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An efficient estimation and removal of noise parameters from current read out digital image sensor using variance transforms

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ABSTRACT
Digital Remote Image (DRI) denoising using thresholding methods means find appropriate value (threshold) which separates noise values to actual image values without affecting the significant features of the image. The aim of this project is to develop a best poisson noise removal filter from the comparative study analysis of filtering methods and successive approximation based thresholding technique. To estimation poisson noise this is de-noised using successive approximation and filtering techniques. First the noise is removed by median filter and then removed by wiener filter. Second noisy image is denoised with the help of wavelet based techniques using thresholding Third thresholding is applied on the result of first and second simultaneously for image denoising and fourth PSNR (Peak Signal to Noise Ratio), MSE (Mean Square Error) calculated and results are compared in all cases.

KEY WORD — Poisson noise, Threshold method, PSNR, MSE, Image denoising, noise parameter estimation.

I. INTRODUCTION

Noise is undesired information that contaminates the image. An image is unfortunately corrupted by various factors. The distortions of images by noise are common during its acquisition, processing, compression, transmission, and reproduction. It is clear that the removing of the noise from the image facilitate the processing. Improving signal-to-noise ratio (SNR) in digital remote imaging (DRI) without sacrificing spatial resolution, contrast, or scan-time could improve diagnostic value. While time averaging increases SNR, with SNR $\propto \sqrt{}$ (scan-time), extending the scan-time is expensive, prone to motion artifacts, and unacceptable in many DRI applications. Indeed, parallel imaging techniques, such as sensitivity encoding (SENSE) and generalized auto calibrating partially parallel acquisitions (GRAPPA), are commonly used to shorten scan-times. Images reconstructed with these techniques exhibit spatially varying noise statistics, which limit the applicability of conventional denoising techniques. Several denoising methods have been proposed to enhance the SNR of images acquired using parallel imaging techniques. One method, anisotropic diffusion filtering (ADF), effectively improves SNR while preserving edges by averaging the pixels in the direction orthogonal to the local image signal gradient. ADF can potentially remove small features and alter the image statistics, although adaptively accounting for DRI's spatially varying noise characteristics can offer improvements, this is practically challenged by the unavailability of the image noise matrix.

Wavelet-based filters have also been applied to DRI. These are prone to produce edge and blurring artifacts. Recently, denoising methods employing nonlocal means (NLM) were applied to increase the DRI SNR by reducing variations among pixels in the image with close similarity indices. The robustness of the determination of pixel similarity is enhanced by comparing small image regions centered at each pixel, rather than pixel-by-pixel comparisons. While adaptive NLM denoising (involving the estimation and incorporation of spatial variations in the noise power) offers improved performance, NLM can still affect image statistics and its computational burden is high compared to other approaches. In this study, we introduce a new, time efficient, image denoising method by applying spectral subtraction directly to DRI acquisitions in *k*-space. Spectral subtraction is well established for the suppression of additive Gaussian noise (AGN) and is commonly used in image processing. It has been applied to the time-course of functional DRI (fDRI) data to facilitate event detection, but not the SNR enhancement of routine DRIs *per se*. We test spectral subtraction denoising (SSD) on both numerical simulations, as well as experimental DRI data including parallel SENSE image reconstruction, and compare its performance with ADF.

II. PREVIOUS METHOD

Propose a method for estimating unknown noise parameters from Poisson corrupted images using properties of variance stabilization. Estimation technique yields noise parameters that are comparable in accuracy to the state-of-art methods.

III. PROPOSED METHOD

To estimation poisson noise this is de-noised using successive approximation and filtering techniques. First the noise is removed by median filter; and then removed by wiener filter. Second noisy image is denoised with the help of wavelet based techniques using thresholding. Third thresholding is applied on the result of first and second simultaneously for image denoising and fourth PSNR (Peak Signal To Noise Ratio), MSE (Mean Square Error) calculated and results are compared in all cases.

IV. NOISE ESTIMATION

Different methods have been proposed to estimate the noise variance from the DRI magnitude data. They either use the background part of the image or some image statistics to find the noise variance. These methods are explained here briefly.

A.Estimating the noise variance from the background

The second moment of the Rayleigh distribution (the signal distribution of the background).
Also the noise can be estimated from the first moment of the Rayleigh distribution.
This can be seen in equation.

$$\sigma = \sqrt{\frac{2}{\pi}}\frac{1}{N}\sum_{i=1}^{N} M_i$$

However, estimating the noise variance based on background areas has some drawbacks. In these methods, the main assumption is that the signal in the background area is always zero and the background area is not selected automatically. These factors affect the result and make it inaccurate.

B.Estimating the noise variance based on local statistics

The first approach for estimating the noise based on local statistics is using the second order moment of the whole image (not only the background). It is proved that for a normal image the shape of the second-order moment distribution is not changed when it gets noisy by Rician noise. In DRI images the second order moment distribution has an unique property which is a maximum in the origin. This maximum appears in the image due to the presence of background in the image. Again, when the image is noisy a shift in the maximum can be seen. This principle is illustrated in figure 1.

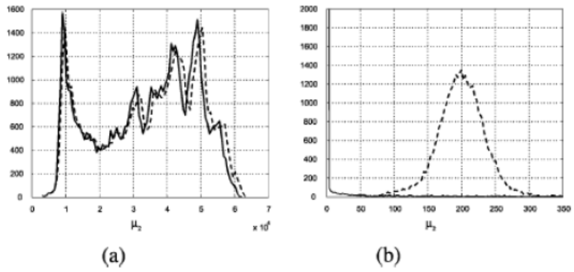

Fig 1.a: Normal image and b: DRI image.

Therefore, the position of the maximum can be used to estimate the noise variance. Equation 2.13 shows this relationship.

$$\sigma^2 = \frac{1}{2} mode\left(\mu_{2ij}\right)$$

The same reasoning can also be applied for the local mean distribution of the DRI image. Again, due to the background area a maximum can be seen in origin. This maximum will be shifted when the image is noisy. Therefore, the variance can be estimated by finding the maximum of the local mean.

V. FUNCTION OF THE SYSTEM

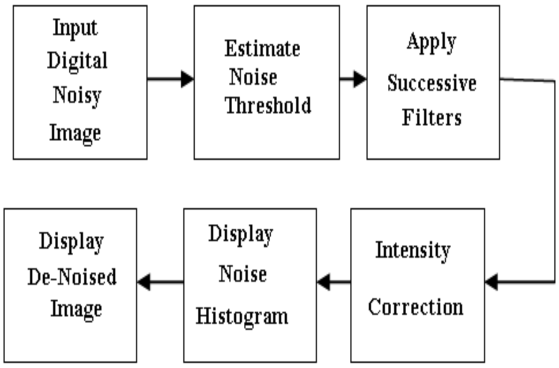

Fig: 2 Functional block diagram of the system

Poisson noise, is a basic form of uncertainty associated with the measurement of light, inherent to the quantized nature of light and the independence of photon detections. Its expected magnitude is signal dependent and constitutes the dominant source of image noise except in low-light conditions.

VI. FILTERING TECHNIQUES

A. Median filtering

Median filtering is a nonlinear method used to remove noise from images.It is widely used as it is very effective at removing noise while preserving edges. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels.Median filtering is one kind of smoothing technique and effective at removing noise in smooth patches or smooth regions of a image.It is particularly effective for filtering of impulsive noise Median filter is a spatial filtering operation, so it uses a 2-D mask that is applied to each pixel in the input image. The median is calculated by first sorting all the pixel values from the surrounding neighborhood into numerical order and then replacing the pixel being considered with the middle pixel value.

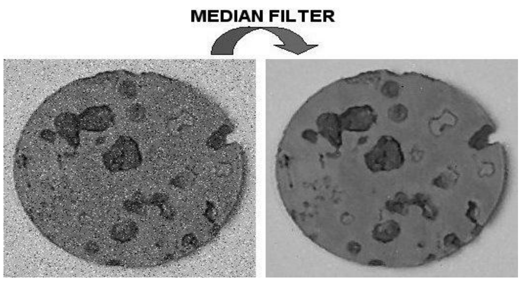

Fig: 3 Median filteringimage

B. Wiener filtering

The Wiener filter is a filter used to produce an estimate of a desired image by linear time-invariant filtering an observed noisy image. The Wiener filter minimizes the mean square error between the estimated random process and the desired process.Wiener filtering is a general way of finding the best reconstruction of a noisy image. The “universal” Wiener filter is to multiply components by S2/(S2+N2), which is smooth tapering of noisy components towards zero.

Wiener Filter for Additive Noise Reduction Consider a signal x(m) observed in a broadband additive noise n(m)., and model as: $y(m) = x(m) + n(m)$

Assuming that the signal and the noise are uncorrelated, it follows that the autocorrelation matrix of the noisy signal is the sum of the autocorrelation matrix of the signal x(m) and the noise n(m):

$$R_{yy} = R_{xx} + R_{nn}$$

where R_{yy}, R_{xx} and R_{nn} are the autocorrelation matrices of the noisy signal, the noise-free signal and the noise respectively, and r_{xy} is the cross-correlation vector of the noisy signal and the noise-free signal.
Wiener filter algorithm is

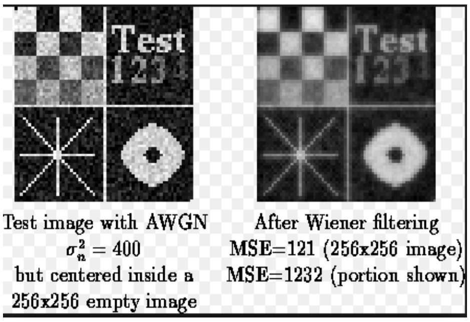

Fig: 4 Wiener filtering image

C. Average filtering

Average filter is windowed filter of linear class, that smoothes signal (image). An average filter smoothes data by replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to low-pass filtering with the response of the smoothing

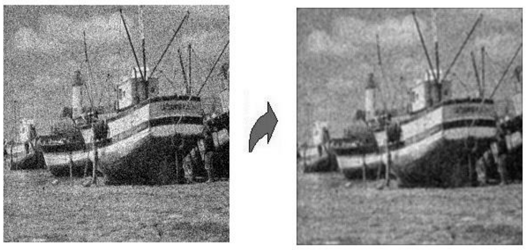

Fig: 5 Average filtering image

VII. DENOISING METHODS

Different denoising methods have been used to improve the quality and increasing the SNR of DRI images. The SNR of an MR image can be represented by the equation.

SNR = C.f (Ob).g (Im)

Where C is a constant depending on the physical properties of the system like magnetic flux, f (Ob) is related on the dimensions of the target, and g (Im) is based on selected imaging factors. The last function can be measured knowing readout frequency ω_0, voxel dimension Vh and the imaging time T (g (Im) = ω0Vh√T). It is obvious that having better resolution leads to less SNR. Therefore, applying a proper denoising technique provides the opportunity of accessing to an image with acceptable quality along with higher SNR.

There are two general categories for the denoising methods: acquisition-based and post acquisition filtering methods. The former methods involve increasing the scan times, performing several similar measurements and averaging them, increasing the voxel dimension or using more advanced hardware. However, using this type of noise reduction methods increases both the acquisition time and the expenses. Therefore, the second group can be considered as an efficient and affordable technique for DRI image denoising. One important difference in post acquisition-based denoising methods is the data they are applied to (raw, magnitude, squared magnitude). Some common methods of DRI denoising are described here.

A. Gaussian filtering

This is one of the most basic methods for denoising DRI images. However, it removes sharp edges and fine details as it is a smoothing filter.

B. Bilateral filtering

This method can be described as weighted averaging method. Two weight factors are used in this method. One of them is based on the spatial distance difference while the other is based on the intensity difference.

The bilateral filtering performs better than linear filtering methods in case of smoothing and keeping the edges. However, it still removes some details.

C. Anisotropic Diffusion Filtering

This method is based on Linear Minimum Mean Square Error (LMMSE) estimator that is combined with a Partial Differential Equation (PDE).

$$K(x) = 1 - \frac{4\sigma^2\left(\left\langle M(x)^2\right\rangle - 2\sigma\right)}{\left\langle M(x)^4\right\rangle - \left\langle M(x)^2\right\rangle^2}$$

Although this filter preserve edges by averaging orthogonal to the local gradient, but it still removes detailed information. It also modifies the image statistics because of its edge improving characteristic.

D. Wavelet denoising

The wavelet transform function is used to analyze a signal in its different scales i.e. detailed and approximation structures. In contrast to the Fourier transform that is used to present the spectral content of a signal, wavelet transform can be used to evaluate the local properties of a signal. Furthermore, the wavelet transform can be used to detect edges. To perform a wavelet transform, a specific wavelet is selected. The wavelet is brought to a specific scale and also shifted. Then the correlation of the analyzed signal and the wavelet is explored. The result determines the properties of the signal in that scale. The whole process can also be defined as a digital filter bank consisting low and high pass filters. These filters are applied on the low pass results until the desired level. The output of the final low pass filter presents the approximation of the analyzed signal while the output of the high pass filter can be considered as the detailed part (the high frequency part) of the signal. The wavelets are generated by dilation and translation of a general wavelet function called mother wavelet φ (x).

The simplest form of the wavelet transform is the continuous wavelet transform. However, this method is redundant and shift invariant. They are used often for signal characterization. Therefore, the other class of wavelet transforms i.e. discrete wavelet transform (DWT) is introduced. This class of waveforms can be considered as simple sampling of the Continuous one. A common DWT wavelet coefficient and approximation coefficient basis can be represented.

The DWT method is not shift invariant. Therefore, it is not suitable for some applications such as pattern identification and makes some problems for denoising due to not enough redundancy. Therefore, Non-decimated Discrete Wavelet Transform (nDWT) can be used to fulfill the requirements for denoising and pattern recognition. In nDWT, the number of wavelet coefficients is not decreased in each scale. They are achieved by sampling the CWT at all integer locations at each translation.

The basis here are not anymore linearly independent and they form a frame. This method is more redundant and also shifts invariant. Therefore it could be a good option for image denoising.

Different method has been used to denoise an image in wavelet domain. They either based on estimation techniques or thresholding. In the thresholding method, the coefficients that are less than a given threshold are eliminated. There are two general types of thresholding techniques: Soft and Hard Thresholding.

On the other hand, the soft thresholding approach in which the data shrinks in each try and is a better option for discontinuities can be defined as equation.

$$\eta_S(\omega, t) = \begin{cases} w - t & \omega \geq t \\ 0 & |\omega| < t \\ \omega + t & \omega \leq -t \end{cases}$$

The main task in this part is to find an optimal threshold. Different methods have been used. In the next section one of the methods that is used to find an optimal thresholding and is a basis for the purpose of this project is introduced.

Noise Invalidation denoising

Noise invalidation Denoising can be considered as a method which works in the wavelet domain. As it was mentioned before, several methods are available for noise filtering in wavelet domain. They are designed to estimate a threshold value and then use a thersholding method to remove the noise coefficients from an image. However the main logic of these methods is based on some characteristics of the noise free signal and they are often application based. On the contrary, NIDe approach for denoising relies on the noise properties. It defines a confidence noise area and considers the data outside of this area as a noise free signal. It should be noted that the original NIDe method performs on signals contaminated with additive Gaussian noise. The basic principles of this method can be described as following.

A signature function can be defined for any variables v and z as g (z; v) with finite mean GE (z) and variance Gvar (z) over the random noise vector V. Therefore, the signature for N samples of the random noise and its mean and variance can be defined as equations respectively.

$$g\left(z, v^N\right) = \frac{1}{N}\sum_{i=1}^{N} g\left(z, v_i\right)$$

$$E\left(g\left(z, v^N\right)\right) = G_E\left(z\right)$$

$$var\left(g\left(z, v^N\right)\right) = \frac{1}{N} G_{var}\left(z\right)$$

The noise signature function that is used for this method is based on Absolute Noise Sorting (ANS).
The mean and variance of this signature can be formulated as following equations

$$L_N\left(z\right) = F\left(z\right) - \lambda\sqrt{\frac{1}{N}F\left(z\right)\left(1 - F\left(z\right)\right)}$$

$$U_N\left(z\right) = F\left(z\right) - \lambda\sqrt{\frac{1}{N}F\left(z\right)\left(1 - F\left(z\right)\right)}$$

According to the equations, the boundaries are functions of mean and standard deviation of the sorted noise only data. _is the controlling factor to increase the probability and at the same time to prevent having very loose boundaries.

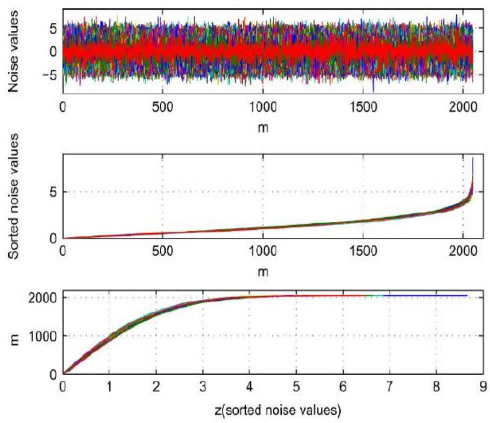

Fig 6: Effect of sorting the absolute values

Considering a noisy signal with coefficients as the noiseless data, the mean and variance of samples of a random process noisy data can be represented.

The expected value of the signature function of noisy data.As the noise only data that was described before, sorting the noisy data leads to a dense area of data. Comparing this area with the noise only confidence area will determine a point at which the noisy data leave the noise confidence area.

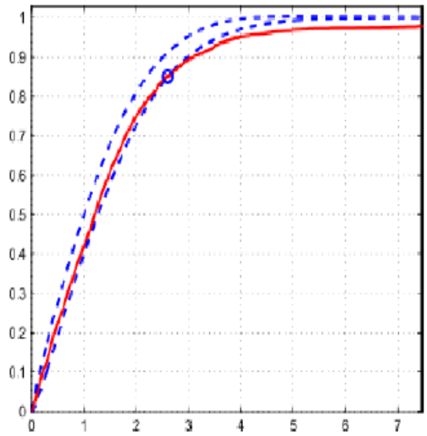

Fig 7: Solid line is the noisy data and dashed lines represent the noise only boundaries

E. Non Local Mean (NLM) filters

The NLM filters are a weighted averaging filter based on the intensity similarity of the pixels. The factor that can discriminate between these two methods or other similar methods is the comparing region. In contrast to bilateral filtering those find the similarity of a pixel with its neighborhood.For a NLM filter on a noisy image Y, the output can be described as equation.

$$NLM\left(Y\left(p\right)\right)=\sum_{\forall q\in N_p} w\left(p,q\right)Y\left(q\right)$$

Here, the weights are calculated according to the similarity of the squared window neighborhoods of two pixels p and q with Radius of Rsim. The weights w (p; q) can be driven based on the equations.

As it was mentioned before, the noise bias in the magnitude image is hard to remove. But it can be removed easily from the squared magnitude image. Based on this assumption, a version of NLM filtering called Unbiased Non Local Mean filtering (UNLM) is developed. It is described based on the equation.

$$UNLM\left(Y\right)=\sqrt{NLM\left(Y\right)^2-2\sigma^2}$$

VIII. EXPERIMENTAL RESULTS

MATLAB is a software tool and programming environment that has become commonplace among scientists and engineers. For the engineering professional it is a useful programming language for scientific computing, data processing, and visualization of results. Many useful mathematical functions and graphical features are integrated with the language. MATLAB is a powerful language for many applications as it has high-level functionality for science and engineering applications coupled with the flexibility of a general-purpose programming environment. Throughout this course, we primarily use MATLAB for simulating dynamic systems and the analysis and visualization of experimental data. This chapter does not provide a complete description of MATLAB programming, but rather an introduction to the basic capability and the basic syntax. As the title says, this chapter is a primer, not complete product documentation. In this chapter we provide some simple examples to get the student started and familiar with programming in the environment. There is extensive documentation on the Math works web site as well as the help feature built into the MATLAB environment. All the commands presented in this chapter have detailed explanations of the functionality via the built in help. This chapter is also not a general introduction to programming. Most of the functionality will be presented through very simple (trivial) examples, just to present the basic syntax and capability. More complete and complicated programs are included at the end of the chapter. If you are an experienced programmer, you should pay particular attention to the sections on array operations and mathematics as this feature is one of the biggest differences with traditional programming languages.

We emphasize that this chapter is only an introduction to the basic functionality of MATLAB. There is much more to learn than contained here. Also, you should not feel frustrated if you do not understand everything the first time you read this. Programming requires time to learn and much practice. We will be using MATLAB throughout this course so you will get plenty of time to practice; this is only the start. To get the most out of this chapter you should read the notes with MATLAB open and type each command and write each program as you read this primer. Make some variations so that you understand each command and program. There are problems in the chapter meant to give you practice programming in MATLAB. Depending on your past programming experience these activities may vary in difficulty, it will likely be very challenging for someone who has never programmed in the past. Do not worry about the “deliverables” with each problem. The main objective of the problems is to provide some example applications to give you practice and a chance to explore.

TABLE I Image reconstruction performance expressed in *SNR/SSIM*

ISO	Channel	Talbot[9] SNR/SSIM	Foi[13] SNR	Proposed Bartlett SNR/SSIM	Proposed Haar-Fisz SNR/SSIM
400	R	8.1678	17.4215	14.8247	12.5143
	GA	7.1002	21.0457	19.3457	20.3457
	GA	6.8146	14.2142	12.3476	12.2145
	B	13.3472	29.1245	17.3247	16.0754
800	R	10.4371	20.0245	14.3548	13.3468
	GA	6.4706	15.9833	15.3549	14.2648
	GA	7.3454	26.1346	25.1545	20.3648
	B	6.2547	15.2468	13.4679	15.2459
1600	R	10.2548	21.0354	14.6541	13.2987
	GA	7.0011	16.5497	16.2536	14.2154
	GA	9.1163	16.2512	21.2143	20.0234
	B	10.2549	15.7895	17.5471	15.2466
3200	R	10.2354	14.3215	11.2349	11.2679
	GA	5.1235	12.9785	6.1299	6.1254
	GA	6.3159	9.2143	8.2213	5.3198
	B	9.2348	11.2476	9.0681	7.1025

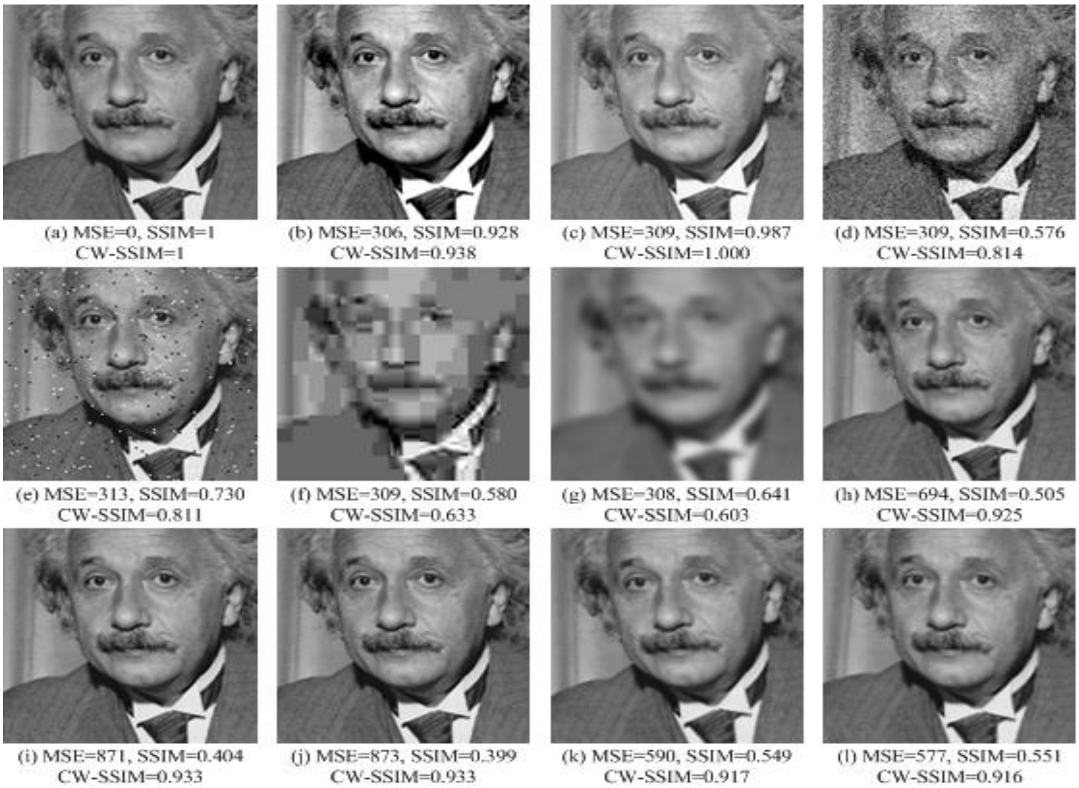

Fig:8 Example of denoising with synthetic noise. Baseline performance of image denoising method.

IX. CONCLUSION

In this project we performed possion noise estimation & filtering of noisy image from digital image sensors then soft & hard thresholding is performed and found the best threshold then finally we combine the result of filtering method and output a de-noised and enhanced image.

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