Simplified Two Step Iterative Algorithm for Enhancement of Blurred Images using Reduced Number of Coefficients

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ABSTRACT
The simulink model of modified TwIST algorithm has been presented in this paper. Restoration has been achieved by a two step filtering approach followed by a contrast enhancement module. The images are blurred using mean blurring function with BSNR of 100. The performances are estimated using MSE, convergence time and objective function.

General Terms
Image processing, Image Restoration, Simulink.

Keywords
Image Restoration, Total Variation, Minimization, Deblurring, and Simulink.

1. INTRODUCTION
Restoration of images has become a major stream in the past two decades. Restoring blurred images for effective information retrieval and feature extraction has been focused by researchers worldwide. Image restoration aims at deblurring the image. The main purpose is to compensate or undo some defects to restore the original image. Restoration can be achieved by various filtering techniques by estimating the degradation function. The principal sources of noise in digital images [1] arise during image acquisition (digitization) and/or transmission. The performance of imaging sensors is affected by a variety of factors, such as environmental conditions during image acquisition, and by the quality of the sensing elements themselves.

For instance, in acquiring images with a CCD camera, light levels and sensor temperatures are major factors affecting the amount if noise in the resulting image. Images are corrupted during transmission principally due to interference in the channel used for transmission. For example an image transmitted using a wireless network might be corrupted as a result of lightning or other atmospheric disturbance.

The parameters of periodic noise typically estimated by inspection of the Fourier spectrum of the image. As noted in the, periodic noise tends to produce frequency spikes that often can be detected even by visual analysis. Another approach is to attempt to infer the periodicity of noise components directly from the image, but this is possible only in simplistic cases. Automated analysis is possible in situations in which the noise spikes are either exceptionally pronounced, or when some knowledge is available about the general location of the frequency components of the interference.

2. RECENT ALGORITHMS
The different approaches for image restoration have been proposed in this section. Expectation-Maximization (EM) algorithm [3], for wavelet based image restoration has been developed by combining the efficiency of both discrete wavelet transform (DWT) and discrete Fourier domain convolution operator. This Maximization approach estimates the noise variance using WAFER (Wavelet Fourier EM Restoration). The convergence depends on the penalty function when concave and the stationary function when it attains global maxima. The objective function can be given as

$$Ax = b + w \tag{1}$$

Where A ∈ Rm×n and b ∈ Rm are known, w is an unknown noise (or perturbation) vector, and x is the true and unknown image to be estimated. Figueiredo et.al has proposed an adaptive total variation image deconvolution algorithm [10] for the total variation of image deconvolution under Majorization Minimization (MM) approach carried out through the linear approach as possible with x and y as real and blurred images

$$y = Hx + n \tag{2}$$

Where H is the observation matrix, n is the number of samples. The image deconvolution under linear observations and white Gaussian noise has been assumed. This formulates the implementation of MM approach by replacing the harder optimization problem with a sequence of simpler ones. They effectively compete with the recent state art methods.

A variational approach for Iterative image Deconvolution has been proposed [13] using over complete representations with prior information on its frame representation.

$$z = Tx + w \tag{3}$$

Where x is the Hilbert space, y is the observation, T is the convolution operator. This approach has been used to minimize the residual energy and penalizing term. This works on the two fronts. One, convex function are penalized to yield a new class of soft thresholding. Other the results are to be restricted to orthonormal bases. Numerical simulations have also been provided. An EM Algorithm for Wavelet-Based Image Restoration has also been proposed [18] based on the wavelet domain. This EM algorithm combines the representation of DWT with the diagonalization of the Fourier transform. The convergence is proved under mild condition and proved globally. This method proved to be competitively best compared to the existing methods through their convergence.

The recent approach for restoration of images is the use of wavelets in a two step process, the TwIST. The two steps, in TwIST are Iterative Shrinkage and Thresholding. It has been shown by Jose Bioucas et.al [2] that TwIST algorithm produces faster convergence compared to conventional IST algorithms even for ill conditioned problems. The TwIST algorithm is to be utilized for restoring blurred/defocused images. When compared to other Iterative Shrinkage/Thresholding (IST) algorithms TwIST is more effective since its convergence is based on both past and present iterations.

3. TwIST

The TwIST algorithm has been proposed to handle highly ill posed denoising problems. Inverse problems abound in many application areas of signal/image processing: remote sensing, radar imaging, tomographic imaging, microscopic imaging, astronomic imaging, digital photography, etc. In an inverse problem, the goal is to estimate an unknown original signal/image x from a (possibly noisy) observation y, produced by an operator K applied to x. For the linear system of ill-conditioned problems

$$y = Kx \tag{4}$$

Where, for different values of x the image is observed.

The TwIST method proposed aims at keeping the good denoising performance of the IST scheme, while still being able to handle ill-posed problems as efficiently as the IST algorithm. In this method a new class of iterative methods, called TwIST, which have the form of Two-step Iterative Shrinkage/Thresholding (TwIST) algorithms has been introduced. The update equation depends on the two previous estimates (thus, the term two-step), rather than only on the previous one. This class contains and extends the Iterative Shrinkage/Thresholding (IST) methods recently introduced.

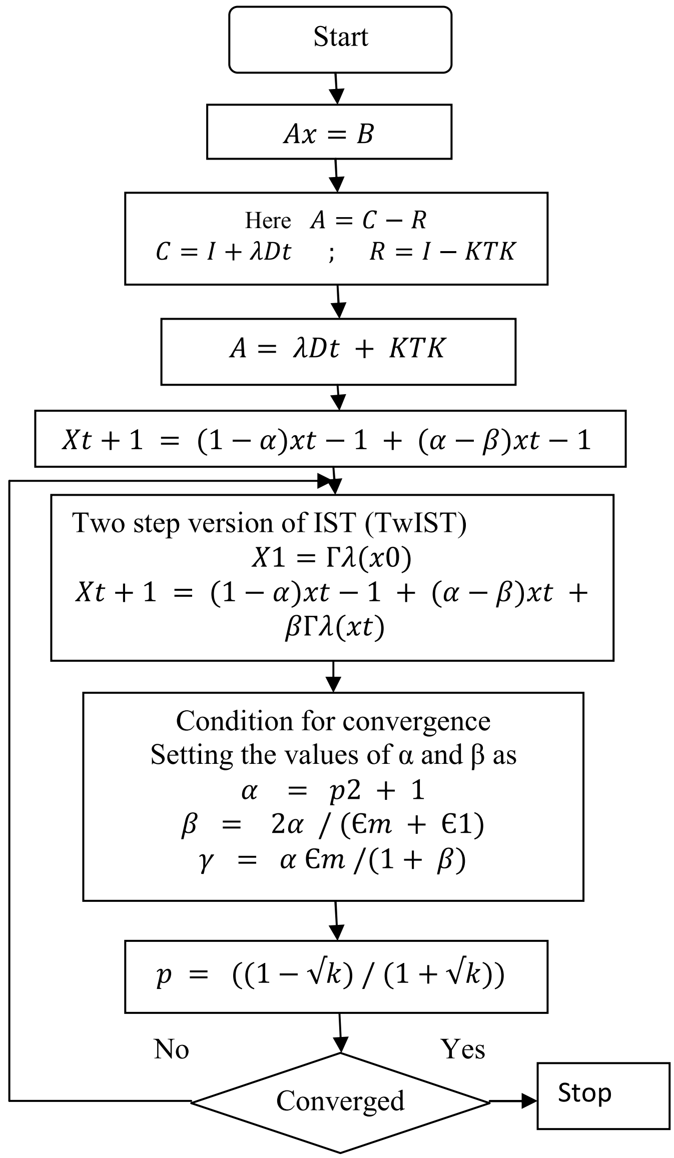

Figure 1: Fluxogram of TwIST algorithm

Algorithm:

Step 1: Start

Step 2: Consider the linear function

$$Ax = B \tag{5}$$

Step 3: The value A is splitted to C and R such that where $A = C - R$

$C = I + \lambda Dt$; $R = I - KTK$
(6)

Step 4: Thus the value A obtains the form

$$A = \lambda Dt + KTK \tag{7}$$

Step 5: Here then the process is to find the value of xt+1

$$Xt + 1 \; = \; (1-\alpha)xt - 1 \; + \; (\alpha-\beta)xt - 1 \; + \; (1-\gamma)xt + \; \beta\Gamma\lambda(xt)A \; = \; \lambda Dt \; + \; KTK \tag{8}$$

Step 6: Then the process of the TwIST is preformed.

$$X1 = \Gamma\lambda(x0) \tag{9}$$

$$Xt + 1 \; = \; (1-\alpha)xt - 1 \; + \; (\alpha-\beta)xt \; + \; \beta\Gamma\lambda(xt) \tag{10}$$

Step 7: Then the different values of α and β are set as follows.

$$\alpha \;\; = \;\; p2 \; + \; 1 \tag{11}$$

$$\beta \;\; = \;\; 2\alpha \; / \; (\epsilon m \; + \; \epsilon 1) \tag{12}$$

Where the value of p is given as

$$p \; = \; ((1-\sqrt{k}) \; / \; (1+\sqrt{k})) \; < \; 1 \tag{13}$$

Step 8: Thus if convergence is proved the iteration is stopped else goto step 6.

4. MODIFIED TwIST

The modified TwIST with minimum number of coordinates when compared to the original TwIST algorithm. The image is being treated with the value of blurred signal to noise ratio. This modified process if image restoration depends on less number of coefficients, where the original TwIST algorithm depends on two coefficients. This modified algorithm uses the values of conjugation matrix, and the blurred image. The CPU time of the modified algorithm has been found to be less than the original TwIST algorithm. Hence this proposed method is proved to be an efficient restoration method.

Algorithm:

Step 1: The input test image is taken in the input to image file

Step 2: The image is being treated with noise and the blurred image is obtained

$$y \; = \; real \; (ifft2 \; (fft2(B).* \; fft2(x))) \tag{14}$$

Where B – Blur Operator,

x – Input image

Step 3: The process of restoration is being carried on as follows

$$x0 = real(\frac{fft2(KC}{abs(KC).^2 + 10 * \frac{sigma^2}{varx} .* ifft(y)}) \tag{15}$$

Where KC – Conjugation matrix,

y – Blurred image

Step 4: The restored image is being processed with the enhancement block

Step 5: Then the output for the modified TwIST algorithm is obtained using MATLAB simulink.

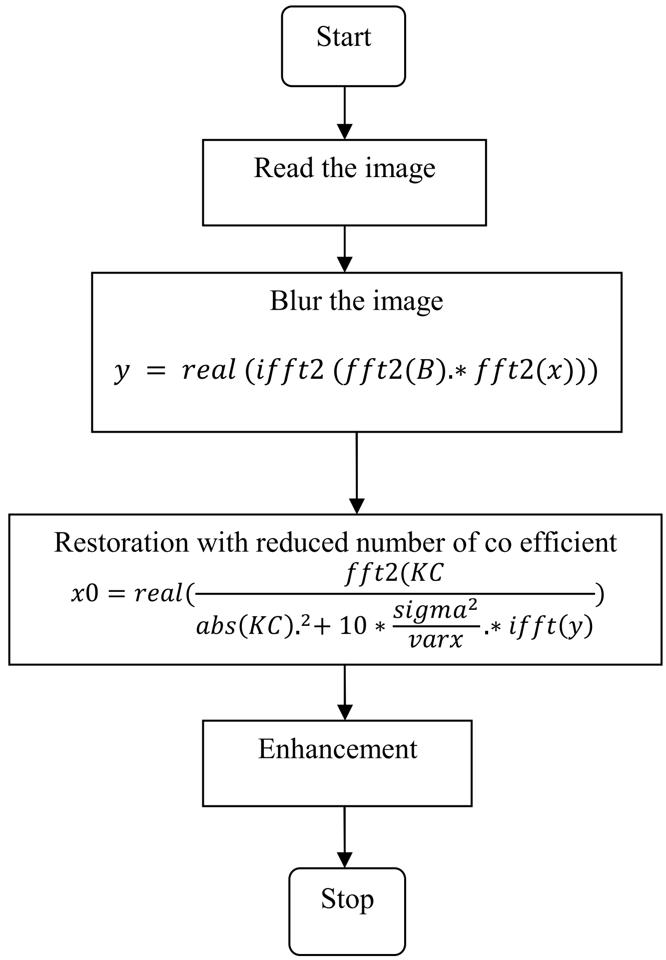

Figure 2: Fluxogram of Modified TwIST algorithm

The modified TwIST is designed using Simulink MATLAB. Figure 3 shows the simulink model for the modified TwIST algorithm. The blocks are used from Video and Image processing block set. The input image is first read form the file with the image from file block. The original image can be viewed through the video viewer 1. This image is being treated with the mean blur operator and the blur matrix is obtained. The resulting blur matrix is normalized to form the circular blur matrix. Then the BSNR value is set and the blurred image is obtained. The blurred image is viewed through the video viewer 2. The blurred image is treated the concept of total variation, and concept of modified two step iteration is performed using the original matrix and the conjugation matrix of the blurred image. The modified algorithm depends on the function of the Fast Fourier Transform and Inverse Fast Fourier Transform. The image is thus restored with these transforms. And the restored image is viewed through the image viewer 3. To enhance the restored image and to match the restored image with the expected output, the image is further processed with the enhancement process. So the restored image is being enhanced using the contrast adjustment block.

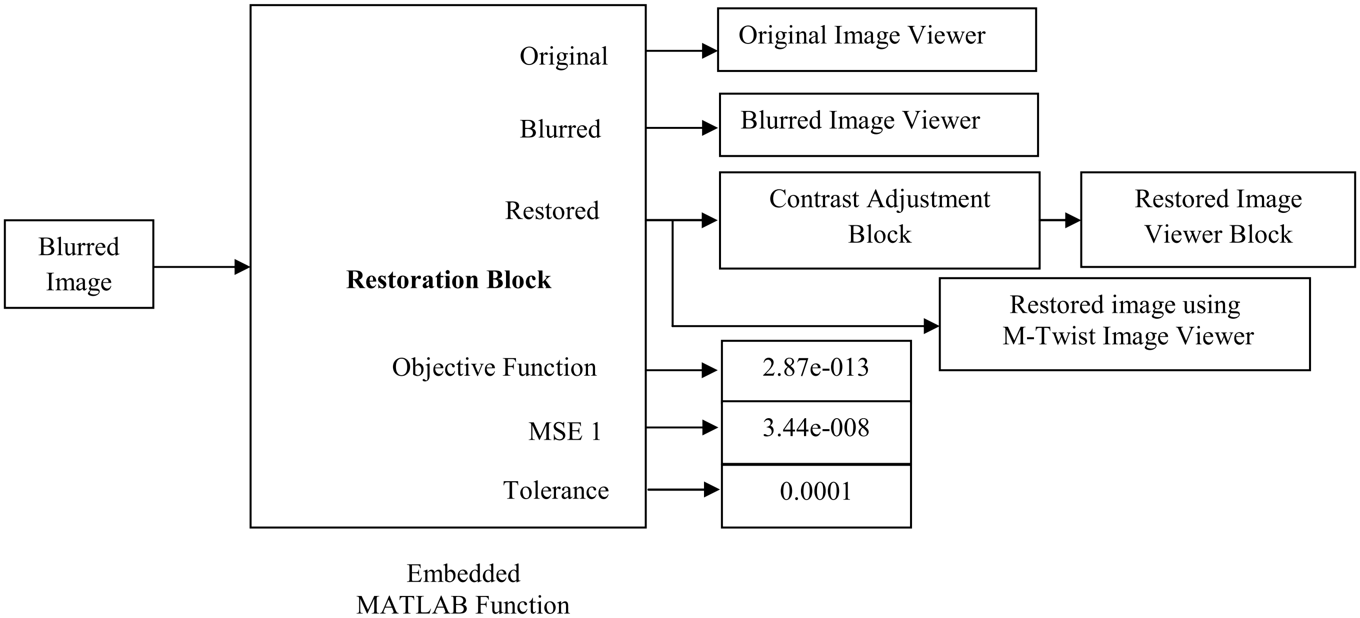

Figure 3: Simulink Model for the Propose Algorithm

5. RESULTS AND DISCUSSION

The modified simulink model output has been tested on various test images and the value of the objective function, Mean Square Error has been tabulated. These values are being compared with the original TwIST algorithm and the values are being compared in the following table.

Table 1 : Evaluation Parameters

Image	MSE		Objective function	
	Proposed	Twist	Proposed	Twist
Test image 1	3.446	1.381104	2.87	2.116e
Test image 2	9.672	1.734924	6.465	1.677
Test image 3	4.674	1.529149	2.014	2.005
Test image 4	6.297	1.110941	8.276	4.996
Test image 5	2.077	5.647703	3.427	2.529
Test image 6	2.318	1.095908	1.531	1.033

The simulation results of TwIST and the modified TwIST algorithm are presented in this session. For analysis, test images captured under a different sources, have been considered. The test images are resampled, resized in 256 x 256 using uniform sampling procedures. The test image include the cameraman image, satellite image of Sethu Canal, MRI brain image, a textured image, IC testing image and the image of a mechanical automobile part with spherical structures. These standard images are blurred using mean blur estimation matrix with a BSNR of 100, these blurred images are restored using the proposed algorithm and the output of the first step blurring process is enhanced to improve the contrast using bicubic contrast enhancement algorithm. Figure 4 shows the output of TwIST and the modified TwIST. Figure 4 (a). shows the input image, figure 4 (b) shows the blurred image with the BSNR of 100. Figure 4 (c) shows the output of the proposed modified TwIST algorithm. Analysis of these figures shows that the output of the proposed modified TwIST algorithm is comparatively better than the TwIST algorithm. Quantitatively the images are analyzed using MSE and the convergence criteria for the objective function. It can be seen from the table (1) that the cameraman image using TwIST algorithm is 1.381104 and by using modified TwIST algorithm is 2.468. Similarly for other test images also the modified TwIST algorithm has performed well in terms of MSE proving that the restored image is so close to the original image. The objective=e function Ax=B, where A is the blurred image, x is the iter value, B is the original image, is to be minimized for achieving the restoration. It can be inferred from Table 1 that the objective function for test image (1) is2.116 using TwIST algorithm and 2.87 using modified TwIST algorithm. The condition for convergence is same for the modified TwIST algorithm for other images also. This faster rate of convergence can be attributed to the reduced number of operations required to perform the deblurring process. As the number of operations has reduced and the convergence is obtained at a faster rate, the chip level implementation of this algorithm becomes easier and is expected to consume low power making the design robust. It can be noted that even with the reduced number of operations and faster convergence, this algorithm is able to restore the images effectively compared to its counter parts.

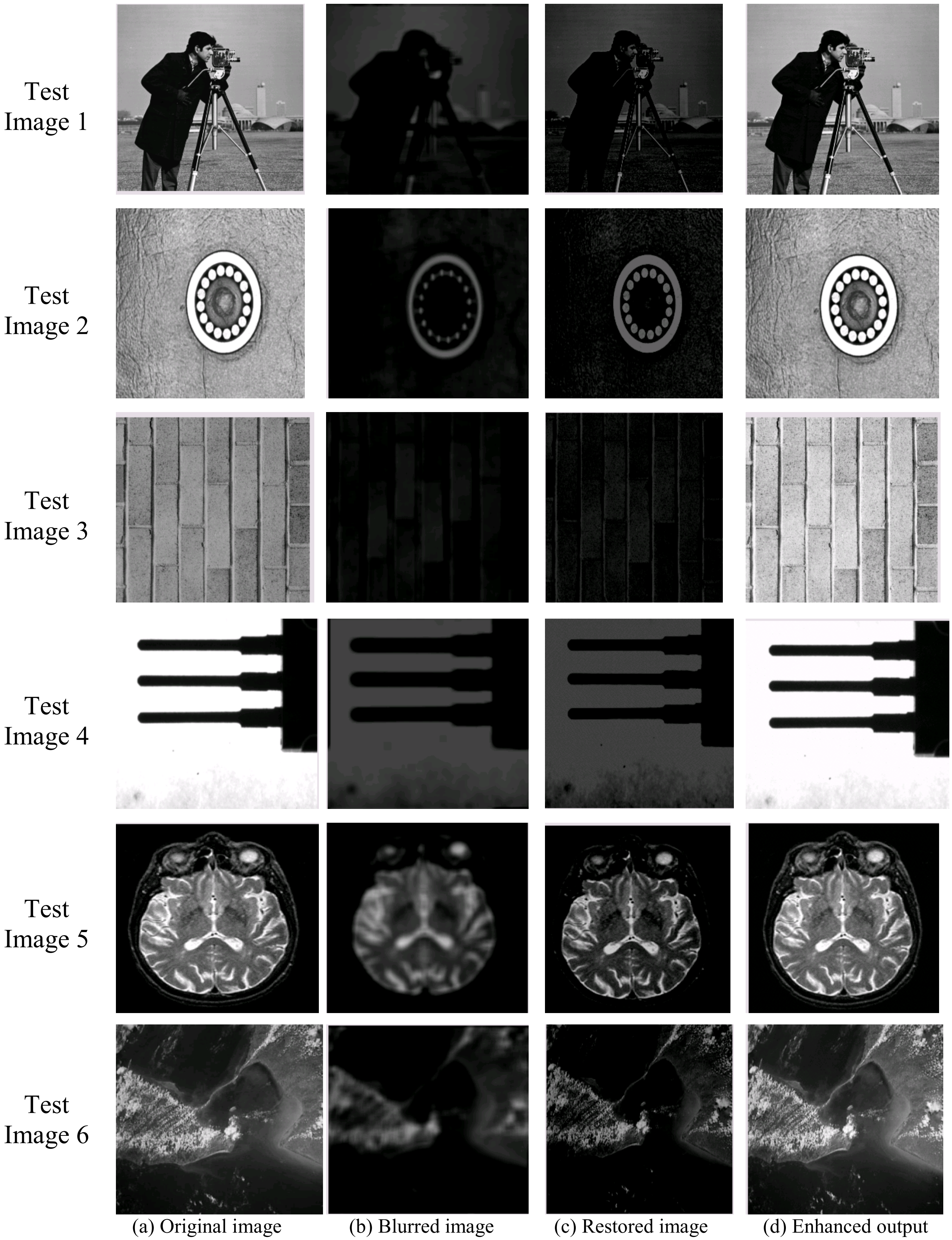

Figure 4 : Simulation results with various images from various sources

6. CONCLUSION

In this paper the simulink model for Restoration of blurred images has been carried out using modified two step iterative algorithm and presented. The reduced convergence time and increased Mean Square Error (MSE) suggest that this scheme can be an effective tool for deblurring highly ill- posed images. The reduced convergence time and number of operations makes its implementation a less power consuming one suitable for low power design.

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