Efficient and Robust Filtering Method for Medical CT Images

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Abstract: This paper introduces a new approach to ensure the certainty of medical diagnosis by eliminating the salt-and-pepper noise (SPN) in medical applications for both gray and coloured computed tomography (CT) images. The proposed approach is based on median filter which utilized for value-preserving and edge-preserving in digital image processing applications, Thus, the proposed approach is called improved adaptive median filter (IAMF). In contrast to the available research in the literature, the introduced method is characterized by the high filtering quality, robust in different noise intensities (low, medium and high) and computed efficiently. The obtained results of the filtering process have been analysed in terms of four main metrics: peak signal to noise ratio (PSNR), structure similarity (SSIM), universal image quality (UIQ) and filter average execution time (AET). The test scenarios were conducted using MATLAB 2019a running on Windows 10 computer. The success of the proposed filter has been validated by the statistical analysis based on the aforementioned metrics using gray and coloured medical CT images. For the worst case scenario in gray and coloured CT images when the noise intensity is 90%, the IAMF enhances the PSNR by 108-129%, the SSIM by 105-153% and the UIQ by 97-100% when they were compared to different filters that existed in the recent literature. These ratios depend on the image quality and image resolution. Moreover, the filter execution time has been improved by five times in gray scenarios and four times in coloured scenarios. Finally, the obtained results are visually verified as well.

Index Terms
Salt and Pepper Noise; Computed Tomography; CT Images; Median Filter; Non-Linear Filter.

1. Introduction

Image processing is a subject of interest in most different areas of knowledge, ranging from equipment for visual inspection, acquisition and analysis of medical images, biometrics, security, photography, cinema to video games based on augmented reality [1]. Digital images like any digital signal may be corrupted due to noise. In general, digital images may be subjected to various types of signal due to different reasons, these include:

- Part of the imaging sensor could be overwhelmed by environmental conditions when the image being taken;
- Malfunctioning pixels in imaging unit or defect in memory locations where the image stored in the physical hardware;
- Inappropriate image sensor temperature’s may add noise to the image;
- Transmission channel interference could distort the digital image.
Impulse noise is one of the common noise types that affect digital images quality. It can be divided into two types: SPN and random valued noise [2]. SPN not only deteriorate the quality of the digital image but rather lead to flood the details of the image. Therefore, eliminating SPN from the digital images is one of the challenges that faces image post-processing such as feature extraction, image super resolution, segmentation, pattern recognition and edge detection [3].

On the other hand, filters are processes that aim to emphasize certain aspects in digital images or reduce noise. These noises can be introduced into the image during the acquisition process, due to hardware limitations in quantization and digitalization. The pixels can be changed causing a sharp difference of the tones between their neighbours. In this situation, when the pixels are modified to zero or the maximum, dark spots or sprinkle of bright are appeared in the image with comparably high contrast towards their surrounding areas [4].

Computed tomography (CT) is one of the medial applications that needs high quality images that are used in radiological diagnostics. CT image can play a crucial role in medical tests because it has the accuracy, speed and the ability to produce two-dimensions and three-dimensions digital image that show the internal organs of human body [5]. CT images may be corrupted due to one or more of the aforementioned reasons. Any degradation in CT image quality will lead to the absence of paramount medical information that may cause false diagnosis, and hence, threaten the human life [6]. Therefore, the image filtering process become an essential challenge when dealing with medical images.

In general, the non-linear filters are the most successful filters in reducing SPN. The median filter is one of the most common non-linear filters for eliminating SPN. Its essential merits over linear filtering are maintain the values of the data, outliers’ robustness and edges preservation [7]. However, it has numerous weaknesses in terms of processing the corrupted and non-corrupted pixels, and using a fixed size window [8] [9]. The other sections of this paper are arranged as follows. Section II reviews the related works and spot the light to this paper contributions. Section III presents the proposed approach that leads to enhance the picture performance. Section IV analyses and discusses the obtained results of the introduced filter and other filters available in the literature. Finally, Section V concludes the entire paper.

2. Related work

At present, there are thousands of researches that are based on median filter available in the literature. Therefore, the paper at hand surveys the most common methodologies used by the authors to retrieve digital images which are corrupted by SPN. Tukey [10] in 1978 introduced the standard median filter concept by using the median of neighbourhood pixel values instead of the original pixel value. The Tukey’s approach succeeded in eliminating the impulse noise. However, it suffered from local information lost due to manipulating useful or uncorrupted pixels and resulted in important details damaged.

In order to overcome the aforementioned weakness of standard median filter, many researchers proposed different improved methodologies based on the main concept presented by Tukey. Wang et al. in [11] proposed an effective switching median algorithm for eliminating SPN in digital images by using local outliers factor incorporating with boundary discriminative noise detection. Zhu et al. in [12] introduced quaternion switching vector median filter which used a new colour distance metric to restore the information from coloured images corrupted by impulse noise.

Progressive switching median filter was proposed by Wang et al. in [13] to retrieve the distorted image by impulse noise. The authors argued that their proposed approach outperformed the standard median filter especially for digital images corrupted by high impulse noise. Boo et al. in [14] introduced an improved progressive median filter. Their suggested approach is depending on the number of uncorrupted pixels to decide the median and mean values. In addition, the authors argued that the obtained results showed better image restoration performance when it compared to Wang’s approach presented in [13].
Wang et al. in [15] proposed a new algorithm by integrating based on standard median filter. The main goal of their approach was to increase the probability of similar original input by pre-identifying the input pixels in order to restrain the influence of impulse noise from being accumulated on the output pixels. While Ghani et al. in [16] proposed a modified strategy to minimize the number of replacements in standard median filter. They argued that the proposed approach showed a good performance when it evaluated over 'LENA' image.

Xu et al. in [17] introduced a novel approach by adopting fuzzy logic strategies in restoring the corrupted image by impulse noise. The authors argued that the obtained results showed that the developed fuzzy-based filter performed better than the existing filtering algorithms in terms of detail preservation and noise suppression. Toh et al. in [18] proposed two-step noise adaptive fuzzy switching median filter. The first stage identified the noise pixels and second stage filtered the corrupted pixels while the noise-free pixels were left unchanged. Another contribution of Toh introduced in [19] by developing a novel approach called cluster-based adaptive fuzzy switching median. The main important outcome Toh’s approach represented in high processing time of the developed filter which made it applicable in digital cameras.

Zhang et al. in [20] proposed a new approach called new adaptive weighted mean filter. In Zhang’s approach, an adaptive window size was initially identified, then the window being continuously enlarged until the maximum and minimum value of two consecutive windows were equal respectively. Bappy et al. in [21] integrated the total variation minimization technique and hybrid median filter in order to efficiently retrieve X-Ray images. The authors argued that the proposed approach enhanced the filter computational speed and retrieval quality of the medical image to eliminate staircase effect and false edges. Zhang in [22] introduced morphological lifting scheme and median filter. Different signals had been used during the simulation studies and the authors argued that the obtained results showed the feasibility and the effectiveness of the introduced filter in various noise environments.

One of the most interesting studies in the field of this paper was conducted by Noor et al in [23]. The authors reviewed previously published works that were conducted by the authors in [24]-[31] and discussed their drawbacks. In addition, Noor’s paper introduced a new algorithm based on Median Filter and convolutional neural network (MFCNN) for reducing SPN in different types of images and argued that it performed better than the published work in [24]-[31]. Hence, the proposed IAMF approach in this paper has been compared to Noor’s et al work only without the need to re-do the same comparisons.

To address the problems that exist in current literature, this paper proposes a new filtering method based on median filter to eliminate SPN in CT images. The introduced method is capable of efficiently detecting noisy pixels and correcting them accordingly. The proposed method attains noise elimination, whereas the detailed information of the whole image is well preserved. The main contributions of this paper are:

1) Developing a new filtering algorithm that is capable of neatly removing the SPN from real medical CT images (i.e. grey and coloured images) with different resolutions;
2) In contrast to the previously published algorithms in the literature, the developed algorithm at hand is characterized by the high filtering quality, robust performance in various noise intensities (low, medium and high);
3) Developing more numerically efficient algorithm than the published work in the literature in order to improve the filter execution speed.

3. Propose Approach
This section details the proposed approach assumptions, the flowchart of introduced algorithm and definitions. Salt-and-pepper noise is a type of significant impulse noise, which has constant values at a maximum and minimum in the image.

Suppose $X = [x_{ab}]$ is an $m \times n$ matrix where $x_{ab}$ is an unsigned integer number and $0 \leq x_{ab} \leq 255$. If $x_{ab} = 0$ or $x_{ab} = 255$ then $X_{ab}$ is called corrupted entry of $X$, else $x_{ab}$ is called normal entry of $X$. 


Assume that $X$ is an image matrix (MM). Then $X$ is named as noise image matrix (NMM) if for some $a$ and $b$, $X_{ab}$ is a corrupted entry of $X$. Let $X$ be NMM, then $Y = [y_{ab}]$ is an $m \times n$ matrix and $Y$ is named as binary matrix of $X$, where:

$$y_{ab} = \begin{cases} 0, & X_{ab} \text{ is a corrupted entry of } X \\ 1, & \text{otherwise} \end{cases}$$ (1)

$$P_{xz} = x_{zz} \cdots x_{z1} x_{z2} \cdots x_{zn} x_{zn} \cdots x_{z(k)} : \cdots : \cdots :$$
$$x_{iz} \cdots x_{i1} x_{i2} \cdots x_{in} x_{zn} \cdots x_{i(k)} x_{iz} \cdots x_{i1} x_{i2} \cdots x_{in} x_{zn} \cdots x_{i(k)} x \cdots : \cdots : \cdots :$$
$$x_{z2} \cdots x_{z1} x_{z2} \cdots x_{zn} x_{zn} \cdots x_{z(k)} x_{z2} \cdots x_{z1} x_{z2} \cdots x_{zn} x_{zn} \cdots x_{z(k)} x$$

$$x(s)_2 \cdots x(s)_1 x(s)_1 x(s)_2 \cdots x(s)_n x(s)_n \cdots x(s)(k)$$ (2)

The above matrix is illustrated by a numerical example in the appendix (example A1).

$$X^q_{ab} = (p(a+z-q)(b+z-q)) : \cdots : p(a+z)(b+z) \cdots \cdots p(a+z-q)(b+z+q) :$$
$$: p(a+z-q)(b+z-q) : \cdots : p(a+z)(b+z+q) :_{(2q+1)x}$$

Suppose $X = [x_{ab}]_{m \times n}$ and $z \in \{1,2,\ldots,NMM\{m,n\}}$. Then $P^z_X = [p_{gh}]_{(m+2z)\times(n+2z)}$ is called $z$-symmetric pad matrix of $X$ and it is defined as shown in eq.2 where $s = m - z + 1$ and $k = n - z + 1$. Assume $X = [x_{ab}]_{m \times n}$, $P^z_X$ be the $z$-symmetric pad matrix of $X$ and $q \in \{1,2,\ldots,z\}$. Then the matrix $X^q_{ab}$ is defined in eq. 3. Where $X^q_{ab}$ is a $q$-approximate matrix of $x_{ab}$ in $P^z_X$ (see example A2 in the appendix). If $X^q_{ab}$ is a $q$-approximate matrix Then the given matrix $F^q_{ab} = [f_{iu}]_{1 \times(2q+1)^2}$ containing all the entries of $X^q_{ab}$ and it is being called entry matrix ($E_{mat}$) of $X^q_{ab}$ (see example A3 in the appendix). If $X^q_{ab}$ is a $q$-approximate matrix of $x_{ab}$. Then $E^q_{ab} = [t_1v]$ contains all normal entries of $X^q_{ab}$ and it is being called normal entry matrix ($N_{em}$) of $X^q_{ab}$ (see example A2 in the appendix).

Suppose that $E^q_{ab} = [t_1v]_{1 \times w}$ is the $N_{em}$ of $x_{ab}$. Then the quantity $mE^q_{ab}$ is named as median of $F^q_{ab}$. In this paper the zero matrix is denoted by $[0]$.

$$mE^q_{ab} = \left\{ t_1^{\lfloor \frac{w+1}{2} \rfloor}, t_1^{\lfloor \frac{w+1}{2} \rfloor} \in I, \frac{1}{2} \left(t_1^{\lfloor \frac{w+1}{2} \rfloor} + t_1^{\lfloor \frac{w+1}{2} \rfloor} \right), \frac{w}{2} \in I \right\}$$ (4)

The traditional median filter is not effective at high noise intensities. While in adaptive median filter, if the window size is small, all the pixels inside the window will be considered as corrupted pixels. On the other hand, if the window size is large, the pixels that most similar to the original pixel will be lost. In order to overcome these problems, the suggested filter called improved adaptive median filter (IAMF) and implementation steps are illustrated in Figure 1.
Figure 1. The complete flowchart of the proposed filter (AIMF).
The flowchart of the suggested filter is demonstrated in Fig. 1 and it includes the following steps:

- **Step One**: read a \((N \times M \times M) X = [x_{ab}]_{m \times n}\) such that \(N \times M \times m, n \geq 3\)
- **Step Two**: write the binary matrix \(Y = [y_{ab}]\) of \(X\)
- **Step Three**: write \(P^2_x\) and \(P^2_y\)
- **Step Four**: for all \(a\) and \(b\)
  - If \(y_{ab} = 1\) then store the value of \(x_{ab}\)
  - Else if \(y_{ab} \neq 0\) then
    1) Determine \(E^1_{ab}\) for \(x_{ab}\)
    2) Calculate \(mE^1_{ab}\)
    3) Overwrite this value to \(x_{ab}\)
  - Else if \(y_{ab} \neq 0\) then
    1) Determine \(E^2_{ab}\) for \(x_{ab}\)
    2) Calculate \(mE^2_{ab}\)
    3) Overwrite this value to \(x_{ab}\)
  - Else store the value of \(X_{ab}\)
- **Step Five**: rewrite \(Y\) of \(N \times M \times X\)
- **Step Six**: rewrite \(P^1_x\) and \(P^1_y\)
- **Step Seven**: for all \(a\) and \(b\)
  1) If \(y_{ab} = 1\) then store the value of \(x_{ab}\)
  2) Else if \(y_{ab} \neq 0\) then
    a) Determine \(E^1_{ab}\) for \(x_{ab}\)
    b) Calculate \(mE^1_{ab}\)
    c) Overwrite this value to \(x_{ab}\)
  3) Else store the value of \(X_{ab}\)

Despite of the calculations’ simplicity, the proposed filter characterized by its high efficiency in rejecting the SPN without any degradation in output CT image quality. In addition, it is reliable to be applied in different noisy environments and helps to save human life by enabling the doctors to make correct diagnosis based-on filtered image.

4. Result and Discussion

Three assessment metrics are used to evaluate the performance of the filters numerically. The first metric is the peak signal to noise ratio (PSNR) which is defined in eq. 5.

\[
PSNR = 10 \log_{10} \frac{255^2}{\frac{1}{N \times O} \sum_{a=1}^{N} \sum_{b=1}^{O} (v(a,b) - w(a,b))^2}
\]

Where \(v(a, b)\) is the original image, \(w(a, b)\) is the corrupted image and \(N \times O\) is the image size. The second metric is the structure similarity (SSIM) which is given in eq. 6

\[
SSIM = \frac{(2\mu_v \mu_w + T_1) + (2\sigma_v \sigma_w + T_2)}{(\mu_v^2 + \mu_w^2 + T_1) + (\sigma_v^2 + \sigma_w^2 + T_2)}
\]

Where \(\mu_v, \mu_w, \sigma_v, \sigma_w\) and \(\sigma_v \sigma_w\) are mean the intensities, standard deviations and cross covariance for images \(V\) and \(W\) respectively. In addition, \(T_1 = (J_1Q)^2\) and \(T_2 = (J_2Q)^2\), such that \(J_1 \times J_2 \ll 1\) and \(Q = 255\)
for 8-bits gray images. In this work, the $J_1$ and $J_2$ are selected to be equal to 0.01 and 0.03 respectively.

The third evaluation metric is the universal image quality index (UIQ) which is defined in eq. 7.

$$UIQ = \frac{4\sigma_{uv}V^--W^-}{(\sigma_u^2+\sigma_v^2)(V^-^2+W^-^2)}$$  \hspace{1cm} (7)

Where $V^-$ and $W^-$ are given by:

$$V^- = \frac{1}{N} \sum_{i=1}^{N} V_a$$ \hspace{1cm} (8)

$$W^- = \frac{1}{O} \sum_{b=1}^{O} W_b$$ \hspace{1cm} (9)

The final metric is the AET of the filter which represents the duration that is taken by the filter to retrieve the original image as output from the degraded input image.

The results of the suggested method are presented and compared with the MFCNN that was introduced by Noor et al in [23]. Various real medical CT images (NIH-CT images database [32]) with different resolutions are used to observe the performance of the methods for both gray and colored CT images. All the test scenarios were conducted using MATLAB 2019a running on Windows 10 computer with Core i5-3330 Intel processor and 8 GB of RAM.

Table 1 and Table 2 demonstrate the detailed information of the gray and colored medical CT images respectively that were used to observe and verify the filters. The noise intensity levels for the experimental scenarios were classified to three levels: 20% and 40% represent the low noise environment, 60% simulates the medium noise conditions and finally 90% imitates the heavy noise cases. At each noise level, the average values of PSNR, SSIM, UIQ and filter execution time are evaluated. The results in Table 3 and Table 4 show the superiority of the suggested method in terms of the aforementioned performance criteria that are used in the evaluation.

Table 1.

| NIH Database | Resolution (pixel) | Number of Images |
|--------------|--------------------|------------------|
| Group A      | 435×399            | 10               |
| Group B      | 432×432            | 10               |
| Group C      | 900×992            | 10               |

Table 2.

| NIH Database | Resolution (pixel) | Number of Images |
|--------------|--------------------|------------------|
| Group D      | 1141×1200          | 10               |
| Group E      | 993×1298           | 10               |
| Group F      | 1282×692           | 10               |
The Proposed filter gives the highest values of PSNR, SSIM and UIQ, while it utilizes the filtering algorithm with minimum AET. When it compared to MFCNN that was proposed in [23]. The obtained results illustrate that the proposed filter is more robust and efficient especially in medium and high noise conditions as illustrated in Table III and Table IV for gray and colored scenarios respectively. In addition, the results are visually verified in Figure 2 to Figure 7 for gray and colored scenarios respectively. Actually, when the noise intensity is 80%, the MFCNN restore the CT images with a noticeable distortion and some residual. SPN appears as demonstrated in image ” o “ of Figure 2 to Figure 7. While the image ” s “ of Figure 2 to Figure 7 shows how MFCNN failed to retrieve the CT images under high noise level. On the other hand, the IAMF can recover the CT images with good quality as illustrated in images ” p “ and ” t “ of Figure 2 to Figure 7. In addition, some SPN appeared clearly as raindrop effect and can be observed in image ” o “ of Figure 2 to Figure 7. This indicates the robustness of the developed filter under low, medium and high noise level scenarios. In the context of the comparison between MFCNN and IAMF, the proposed filter performs the filtering process faster than the MFCNN by approximately five times in gray CT images and four times in colored CT images.

Finally, it should be noted that MFCNN when applied to the colored CT images produces colored artifacts that damage the image as indicated in images ” o “ and ” s “ of Figure 5 to Figure 7. While IAMF can suppress efficiently SPN from the colored medical CT images without producing these artifacts as illustrated in images ” p “ and ” t “ of Figure 5 to Figure 7.

5. Conclusion

This paper presents a new filtering approach for medical CT images called IAMF. The introduced filter eliminated the SPN more effectively and efficiently than the recent approach presented in [23]. The proposed filter can be applied directly to gray and colored medical CT images with different resolutions at various noise intensities. Finally, the developed filter successfully in overcoming the previous algorithms in terms of PSNR, SSIM, UIQ and AET as well as the abstracted vision. The suggested future work is developing and modelling the proposed approach using field programmable gated array (FPGA) platform and deploying the introduced scheme in real-time scenarios.

| Criteria | Noise Level | Group A | Group B | Group C |
|----------|-------------|---------|---------|---------|
|          |             | IAMF    | MFCNN   | IAMF    | MFCNN   |
| PSNR (db)| 20%         | 39.219  | 34.695  | 32.8843 | 32.0238 |
|          | 32.0238     | 49.7899 | 43.4529 |
| SSIM     | 0.9763      | 0.9757  | 0.9787  | 0.9792  |
|          | 0.9972      | 0.9972  | 0.9891  |
| UIQ      | 0.9763      | 0.9532  | 0.9614  | 0.9802  |
|          | 0.9927      | 0.9927  | 0.9891  |
| AET (sec)| 1.0960      | 5.8140  | 1.0921  | 5.6280  |
|          | 3.8872      | 3.8872  | 17.401  |
| PSNR (db)| 34.4664     | 28.9425 | 29.7669 | 27.5221 |
|          | 44.2629     | 44.2629 | 44.2629 |
| SSIM     | 0.9741      | 0.9105  | 0.9625  | 0.9442  |
|          | 0.9905      | 0.9905  | 0.9629  |
| UIQ      | 0.9556      | 0.8908  | 0.9521  | 0.9019  |
|          | 0.9801      | 0.9801  | 0.9385  |
| AET (sec)| 1.1161      | 5.9221  | 1.1120  | 5.7321  |
|          | 3.9591      | 3.9591  | 17.7240 |
| Criteria | Noise Level | Group D | Group E | Group F |
|----------|-------------|---------|---------|---------|
|          | IAMF | MFCNN | IAMF | MFCNN | IAMF | MFCNN |
| PSNR (db) | 60% | 31.1295 | 23.4609 | 27.3713 | 23.0175 | 40.6762 | 30.7139 |
| SSIM     | 0.9466 | 0.7605 | 0.9382 | 0.8671 | 0.9793 | 0.8809 |
| UIQ      | 0.9238 | 0.8421 | 0.9442 | 0.5776 | 0.96 | 0.813 |
| AET (sec)| 1.1373 | 6.0342 | 1.1330 | 5.8410 | 4.0342 | 8.0591 |
| PSNR (db) | 80% | 27.4277 | 15.5655 | 24.347 | 15.9971 | 36.7688 | 20.2076 |
| SSIM     | 0.8854 | 0.417 | 0.8891 | 0.5962 | 0.9553 | 0.6047 |
| UIQ      | 0.881 | 0.553 | 0.9205 | 0.3984 | 0.7797 |
| AET (sec)| 1.1592 | 6.1500 | 1.1553 | 5.9531 | 4.1121 | 18.4060 |
| PSNR (db) | 90% | 24.5098 | 9.4579 | 21.4866 | 10.2695 | 32.7528 | 9.7357 |
| SSIM     | 0.8025 | 0.1851 | 0.8284 | 0.2786 | 0.9186 | 0.2825 |
| UIQ      | 0.8676 | 0.2974 | 0.9109 | 0.1848 | 0.9163 | 0.3028 |
| AET (sec)| 1.2051 | 6.3964 | 1.2012 | 6.1913 | 4.2762 | 19.1421 |

**Table 4. The Comprehensive Result of Gray Medical CT Images.**
| Metric   | Method | PSNR (db)  | SSIM     | UIQ      | AET (sec) |
|----------|--------|------------|----------|----------|-----------|
|          | 80%    | 19.1173    | 0.7128   | 0.9593   | 45.438    |
|          |        | 7.2173     | 0.3328   | 0.6578   | 182.780   |
|          |        | 19.4967    | 0.6642   | 0.9164   | 41.103    |
|          |        | 7.4967     | 0.2642   | 0.5864   | 168.522   |
|          |        | 22.0035    | 0.6459   | 0.9142   | 41.909    |
|          |        | 10.0011    | 0.2359   | 0.6142   | 171.827   |
|          | 90%    | 17.8455    | 0.6595   | 0.9519   | 46.328    |
|          |        | 3.8455     | 0.1595   | 0.4419   | 189.948   |
|          |        | 18.5960    | 0.6328   | 0.9057   | 41.909    |
|          |        | 4.5900     | 0.0828   | 0.3988   | 171.827   |
|          |        | 21.3181    | 0.6038   | 0.9012   | 25.718    |
|          |        | 7.0181     | 0.0738   | 0.3712   | 105.446   |

PSNR (db) and SSIM results for different methods at 80% and 90% compression rates. UIQ and AET (sec) also provided.
Figure 2. Sample of the obtained visual results for Group A of the NIH-CT Database.
Figure 3. Sample of the obtained visual results for Group B of the NIH-CT Database.
Figure 4. Sample of the obtained visual results for Group C of the NIH-CT Database.
Figure 5. Sample of the obtained visual results for Group D of the NIH-CT Database.
Figure 6. Sample of the obtained visual results for Group E of the NIH-CT Database.
Figure 7. Sample of the obtained visual results for Group F of the NIH-CT Database.
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Appendix

Example A1: Assume \( X = \begin{bmatrix} 10 & 11 & 12 & 20 & 21 & 255 & 0 & 31 & 32 \end{bmatrix} \) then the three-symmetric pad matrix of \( X \) will be:

\[
\begin{bmatrix}
32 & 31 & 0 & 255 & 21 & 20 & 12 & 11 & 10
& 12 & 11 & 10 & 225 & 21 & 20 & 32 & 31 & 0
& 0 & 31 & 32 & 20 & 21 & 255 & 10 & 11 & 12
& 32 & 31 & 0 & 255 & 21 & 20 & 12 & 11 & 10
& 10 & 11 & 12
\end{bmatrix}
\]

Example A2: Based on numerical example A1, then 1-approximate matrix of \( x_{21}^3 \) denoted by \( X_{21}^3 \) is:

\[
\begin{bmatrix}
10 & 10 & 11 & 20 & 21 & 0 & 0 & 31
\end{bmatrix}
\]

Example A3: Based on numerical example A2, then \( f_{21}^3 = \begin{bmatrix} 0 & 0 & 10 & 10 & 11 & 20 & 20 & 21 & 31 \end{bmatrix} \)

Example A4: Based on numerical example A3, then \( e_{21}^3 = \begin{bmatrix} 10 & 10 & 11 & 20 & 20 & 21 & 31 \end{bmatrix} \)