ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

Laplacain Kernel Set Based Smoothen of Motion Blur Ultrasound Image

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ABSTRACT: Biomedical image processing has experienced dramatic expansion, and has been an interdisciplinary research field attracting expertise from applied mathematics, computer sciences, engineering, statistics, physics, biology and medicine. The aim the paper is to investigate the advanced restoration and enhancement filters, identify their merits and demerits and propose new filters to overcome the drawbacks of the existing filters. Experiments were carried out with twenty set of kernel matrices on motion blur ultrasound image. The performance parameters such as signal to noise ratio (SNR), peak signal to noise ratio (PSNR), root mean square error (RMSE), mean absolute error (MAE), and Pearson correlation coefficient (PCC) have been estimated and compared. Kernel based filtering process provides sharpen ultrasound image with high image characteristics parameters as compared to blur ultrasound images.

KEYWORDS: Ultrasound, Kernel Set, PSNR, SNR, MAE, PCC.

I.INTRODUCTION

Medical imaging has become increasingly important in bio-medical research and clinical practice. It is the driving force in the development of modern volumetric digital imaging techniques [1]. Some of the imaging techniques that noninvasively can reveal tumors and fractures with a minimal hazard to the living tissue are MRI, X-ray, and ultrasound. Especially segmentation, registration and temporal analysis are image processing tasks suitable for computer algorithms. Ultrasound has been used to image the human body for over half a century. Dr. Karl Theo Dussik, an Austrian neurologist, was the first to apply ultrasound as a medical diagnostic tool to image the brain [2-3]. Today, ultrasound is one of the most widely used imaging technologies in medicine. It is portable, free of radiation risk, and relatively inexpensive when compared with other imaging modalities, such as magnetic resonance and computed tomography. Furthermore, ultrasound images are tomographic, i.e., offering a “cross-sectional” view of anatomical structures. The images can be acquired in “real time,” thus providing instantaneous visual guidance for many interventional procedures including those for regional anesthesia and pain management. Various motion artifacts may arise in the ultrasound image [4-6].

Ultrasound medical images are known to be affected by blur. Blur degrades US images by the reasons of Gaussian noise, employing a denoising procedure on the degraded image, imperfect resolution of the imaging system, losing information throughout the acquisition process, and employing low-pass filters for reducing noise leads to blur amplification. Blur has diverse types such as, atmospheric turbulence, Average, Box, Gaussian, Pillbox blur, and so on. Image deblurring is an essential topic in the area of image processing [7]. The deblurring process results in sharpened details, better image quality and visualization. The image restoration is a vital phase to recover images from their degradations; these techniques are considered as direct techniques when the outcome is formed in a one-step mode. Consistently, it's considered as indirect techniques when the outcome is acquired with a number of iterations. Famous restoration methods such as Wiener Filtering and Richardson-Lucy are examples of direct and indirect methods. The problems with these techniques are the essential need for the point-spread function (PSF), and determining the sufficient iterations required to restore the image. Therefore, the use of kernels is more suitable, because determining the PSF and/or the number of iteration is not required [8-10]. Using kernels to deblur images is very simple. The basic concept is to convolve the kernel with the blurry image to obtain a sharper image. It takes one mathematical operation only, and it's fast and reliable. Suppose the degraded image is (D), the kernel is (K), and the convolution process is ($\otimes$), the restored image (R) can be described as the subsequent:

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$$R = D \otimes K$$

Laplacian kernels are well-known in the sharpening field. The problem is it contains only few sets of kernels. Therefore, the process of sharpening cannot be tuned well; the kernels either sharpen more or less than the desired amount. Thus, more sets of Kernels are demanded. This paper presents twenty novel kernels to tune and get the exact sharpening amount [11-15].

II.METHODOLOGY

In order to proceed with the research work image processing toolbox is used. The work is divided into two major parts. The main goal of image enhancement is to reduce redundancy in the image as much as possible. Kernel set method is one of simple and easy to implement image sharpening algorithms. The kernel set used in the research work are given below. The image is converted into double data type and then multi dimensional filter is applied on the input image. Two different boundary conditions are taken for the filtering process i.e. symmetric (input array values outside the bounds of the array are computed by mirror-reflecting the array across the array border) and replicate (input array values outside the bounds of the array are assumed to equal the nearest array border value.

$$\begin{bmatrix} 0 & -1 & 0 \\ 0 & 3 & 0 \\ 0 & -1 & 0 \end{bmatrix} \quad \begin{bmatrix} -1 & 0 & -1 \\ 0 & 5 & 0 \\ -1 & 0 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & 2 & -1 \\ 0 & 1 & 0 \\ -1 & 2 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & 0 & -1 \\ 2 & 1 & 2 \\ -1 & 0 & -1 \end{bmatrix}$$

$$K=1 \qquad K=2 \qquad K=3 \qquad K=4$$

$$\begin{bmatrix} -1 & 0 & -1 \\ -1 & 7 & -1 \\ -1 & 0 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & -1 & -1 \\ 0 & 7 & 0 \\ -1 & -1 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & -1 & -1 \\ 1 & 5 & 1 \\ -1 & -1 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & 1 & -1 \\ 0 & 3 & 0 \\ -1 & 1 & -1 \end{bmatrix}$$

$$K=5 \qquad K=6 \qquad K=7 \qquad K=8$$

$$\begin{bmatrix} 0 & -2 & 0 \\ 0 & 5 & 0 \\ 0 & -2 & 0 \end{bmatrix} \quad \begin{bmatrix} -2 & 0 & -2 \\ 0 & 9 & 0 \\ -2 & 0 & -2 \end{bmatrix} \quad \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix} \quad \begin{bmatrix} -1 & 0 & -1 \\ -2 & 9 & -2 \\ -1 & 0 & -1 \end{bmatrix}$$

$$K=9 \qquad K=10 \qquad K=11 \qquad K=12$$

$$\begin{bmatrix} -2 & -1 & -2 \\ 0 & 11 & 0 \\ -2 & -1 & -2 \end{bmatrix} \quad \begin{bmatrix} -1 & -2 & -1 \\ 0 & 11 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad \begin{bmatrix} -1 & -2 & -1 \\ -1 & 11 & -1 \\ -1 & -2 & -1 \end{bmatrix} \quad \begin{bmatrix} 0 & -2 & 0 \\ -1 & 7 & -1 \\ 0 & -2 & 0 \end{bmatrix}$$

$$K=13 \qquad K=14 \qquad K=15 \qquad K=16$$

$$\begin{bmatrix} 0 & 0 & 0 \\ -1 & 3 & -1 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} -2 & 0 & -2 \\ -1 & 11 & -1 \\ -2 & 0 & -2 \end{bmatrix} \quad \begin{bmatrix} 0 & -1 & 0 \\ -2 & 7 & -2 \\ 0 & -1 & 0 \end{bmatrix} \quad \begin{bmatrix} -2 & 0 & -2 \\ 1 & 7 & 1 \\ -2 & 0 & -2 \end{bmatrix}$$

$$K=17 \qquad K=18 \qquad K=19 \qquad K=20$$

In second part various image characteristic parameters such as signal to noise ratio (SNR), peak signal to noise ratio (PSNR), root mean square error (RMSE), Pearson correlation coefficient (PCC), and mean absolute error (MAE) are estimated for compressed image with respect to original image. The algorithm designed to compute image characteristics parameters. Compressed image degrade the quality of the image which needed to be investigated. Root

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mean square error (RMSE) corresponds to pixels in the reference image Ir and the fused image If . If the reference image and fused image are alike give the RMSE value equal to zero and it will increase when the dissimilarity increases between the reference and fused image.

$$RMSE = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(I_r(x,y) - I_f(x,y))^2}$$

Peak signal to noise ratio (PSNR) value will be high when the fused and reference images are alike and higher value implies better fusion. PSNR is calculated by follow equation.

$$PSNR = 20\log_{10}\left(\frac{L^2}{\sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}(I_r(x,y) - I_f(x,y))^2}}\right)$$

Signal to noise ratio (SNR) is calculated using following formula

$$SNR = 10\log_{10}\left(\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I_r(x,y) - I_f(x,y))^2}{\sum_{x=1}^{M}\sum_{y=1}^{N}(I_r(x,y)}\right)$$

Pearson correlation coefficient is computed using following formula

$$PCC = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (y_i - y_m)^2}}$$

where xi is the intensity of the ith pixel in image 1, yi is the intensity of the ith pixel in image 2, xm is the mean intensity of image 1, and ym is the mean intensity of image 2.

In addition to these parameters MAE is also calculated using following equation

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|I_x(i,j) - I_y(i,j)\right|$$

III.RESULT AND DISCUSSION

A motion blur of 16 bits and 45 degrees is added to the ultrasound image. The blurred image is subjected to image sharpening algorithm with twenty different kernel matrices. Figure 1 shows the reconstructed image. It is observed from the results that the image reconstructed using K2, K4, K5, K10, K12, K13, and K20 shows better resolution image then reconstructed image using other kernel matrix. Table 1 shows the computed values of image characteristics parameters. The maximum and minimum value of SNR for reconstructed image using all the matrices is 0.15 dB and 0.01 dB respectively. 18.86 dB ad 17.22 dB are the maximum and minimum computed PSNR values. Computed RMSE minimum value is 120.17 and maximum value is 155.82. Similarly, MAE is computed value is 20.85 and 25.59. The correlation coefficient between the original image and reconstructed image is 571896 and 532548. Figure 2 shows the graphical representation of computed SNR values for all the kernel matrices. The PSNR is shown in Fig. 3 and RMSE is shown in Fig. 4. In the graph x-axis represents the kernel matrix and y-axis the magnitude.

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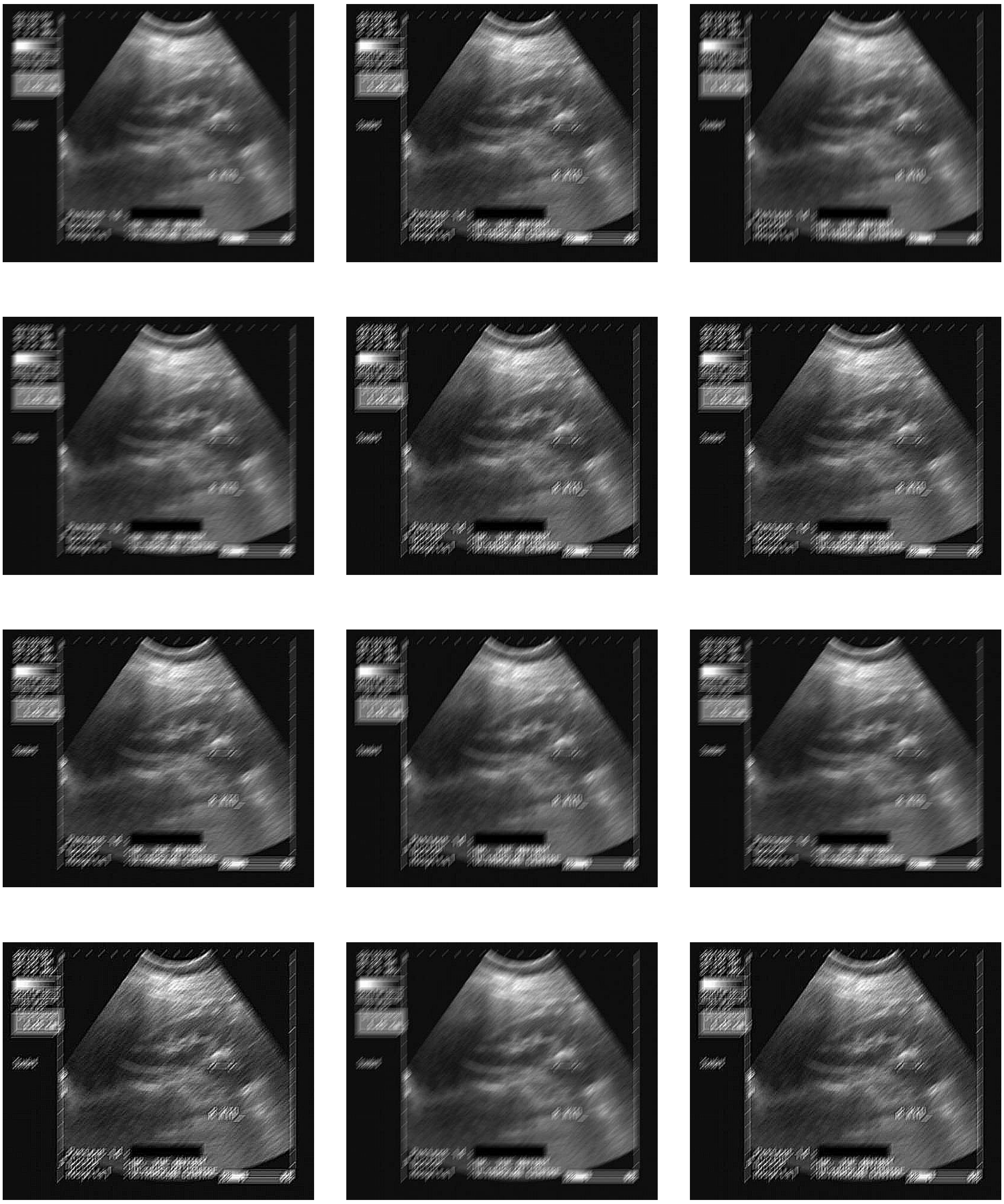

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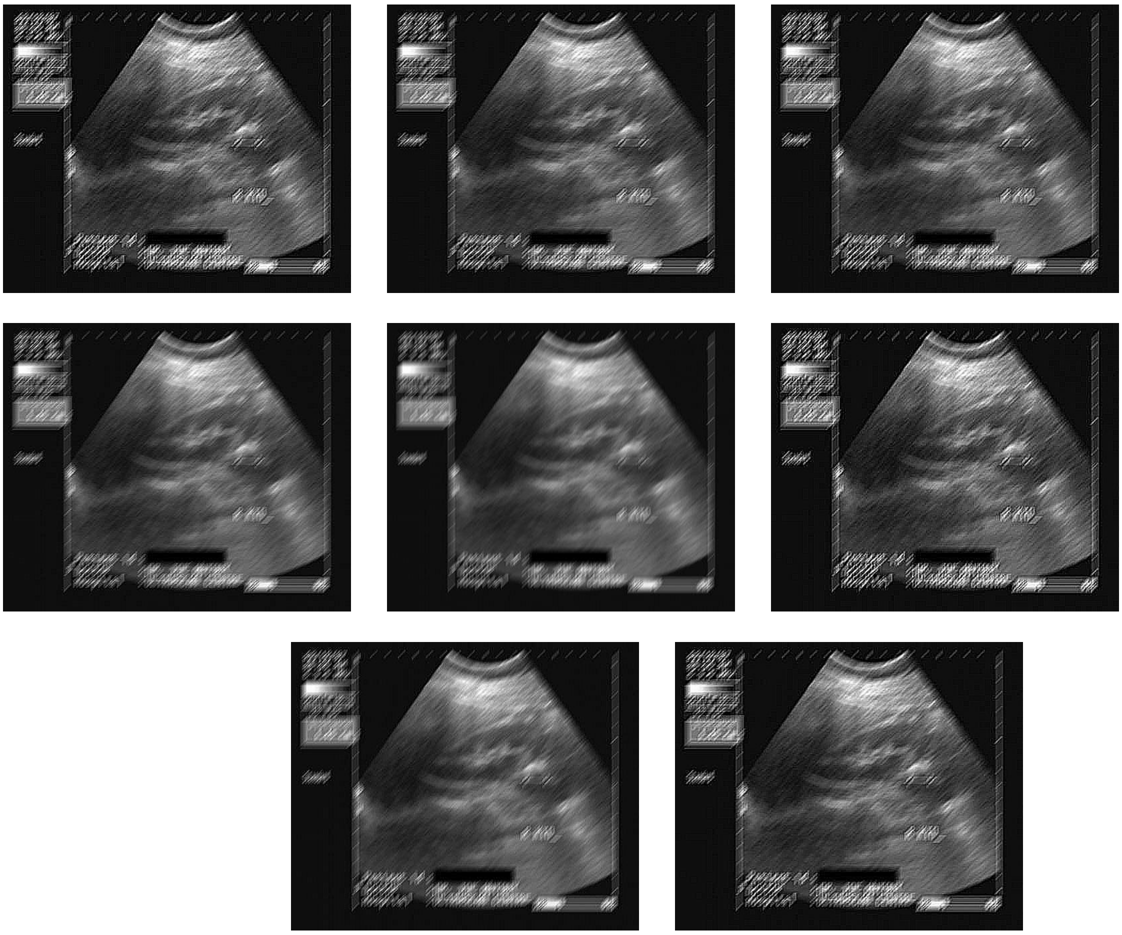

Fig. 1 Improved motion blurred reconstructed US image of kidney with stone twenty different kernel matrix

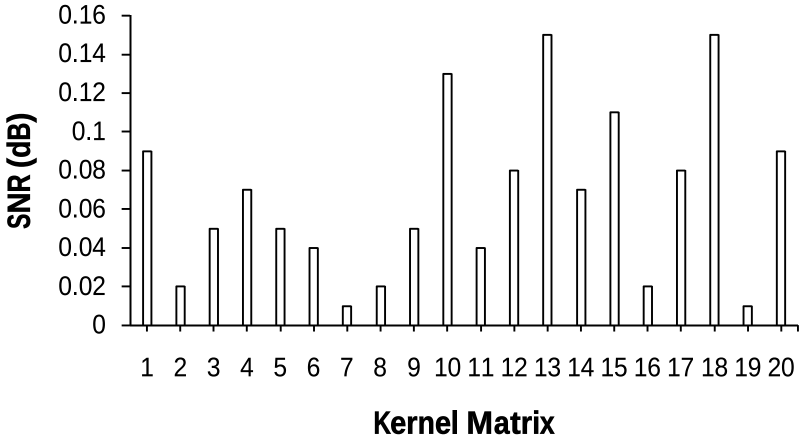

Fig. 2 Computed values of SNR for motion blur improved US image.

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Table 1 Computed values of image characteristic parameter for reconstructed motion blur US image with different kernel matrices.

Kernel Matric	SNR	PSNR	RMSE	MAE	PCC
K1	0.09	19.49	103.32	19.1	586296.91
K2	0.02	18.88	122.97	20.96	572445.87
K3	0.05	19.31	109.78	19.78	582248.23
K4	0.07	19.39	108.71	19.58	584021.37
K5	0.05	18.46	131.03	21.97	562681.89
K6	0.04	18.50	131.61	22.00	563694.65
K7	0.01	18.86	124.00	21.10	571987.26
K8	0.02	19.17	114.77	20.17	578924.09
K9	0.05	19.21	112.90	19.98	579882.21
K10	0.13	17.60	149.09	24.44	542216.53
K11	0.04	19.24	110.49	19.78	580624.96
K12	0.08	18.00	138.39	23.07	551371.92
K13	0.15	17.22	155.83	25.59	532548.91
K14	0.07	18.07	140.30	23.17	553525.33
K15	0.11	17.67	146.31	24.19	543683.14
K16	0.02	18.90	119.90	20.75	572750.97
K17	0.08	19.46	104.12	19.23	585571.92
K18	0.15	17.20	154.93	25.49	531759.05
K19	0.01	18.86	120.17	20.85	571896.85
K20	0.09	18.01	143.03	23.43	552296.89

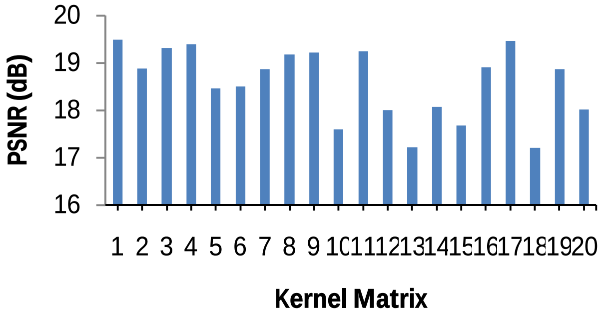

Fig. 3 Computed values of PSNR for motion blur improved US image.

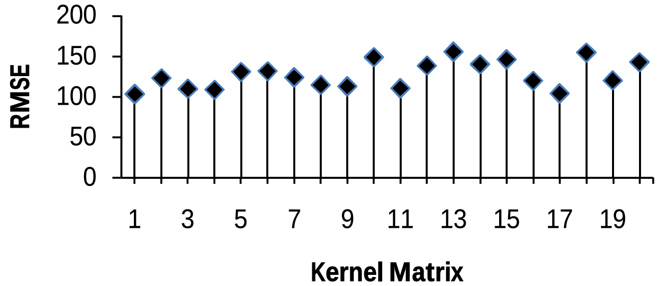

Fig. 4 Computed values of RMSE for motion blur improved US image.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 4, April 2016

VI.CONCLUSION

The research work is carried out to enhance the ultrasound image of kidney containing stone with digital image processing technique. The aim of this thesis was to investigate the advanced restoration and enhancement filters, identify their merits and demerits and propose new filters to overcome the drawbacks of the existing filters. For this purpose kernel set based filters were applied to normal ultrasound image. Also three types of blur such as average blur, motion blur, and pillbox blur were added to the ultrasound image and then subjected to filters for enhancement purpose. experiment motion blur of 16 bits and 45 degree is added to the original ultrasound image and algorithm is applied on it with twenty sets of kernel matrices. The computed image characteristics parameters for kernel set showing improvement are K2 (SNR = 0.02, PSNR = 18.88, RMSE = 122.97, MAE = 20.96), K4 (SNR = 0.07, PSNR = 19.39, RMSE = 108.71, MAE = 19.58), K5 (SNR = 0.05, PSNR = 18.46, RMSE = 131.03, MAE = 21.97), K10 (SNR = 0.13, PSNR = 17.6, RMSE = 149.09, MAE = 24.44), K12 (SNR = 0.08, PSNR = 18, RMSE = 138.39, MAE = 23.07), K13 (SNR = 0.15, PSNR = 17.22, RMSE = 155.83, MAE = 25.59), and K20 (SNR = 0.09, PSNR = 18.01, RMSE = 143.03, MAE = 23.43).

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