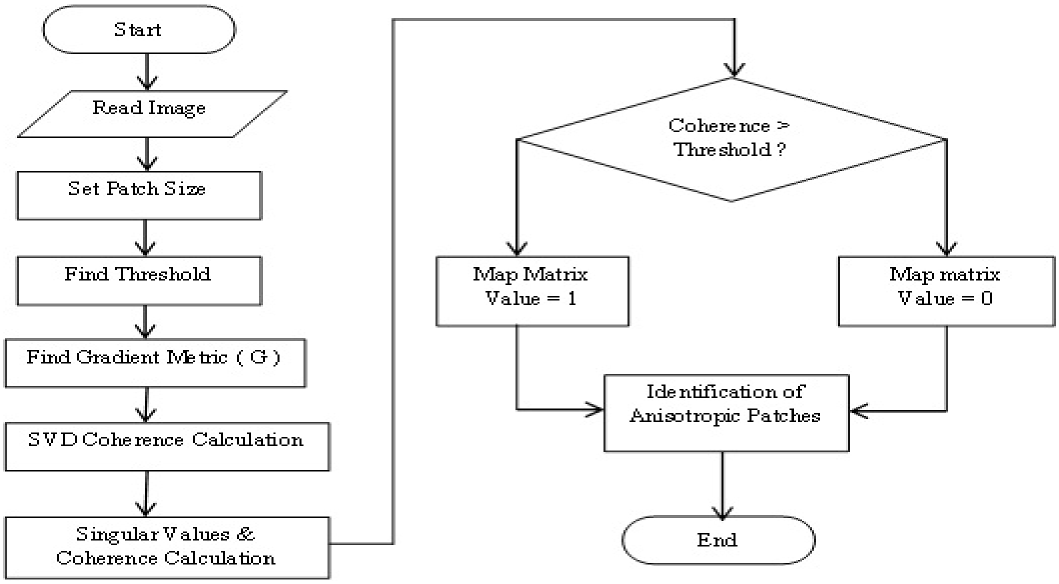


Figure 3. Flowchart for Identifying Anisotropic patches

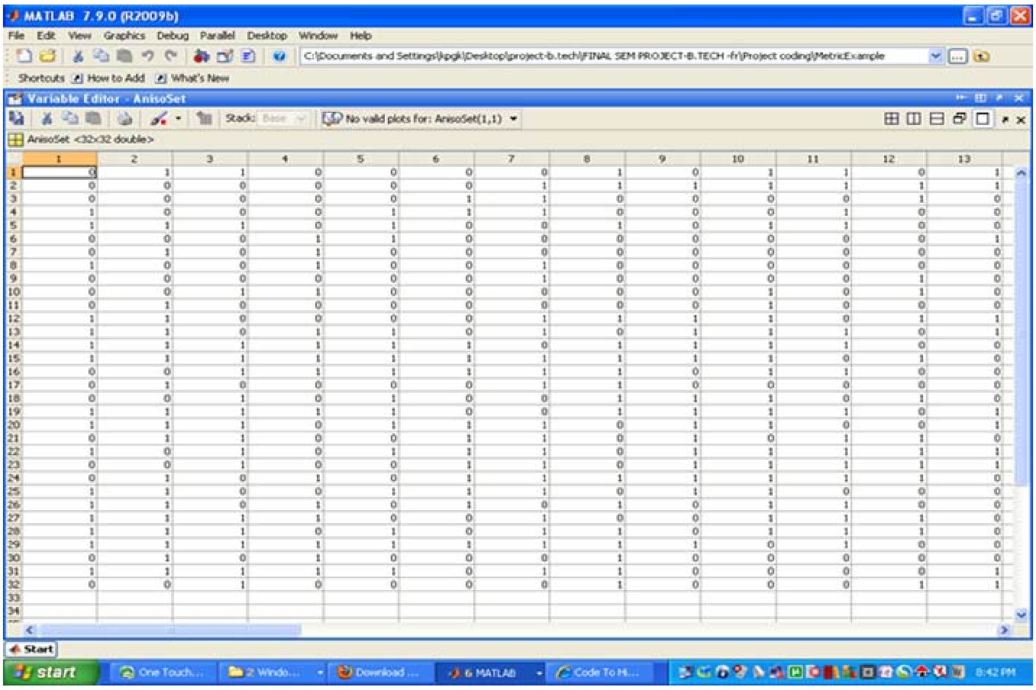


Figure 4. Snapshot showing a Value 1 for Anisotropic patches; Value 0 for other patches

2) Calculation of Image Content Metric

Main aim of this module is Calculation of proposed Metric Q. Image content metric is a quantitative measure for image quality. Calculation of Q takes place, after identification of anisotropic patches for input noisy image. Initially the Q value is set to zero. Then the Q calculation is performed by applying the formula which involves the Coherence and Singular values which were calculated by the first module. The image content metric is calculated as shown in the flowchart below.

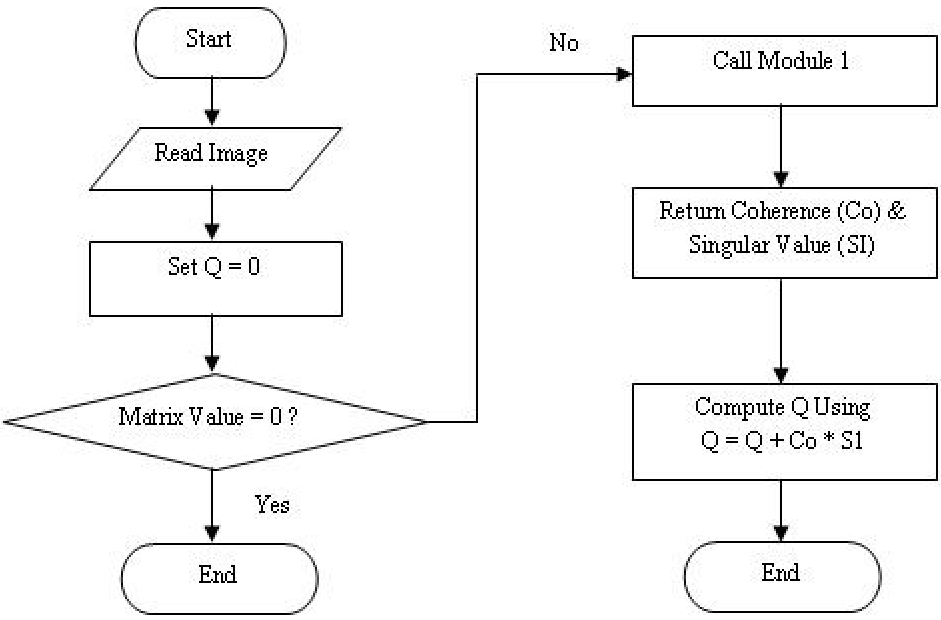


Figure 5. Flowchart for Calculating Image Content Metric Q

3) Optimizing Q using Steering Kernel Regression Algorithm

Main aim of this module is optimizing Q to enhance the performance of the algorithm and also providing the convenient way of tuning the parameters. Steering Kernel Regression is one of the leading 'Black – Box' denoising algorithm. It is based on No – Reference Metric. Hence this algorithm is implemented in this proposed method of estimating Quantitative measure for an image.

In SKR**,** there are two main parameters to tune: the global smoothing parameter h, and the iteration number. The effect of these parameters is generally interdependent in that the smaller the h is, the more iterations are needed to achieve the best output image. Hence in practice, it makes sense to set h to a fixed value (we set it to 2.0 throughout) and to attempt to optimize the iteration number within a reasonable range (here it is in between 1 and 20).

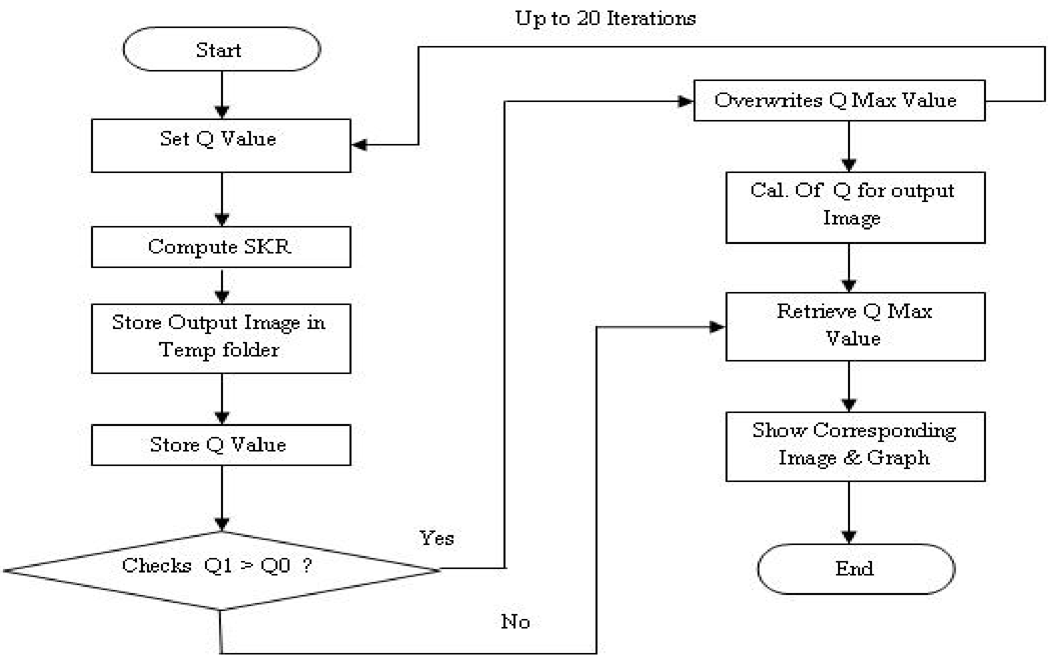


Figure 6. Flowchart for Optimizing Q by SKR Algorithm

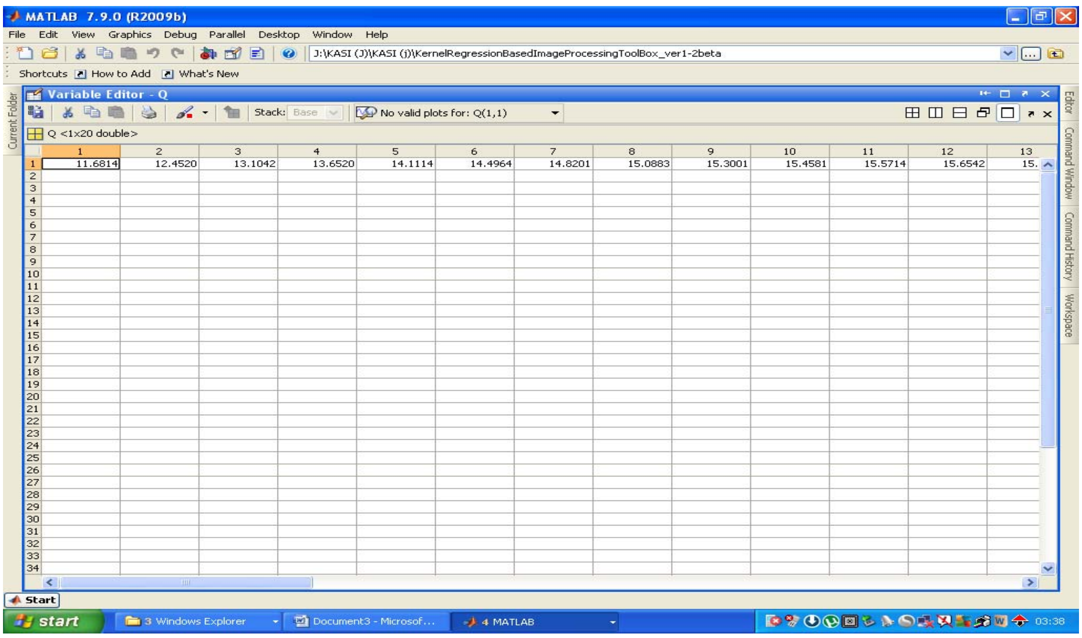


Figure 7. Snapshot of Q values for a Noisy Image at different iterations

The SKR algorithm uses Upscale factor, Elongation factor, Smoothening parameters which are initialized. For implementing SKR, second order kernel regression function, steering sub functions are used. In each iteration, second order kernel regression function is called and Q is calculated at the end of iteration for obtained image by invoking the modules 1and 2 . The value of Q is tabulated for each iteration and finally Q_{max} value should be identified and the corresponding image is shown as final output. However, the Q values are plotted for each iteration.

IV. EXPERIMENTAL RESULTS

The proposed system was tested initially for a sample noisy image of Taj Mahal. It was tested and found that the output denoised image was obtained at 15^{th} iteration .The snapshots along with the graph plotted for the values of Metric Q at various iterations is shown below. Further the test was also carried out for the color imagge and resultantsnapshots are shown. Then a comparitive study of the noisy images of different noises was made and the Qmax is tabulated for each image. Thus the proposed algorithms were tested to give best results for noisy images in presence of different kinds of noises.

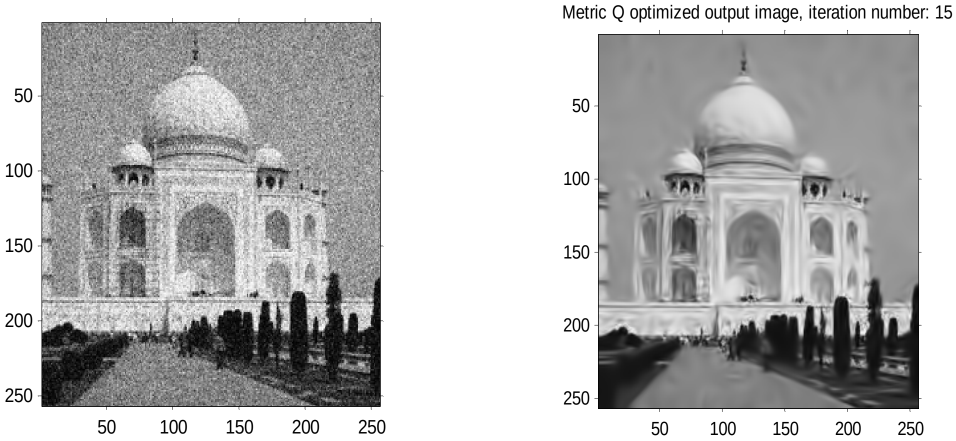


Figure 8. The denoised image output for a noisy Taj Mahal image at 15th iteration

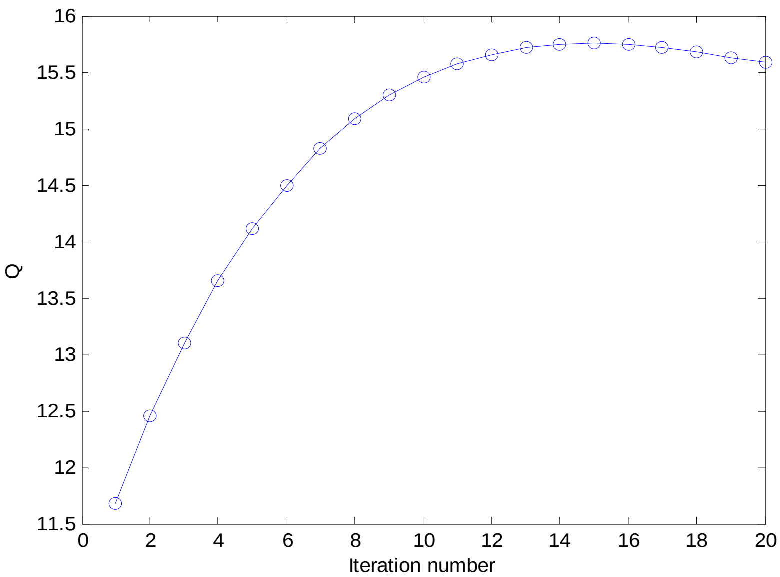
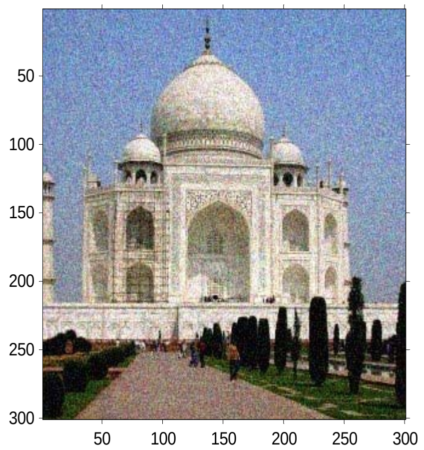


Figure 9. Plotted Q values with Qmax at 15th iteration

As a second case, color noisy image of Taj Mahal was given and tested.



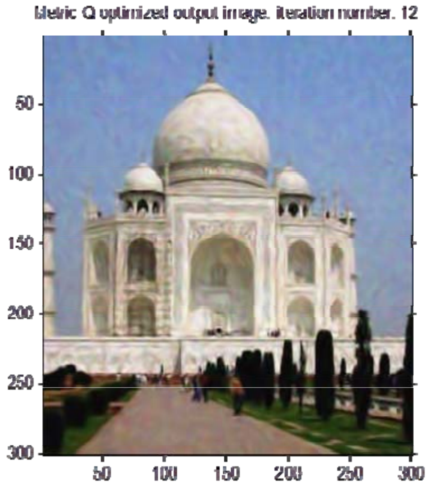


Figure 10. The denoised image output for a Color noisy Taj Mahal image at 12th iteration

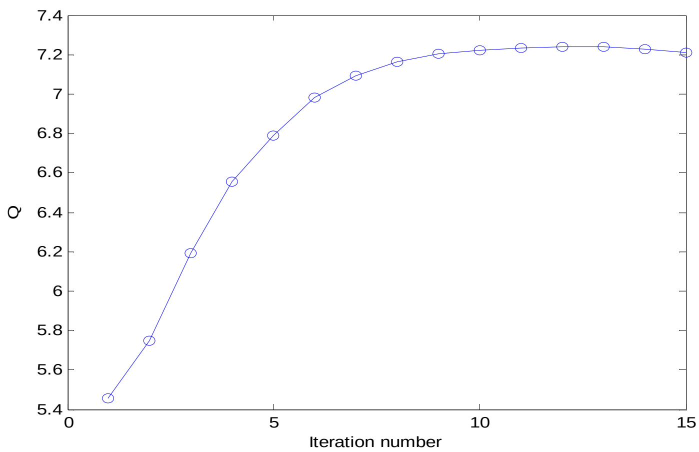


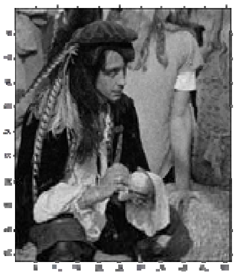
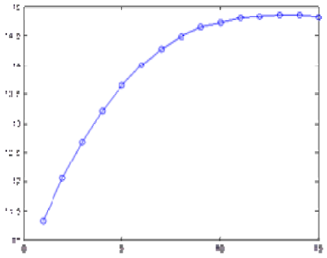
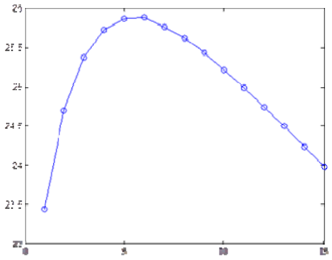
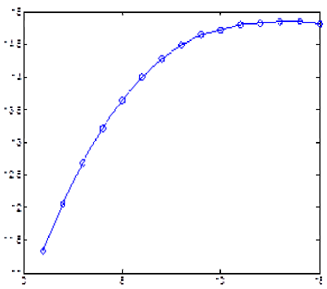
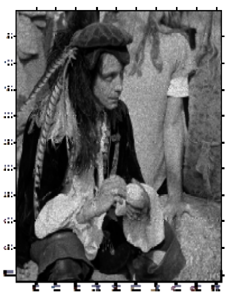
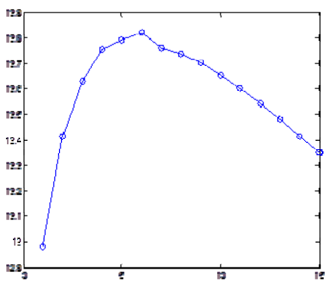
Figure 11. Plotted Q values with Qmax at 12th iteration

The Experiments were carried out for images with different kinds of noises like random, Poisson, Gaussian and Speckle. For all the cases the metric reached a peak as Qmax and begin to decrease gradually. The resultant denoised image was taken at Qmax value. The existing denoising filters operate on only images with Gaussian noises.

TABLE I. Q_{MAX} VALUES OBTAINED FOR IMAGES WITH DIFFERENT TYPES OF NOISES:-

Types of Noise	**Iteration number**	**Q_{max}**
Random Noise	**13**	**14.856**
Poisson Noise	**6**	**25.8851**
Gaussian Noise	**13**	**14.715**
Speckle Noise	**6**	**13.8425**

TABLE II. COMPARISON OF RESULTS FOR IMAGES WITH DIFFERENT TYPES OF NOISES:-

Type of Noise	Image with Noise	Denoised Image	Plotted graph	Itn. No.
Random Qmax= 14.586				13
Poisson Qmax= 25.8851				6
Gaussian Qmax= 14.715				13
Speckle Qmax= 1.8425				6

V. CONCLUSION

In this paper, Proposal of an image content metric which can be used in an unsupervised fashion for parameter optimization of any image denoising algorithm. This metric is based upon the singular value decomposition (SVD) of local image gradients. It is properly correlated with the noise level, sharpness and intensity contrast of the structured regions of an image without any prior knowledge. Simulated and real data experiments on denoising filters demonstrated that this metric can capture the trend of quality change during the denoising process, and can yield parameters that show good visual performance in balancing between denoising and detail preservation. Additional tests using blurred and noisy images from the database confirm that the proposed metric is well-correlated with subjective evaluations.

One of the possible enhancements is extending the use of this metric to the parameter optimization problem in other image restoration algorithms, such as deblurring and super-resolution. Research on designing a metric for video content within the same framework is also worth pursuing. It solves the parameter setting problem in video processing and also remove trial and error method of parameter setting if no 'ground – truth' reference is available. It is also possible to extend Q as a general no-reference image quality metric. Another possible enhancement is to design a Q metric appropriate for cross-image assessment.

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