New Image Noise Reduction Schemes Based on Cellular Automata

Biswapati jana, Pabitra Pal, Jaydeb Bhaumik

Abstract*— *This paper presents noise filtering technique of noisy image using cellular automata (CA). Two new approaches to reduce noise form a noisy image have been proposed. In the first approach, difference values of Moore neighbors form center pixel are calculated, then sorted in ascending order and the center pixel value is updated depending on the present pixel values using CA rule. In second approach, all pixels value of Moore neighbor including center pixel are sorted in ascending order. Then the minimum and maximum values are eliminated form sorted pixel values and the center pixel value is updated using CA rule. Results are compared with other existing filtering technique in terms of Peak Signal to Noise Ratio (PSNR). This comparisons shows that a filter based on CA provides significant improvements over the standard filtering methods.

Index Terms*— *Cellular Automata (CA), Image processing, Noise reduction, Peak signal-to-noise ratio (PSNR).

I. INTRODUCTION

Image enhancement is the processing of images to improve their appearance to human viewers or to enhance the performance of other image processing system. Processing of image in the presence of noise [1-7] is one of the most common problems in this area.

The detection of edges is another essential task in image processing [8-16]. In particular, in processing of biological or medical images, the edge study becomes very important. But in general, we can detect an edge form an image very well if it is less affected by noise. For all cases like pattern recognition, object identification or segmentation noise must be reduced to get better result. So noise reduction is very important issue before processing the image. Image processing using CA is a new emerging approach [17-19] to the researchers.

In this paper two new techniques to reduce noise from an image using cellular automata (CA) have been proposed. The proposed schemes exploit Moor Neighbors of CA to reduce noise from an image. The rest of this paper is organized as follows. In section 2, related work on image processing using CA is discussed. Basic schemes for image filtering have been described in section 3. The overview of cellular automata has been illustrated in section 4 and the proposed methods have been described in section 5. The experimental result and comparison is presented in section 6 and finally the paper is concluded in section 7.

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II. RELATED WORK

Wolfram [20] studied one dimensional (1D) CA with the help of polynomial algebra. Pries [21] studied 1D CA exhibiting group properties based on a similar kind of polynomial algebra. Packard and Wolfram [22] reported some empirical studies on two dimensional (2D) CA depending on five neighborhoods CA. Choudhury *et al*. [24] extended the theory of 1D CA built around matrix algebra for characterizing 2D CA. However, emphasis was laid on special class of additive 2D CA, known as restricted vertical neighborhood CA. In this class of 2D CA the vertical dependency of a site is restricted to either the sites on its top or bottom, but not both. Characterization and applications of some particular uniform and hybrid 2D CA linear rules [22-24] are also reported. C.D.Thomas in his thesis [18] studied the evolution of Cellular Automata for image processing. Ganguli *et al.* [23] studied the theory and application of additive 1D Cellular Automata rules for Pattern classification using matrix theory and characteristic polynomial. Choudhury *et al* [24] studied some extra theory of 1D CA linear rules. This requires introduction of the 1D nine neighborhoods CA and the rules by which the dependencies of a cell are governed. The application of such rules on problem matrix is demonstrated which forms the basis of image processing. He also presents the study of 512 linear Boolean functions, their matrix construction, structure of those matrices and their properties both in uniform as well as in hybrid CA. The effect of these linear rules on a given image is presented. Particularly these rules are used for image transformations like translation, multiplication of one image into several, zooming-in and zooming-out, thickening and thinning of images. While the translation and multiplication can be carried out on any arbitrary image, structured images are needed for others multiple copies of any arbitrary image, if available. P. Jebaraj Selvapeter and Wim Hordijk studied [25] cellular automata for image noise filtering. In their report they proposed a new technique to perform this type of work. To remove noise they use majority CA update rule. This rule is stated as follows: if the center pixel’s (cell) gray level is 0 or 255 (i.e., black or white), then the gray level that is the majority in the local neighborhood replaces the center pixel’s value. If none of the gray levels in the local neighborhood is a majority, then there is a tie. This can be deal with either deterministically or randomly. In the deterministic rule, the center pixel is replaced by the gray level which is in a fixed position in its local neighborhood (e.g., the pixel directly above it). Obviously this choice of the fixed position of their placement pixel is arbitrary (it could also be the pixel directly below, or to the left, etc.). In the random majority rule, the center pixel’s value is replaced by the gray level of a

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randomly chosen pixel in its local neighborhood. In this case, there placement pixel is chosen independently (at random) for each occurrence of a tie. Here we proposed a new technique to reduce noise from image using CA with the help of Moore neighbor pixel information.

III. BASIS OF IMAGE FILTERING

In this section, basics of image filtering are discussed. Digital image processing plays an important role in daily life applications such as television signal transmission, magnetic resonance imaging, computer tomography, geographical information systems and astronomy. However data which are collected by the image sensor are generally contaminated by noise. Noise can be introduced by the data transmission errors and/or data compression. Image noise filtering is necessary before image analysis. But noise filtering still remains a difficult challenge because noise removal introduces artifacts and cause blurring of images. In image processing edge detection is the most important part, and the edge can be detected clearly if there is no noise.

An image can be degraded by either additive or multiplicative noise. The additive noise can be expressed as follows.

$$Gij = Fij + Nij \qquad (1)$$

Where F_{ij} is the intensity of pixel (i, j) in the original image, G_{ij} is the intensity of pixel (i, j) in the degraded image and N_{ij} is the additive noise. The multiplicative noise can be expressed as.

$$Mij = Uij * Nij \qquad (2)$$

Where, U_{ij} is the intensity of pixel (i, j) in the original image, M_{ij} is the intensity of pixel (i, j) in the degraded image and N_{ij} is the multiplicative noise.

Various types of noise are there [1-7], some of them are – Gaussian Noise, Rayleigh Noise, Exponential Noise, Uniform Noise, Impulse Noise, Salt-and-pepper noise etc. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by dead pixels, analog-to-digital converter errors, bit errors in transmission, etc. This can be eliminated in large part by using dark frame subtraction and by interpolating around dark/bright pixels.

To get the original image from the noisy image one should have to use noise filtering techniques, some of them are discussed here.

a. *Mean Filter*

The idea of mean filtering is simply to replace each pixel value in an image with the 'mean' or 'average' value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. An example of mean filtering of a single 3 × 3 window of values is shown in Fig. 1. The center pixel value i.e. 1 is replaced by the mean of all nine values i.e. 5. The unfiltered value is shown in Fig. 1A and median filtered value is shown in Fig. 1B.

Unfiltered value **Mean filtered**

A

5	3	6
2	**1**	9
8	4	7

B

5	3	6
2	**5**	9
8	4	7

Fig. 1: Mean Filter

b. *Median Filter:*

The median filter is very effective at removing noise while not destroying sharp edges in an image. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter for preserving useful detail in the image. The median is a stronger "central indicator" than the average.

As for an example of median filter of a single 3 × 3 window of values is shown in Fig. 2.

Unfiltered value **Median filtered**

A

5	3	6
2	**1**	9
8	4	7

B

5	3	6
2	**5**	9
8	4	7

Fig. 2: Median Filter

By arranging pixel values in ascending order, one can obtain the following sequence: 1, 2, 3, 4, 5, 6, 7, 8, 9. In Fig. 2 the center pixel value i.e. 1 is replaced by the median of all nine values i.e. 5. The unfiltered value is shown in Fig. 2A and median filtered Fig. 2B.

IV. OVERVIEW OF CELLULAR AUTOMATA

In the proposed schemes Cellular Automata (CA) has been employed for noise filtering. Hence for the sake of completeness a brief overview of CA is provided in the following section. Although the concept was proposed almost five decades back by John Von Neumann [26], but in the last two decades, researchers of various fields became interested to use the concept. CA has wide range of applications in the field of pseudo random sequence generation, error correcting code, VLSI circuit testing and image processing. CA consists of a large number of relatively simple individual units, or "cells", which are connected only locally, without the existence of a central control in the system. Each cell is a simple finite automaton that repeatedly updates its own state, where the new cell state depends on the cell's current state and those of its local neighbors.

However, despite the limited functionality of each individual cell, and the interactions being restricted to local neighbors only, the system as a whole is capable of producing intricate patterns, and even of performing complicated computations. In that sense, they form an alternative model of computation, one in which information processing is done in a distributed and highly parallel manner. Because of these properties, CA have been used extensively to study complex systems [32] in nature, such as fluid flow in physics or pattern formation in biology, and also to study image processing now a days. Here, a brief overview of the different ways in which computations can be done by CA is given.

One dimensional CA

In the simplest case, the CA lattice is a one dimensional (1D) array of cells [33, 34], where each cell can be either black or white, and the local neighborhood of a cell consists of the cell itself, the immediate neighbor to the left, and the immediate neighbor to the right, i.e., a radius of 1, or three cells total. So, there are $2^3=8$ possible neighborhoods configurations for a cell. Such a 1D, two-state and radius 1 CA is known as an elementary CA. The CA is completely defined with the help of following parameters.

1. Dimension d belongs to Z+,
2. Finite state set S,
3. Neighborhood vector N = (n_1, n_2…n_m), and
4. Local update rule f.

Hence CA can be defined in terms of 4-tuple A = (d, S, N, f). Some useful terminologies of CA are discussed as follows.

a. Null boundary CA

If the left or right neighborhood of the leftmost or rightmost terminal cell is connected to logic-0, then the CA is referred to as Null boundary CA.

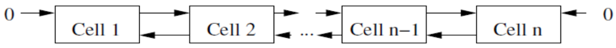

Fig. 3: n-cell Null boundary CA

b. Periodic boundary CA

If the left neighbor of the left most cells is the right most cell and vice versa, then the CA is referred to as periodic boundary CA.

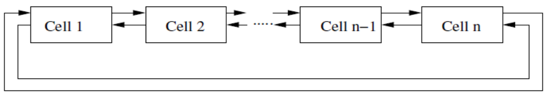

Fig. 4: n-cell Periodic boundary CA

The rule vector of an n-cell CA is defined as the set of rules R = < R1, R2… Ri… ,Rn > that configures the cells of a CA. For example, R = < 230, 123, 255, 67 > is a rule vector which consists of 4 rules. A rule is balanced if it contains equal number of 1s and 0s in its 8-bit binary representation; otherwise it is an unbalanced rule. For example, 11100100 (Rule 228) is a balanced rule where 11100000 (rule 224) is an unbalanced rule.

The CA structure investigated by Wolfram [20] can be viewed as discrete lattice of sites where each cell can assume either the value 0 or 1. The next state of a cell is assumed to depend on itself and on its two neighboring cells for a three neighborhood dependency. The cells evolve in discrete time steps according to some deterministic rule that depends only on local neighborhood. The following example shows one particular CA update rule 110. The 8 possible local neighborhood configurations are listed in the first row, and the next state for the cell is given in the second row.

Neighborhood state	111	110	101	100	011	010	001	000
New State	0	1	1	0	1	1	1	0

Fig. 5: Structure for CA rule110.

Two dimensional CA

The extension to two dimensional (2D) CA is significant for comparisons with many experimental results on pattern formation in physical systems. Depending on the neighbors of 2D CA it is divided into two types, Moore neighborhood and Von Neumann neighborhood. The Moore neighborhood is the set of all cells that are orthogonally or diagonally adjacent to the region of interest. The Moore neighborhood of range r is defined by (3),

$$N^{M}_{(x_0,y_0)} = \{(x,y): |x-x_0| \le r, |y-y_0| \le r\} \quad (3)$$

Moore neighborhoods for ranges r = 1 and 2 are illustrated in fig. 6. The number of cell in the Moore Neighborhood of range r is the odd squares i.e., $(2r+1)^2$ and the first few of which are 1, 9, 25, 49, 81. If the range value r ≥ 2 then it is consider as Extended Moore neighborhood.

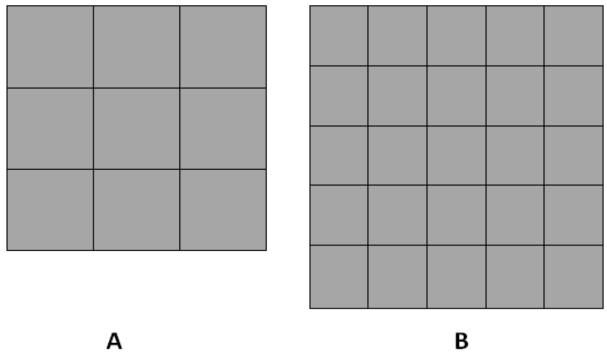

**Fig. 6: A) Moore neighborhood
B) Extended Moore neighborhood**

The Von Neumann neighborhood is the set of all cells that are orthogonally adjacent to the region of interest. The Von Neumann neighborhood of range r is defined by (4),

$$N^{V}_{(x_0,y_0)} = \{(x,y): |x-x_0| + |y-y_0| \le r\} \quad (4)$$

The Von Neumann neighborhoods for ranges r= 1 and 2 are illustrated in Fig. 7. The number of cell in the Von Neumann neighborhood of range r is the centered square number i.e., 2r(r+1) +1 and the first few of which are 1, 5, 13, 25, 41, 61. If the range value r ≥ 2 then it is consider as Extended Von Neumann neighborhood.

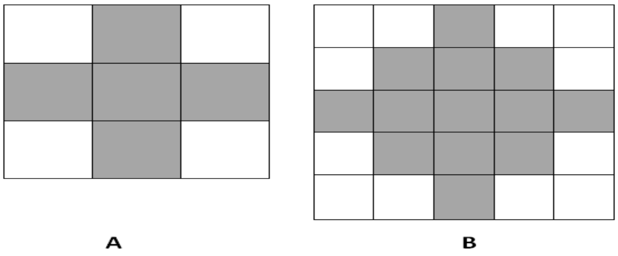

Fig. 7: A) Von Neumann neighborhood B) Extended Von Neumann neighborhood

In a 2D nine neighborhood CA, the next state of a particular cell is affected by the current state of itself and eight cells in its nearest neighborhood also referred as Moore neighborhood as shown in the Fig.8. Such dependencies are accounted by various rules. For the sake of simplicity, in this section we take into consideration only the linear rules. A specific rule convention that is adopted here is as follows:

64	128	256
32	1	2
16	8	4

Fig. 8: 2D rule box

The Central box represents the current cell that is the cell under consideration and all other boxes represent the eight nearest neighbors of that cell. Now each of the cells can be taken as a variable and thus for 2D CA there are 9 variable to be considered. The number within each box represents the rule number characterizing the dependency of the current cell on that particular neighbor only. Rule 1 characterizes dependency of the central cell on itself alone where as such dependency only on its top neighbor is characterized by Rule 128, and dependency on all neighbors is characterized by Rule 511, and so on. These nine rules are called fundamental rules. In case, the cell has dependency on two or more neighboring cells, the rule number will be the arithmetic sum of the numbers of the relevant cells. The number of such rules generated by a combination of these 9-variables is ${}^{9}C_{0} + {}^{9}C_{1} + . . . + {}^{9}C_{9}$ =512 which includes rule characterizing no dependency.

Now, these 512 linear rules have been previously classified by taking into account the number of cells under consideration. The grouping has been Group-N for N=1,2…. 9, includes the rules that refer to the dependency of current cell on the N neighboring cells amongst top, bottom, left, right, top-left, top-right, bottom-left, bottom-right and itself. Thus Group 1 includes 1, 2, 4, 8, 16, 32, 64, 128, and 256. Group 2 includes 3, 5, 6, 9, 10, 12, 17, 18, 20, 24, 33, 34, 36, 40, 48, 65, 66, 68, 72, 80, 96, 129, 130, 132, 136, 144, 160, 192, 257, 258, 260, 264, 272, 288, 320 and 384. If the next state of a cell is depends on the present state of itself and its right neighbor, it is referred to as rule 3(=1+2) and since it is dependent only on two cells that's why it is belong to Group 2. If the next state depends on the present state of itself and all its Moore neighbors, it is referred to as rule 511 (=1+2+4+8+16+32+ 64+128+256) and which is belong to group 9. Similarly rules belonging to other groups can be obtained. It can be noted that number of 1's present in the binary sequence of a rule is same as its group number.

V. PROPOSED CA BASED NOISE REDUCTION SCHEMES

In this section proposed schemes are discussed. A digital image is assumed to be a two dimensional array of $m \times n$ pixels, each with a particular gray value or color. An image can be considered as the lattice configuration of a 2D CA where each cell corresponds to an image pixel, and the possible states are the different gray values or colors. For simplicity, 256-level gray scale image with Moore neighborhood (the eight neighboring cells surrounding a cell) is being considered. Fixed value boundary conditions are applied, i.e., the update rule is only applied to non-boundary cells. Figure 9 shows the flowchart for proposed CA Algorithm-I. A 3×3 mask of a noisy image is considered and the difference between center pixel and its Moore neighbors is computed. All distance values are sorted in ascending order. The center pixel value of considered mask is update by using CA rule 511. The mask is moved in the next location and update process is continued until the last location of noisy image is reached. The center pixel value update has been done by using CA Rule 511.

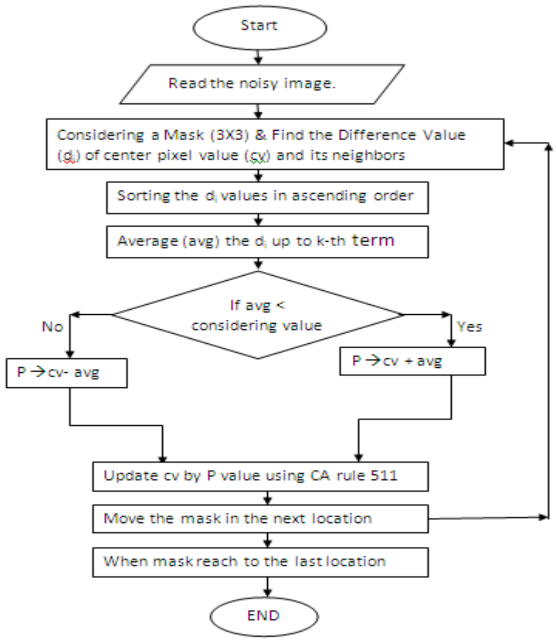

Fig. 9: Flowchart for CA Algorithm-I

Figure 10 shows the flowchart for proposed CA Algorithm-II.

Consider a 3×3 mask of a noisy image. The highest and lowest pixel values from its neighbors are eliminated. The center pixel value is updated using CA rule 511.

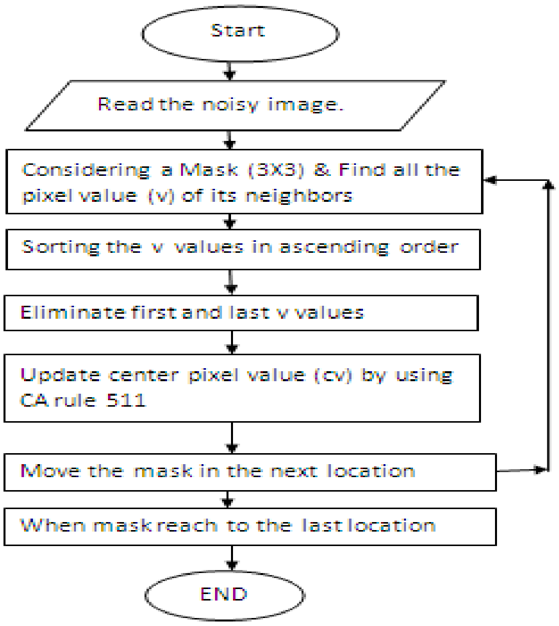

Fig.10: Flowchart for CA Algorithm-II

Algorithms of two proposed techniques are stated as follows.

CA Algorithm-I:

Step 1: Consider a noisy image with m×n matrix of 8 bit gray scale image and 3×3 masks

Step 2: Consider CA of r=2 and cv = center pixel value. So total neighbor n=8 and total cell of CA is 9

Step 3: Calculate d_i = cv- n_i for all i=1 to 8, which belong to the considering mask area

Where d_i = Differences Values,

cv = Center Pixel Value,

n_i = Neighbor Pixel Value (for all i=1 to 8).

Step 4: Sort d_i in ascending order

Step 5: We consider k such that k= n/2 +1 (which is greater than 50% of total cell of CA)

Step 6: Calculate avg $=\sum d_i /k$, for all i = 1 to k

Step 7: Now check if the avg is greater than d_i or not (the value of i is to be considered)

Step 8: If avg > d_i then calculates p=cv- avg, otherwise p=cv+ avg

Step 9: Update center pixel value (cv) by using CA rule 511

Step 10: Move the mask in the next location and go to step 3 until it reach to the last location of noisy image

Step 11: End

CA Algorithm-II:

Step 1: Consider a noisy image with m × n matrix of 8 bit gray scale image and 3 × 3 masks

Step 2: Consider CA of r=2 and center pixel is considered as cv. So total neighbor n=8 and total cell of CA is 9

Step 3: Store the pixel value in v_i for all i=1 to 9, which belong to the considering mask area

Step 4: Sort v_i in ascending order

Step 5: Eliminate minimum and maximum v_i values and Calculate avg $=\sum v_i /k$, for all i = 2 to k and k=n-1

Step 6: Update center pixel value by using CA rule 511

Step 7: Move the mask in the next location and go to step 3 until it reach to the last location of noisy image

Step 8: End

EXPERIMENTAL RESULT OF OUR PROPOSED METHOD

In this section, CA noise filtering schemes are evaluated and compared with standard filtering techniques in terms of peak signal to noise ratio (PSNR).

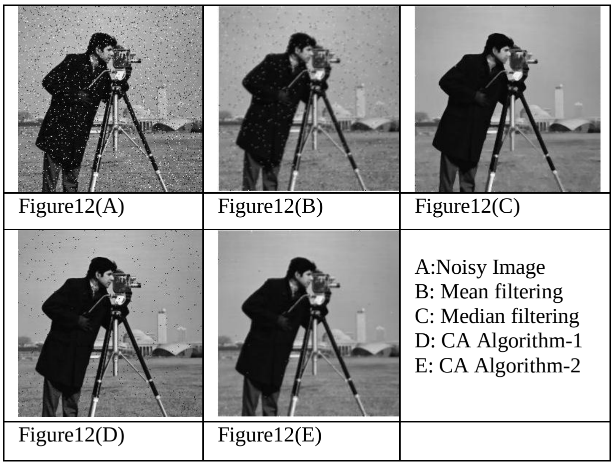

Fig.11: Experimental Result for the "Cameraman" image

The noise ratio is used to represent how much an image is corrupted. For example, if an image is corrupted by 20% impulse noise, then 10% of the pixels in the image are corrupted by positive impulse and 10% of the pixel by negative impulses. The fig. 12 (A) shows the original "Cameraman" noisy image. The results of mean filtering and median filtering for reduced noise are shown in fig. 12(B) and fig. 12(C) respectively. Figure 12(D) and Fig. 12(E) shown the images which reduce noise form image by employing our proposed schemes CA Algorithm-I and CA Algorithm-II respectively.

Noise Ratio:	1%	10%	20%
Median 3X3	12.77	12.44	12.05
Median 5X5	11.31	11.15	11.07
Switching-I	12.77	12.44	12.05
Switching-II	13.44	13.10	12.66
Adaptive Median	12.77	12.44	12.05
CA(Von Neumann)	13.82	13.34	12.83
CA(Moore)	23.75	16.12	14.00
CA Algorithm-I	15.44	15.00	14.65
CA Algorithm-II	25.49	19.53	17.00

Table 1: PSNR values for different filters and noise ratio for the "Cameraman" image

The Table-1 shows that peak signal-to-noise ratio (PSNR) for the "Cameraman" image. The above result shows that the performance of a median filter with 3 × 3, switching-I scheme [38], and adaptive median filter [39] are the same. The performance of switching filter-II [38] is comparable with that of the CA filter with von Neumann neighborhood. But at higher noise levels the CA filter outperforms the switching-II filter. It is clear from the results presented in table-1 that the performance of the CA Algorithm-I is better than the CA Von Neumann neighborhood filter. CA

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Algorithm-II gives the better result than existing filtering techniques. Because in this scheme the minimum and maximum values of pixel are eliminated and the center pixel value is update using CA rule 511.

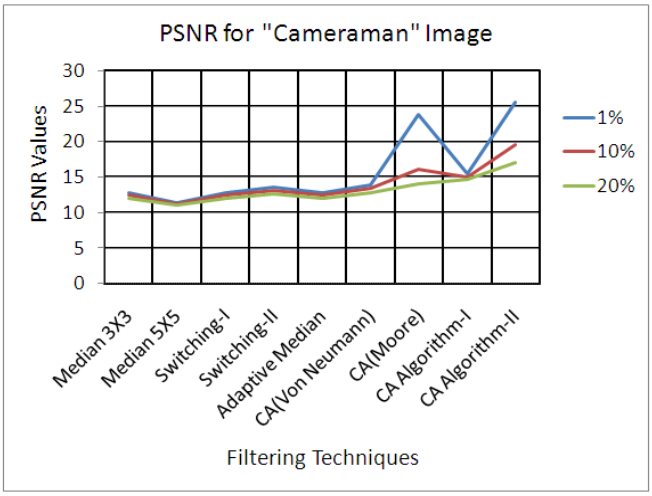

Fig. 12: Graph for Peak Signal to Noise Ratio

VI. CONCLUSION

Two new techniques for noise filtering are proposed in this paper. It is shown that the noise removal schemes based on CA provides better results compared to existing schemes with respect to PSNR. But it is found that the output of CA-based image noise reduction module has to be passed through a high-level image processing unit to produce equations of the lines and edge co-ordinates. In our two approaches it has been found that the result depends on the order of CA. But there will be some trade-off between the blurring of resulted image and order of CA.

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