Image Noise Detection and Identification Using Abstract Matrix and Difference Matrix Techniques

Waleed. A. Mahmoud & Matheel. I. AL-Dargazli***

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Abstract:

The problem of noise identification in one-dimensional (signal) and two dimensional (image) processing is very important in engineering and computer science applications. These noises: salt, pepper, Gaussian and speckle, are different in subjective and objective behaviors. In this paper we firstly check the observed image if it is noisy or noise-free (original) image. Then we propose methods for identification the noise in the observed image named the Abstract Matrix (RM) and the Difference Matrix (DM) methods. AM and DM are matrices that generated from the gray levels of the image .We generate the RM and the DM of the image in the spatial domain; their generations are very fast. According to the distribution of the elements of the AM and DM, we can predict first whether the observed image is the original (it does not need denoising process) or the distorted version (it does need a denoising process) and second identify the noise types.

تحديد وجود التشويش ونوعه بالصور باستخدام تقنيات مصفوفتي المستخلص والأختلاف

الخلاصة:

مشكلة تعريف نوع التشويش في معالجة البعد الواحد (الأشارة) والبعدين (الصورة) هي من المشاكل المهمة في التطبيقات الهندسية وتطبيقات علم الحاسبات. هذه الأنواع من التشويش:الملح، الفلفل، كاوس و التبقع تختلف في سلوكها الذاتي وغير الذاتي. في هذا البحث سوف يدقق في الصورة المرئية أولاً هل تحمل نوع من التشويش لم تكون خالية منه (أصلية). بعدها سوف نفترض طرقاً لتعريف نوع التشويش في الصورة المرئية والمسماة مصفوفة الخلاصة ومصفوفة الأختلاف. هذه المصفوفات تولد من المستويات الرمادية للصورة. تولد هذه المصفوفات في المجال الفضائي بسرعة عالية. ونسبة الى توزيع عناصر هذه المصفوفات، يمكن التنبؤ كون الصورة أصلية (أي لاتحتاج الى عملية رفع للتشوش) ام محطمة (تحتاج الى عملية رفع للتشوش) هذا أولاً . بعدها يعرف نوع ذلك التشوش.

1 Introduction

In many engineering applications like astronomical, medical imaging, broadcast, and optical scanning, the observed images are subject to degradation caused by the electronic components or imaging environment. The degradation process model consists of two parts, the degradation function, and the noise function. If the observed image is the original image, it does not need a denoising [1]. The human can check this using his eye, but how the computer knows that this image is the original image? In real time applications the time is very important issue, so should every incoming image is entered to the denoising process to ensure that every incoming image is as noise-free as possible image? If the answer to this question is *Yes*, this will delay the system because not every observed image will be noisy [2, 3]. Many

* Dept. of Electrical Eng., University of Baghdad, IRAQ.
**Dept. of Computer Science, University of Technology, IRAQ.

https://doi.org/10.30684/etj.24.2A.3
2412-0758/University of Technology-Iraq, Baghdad, Iraq

of the observed images may be the original (noise-free) images and not corrupted by a noise. Hence denoising them will be a trivial and will waste a long time if the computation of the denoising algorithm is heavy. If the answer is *No*, another question appears which is, when to denoise the observed image and when not to denoise it. This is a very important question and should be taken under consideration in the real time applications. Here a proposed method for detecting the noise in the image is introduced based on the second order statistics of the pixels of the image called ***Abstract Matrix (AM)*** **[4, 5]**.

Also sometimes, we need to know the type of the noise that is appear in the noisy image depending on the application that we need. The original image sometimes was found but in another times it does not found. Two types of algorithms are depending on it in this paper with and without original image using AM and ***Difference Matrix (DM)*** methods.

The paper is organized as follows. Some background of the noise is briefly reviewed in section 2. Section 3 presents the ideas of the RM and DM, their generation, and their noisy images. Section 4 presents the DM. The proposed algorithm is introduced in Section 5. Experimental results are included in section 6.

2 The effect of noise in digital images

The degradation process model consists of two parts, the degradation function, and the noise function. The general model in the spatial domain follows:

$$g(r,c) = h(r,c) \otimes \otimes x(r,c) + z(r,c) \qquad (1)$$

Where: $\otimes\otimes$ denotes the two-dimensional convol-ution process, $g(r,c)$ represents the Degraded image, $h(r,c)$ represents the Degradation function, $x(r,c)$ represents the Original image, and $z(r,c)$ is the Additive noise function [6, 7].

This paper is concerning or dealing only with the noise degradation in the degradation process with the assumption that the degradation function $h(r,c)$ causes no degradation, so the only corruption to the image is caused by the noise (i.e. set $h(r,c) = 1$).

Noise is any undesired information that contaminates on image. The digital image acquisition process, which converts an optical image into a continuous electrical signal that is then sampled, is the primary process by which noise appears in digital images. At every step in the process there are fluctuations caused by natural phenomena that add a random value that exact brightness value for a given pixel. Another source of noise, which often arises from the electronic components in the image environment. Noise can be introduced into an image via a multitude of sources, such as communication channels, fault digital circuitry, and thermal noise. Film-grain type noise, which is data dependent, is caused when scanning an image recorded on photographic films [8, 9].

2.1 Noise Types [10]

In typical images, the noise can be modeled with a Gaussian "normal", uniform, speckle, or salt-and-pepper "impulsive" distribution.

2.1.1 Gaussian Noise

Gaussian noise takes the bell-shaped curve distribution, which can be analytically described by:

$$Histogram_{Gaussian} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(gl-m)^2}{2\sigma^2}} \qquad (2)$$

Where **gl** is the gray level, **m** is the mean and σ is the standard deviation (σ^2 = variance)

About 70% of all the value full within the range from one standard deviation (σ) below the mean (m) to one above, and about 95% fall with in twos standard deviations. The Gaussian model is most often used to model natural noise process, such these occurring from electronic noise in the image acquisition system (*i.e. thermal noise*).

2.1.2 Speckle Noise

Speckle Noise is completely different from other types of noise, since it is operates on the images in multiplicative manner (i.e. the pixel value of the noise is multiplied by the pixel value of the original image), where the other types of noise mentioned above being additive (the pixel value of the noise is added to the pixel value of the original image). The Speckle noise can be modeled by the following equation [1]:

$$g(r,c) = x(r,c) + x(r,c) \cdot * z_u(r,c) \qquad (3)$$

Where $x(r,c)$, $z_u(r,c)$, and $g(r,c)$, are the original image, uniform noise (discussed in the previous section), and the distorted version image respectively. The operation ($\cdot *$) is pixel-by-pixel multiplication. Figure 1 shows example of these types of noise, and how they are distributed.

2.1.3 Salt and Pepper Noise

In the salt-and-pepper noise model there are only two possible values, a and b, and the probability of each is typically less than 0.1. With numbers greater than 0.1 values, the noise will dominate the image. For an 8-bit image, the typical value for pepper-noise is 0 and for salt-noise 255.

$$Histogram\ (S\&P) = \begin{cases} A & for \quad g=a \\ B & for \quad g=b \end{cases} \qquad (4)$$

Malfunctioning pixel elements in the camera sensors, faulty memory locations, or timing errors typically causes the salt-and-pepper type noise. Usually, the speckle noise image appears similar to that of Gaussian noise images but darker. Salt-and-pepper type noise appears in the image as dots contaminate the image.

3 Concept of Recursive Matrix (AM)

The Recursive Matrix (AM) is a square matrix which can be generated from the grayscale levels of the image. Whereby its dimension equal to the maximum levels in the image. This process produced by segmenting the image in a large number of frame pixels, such that each pixel frame (PF) consists of two neighbor pixels. These frames will be overlapped when they are viewing in a raw vector wise. This means that the second pixel from the first frame represents the first pixel in the second frame in this vector. In this way the image row of 256 pixels will be consists of 255 pixels frames. This because the last (PF) is the combination of the last pixels in the row and the pixel before it. The generation of the frames stops to this number of frames in each row. This is because the relation of the gray level of the last pixel, with the gray level of the first pixel in the next row, means nothing in the recognition view of the image. Hence, the number of the frames N_f for an image with dimension of Bi, Bj is given by [4]:

$$N_f = B_f \times (B_f - 1) \quad (5)$$

Where B_f is the matrix dimension.

In addition, the number of comparisons can be produced by [1]:

$$N_{op} = N_f \times (N_f - 1) \quad (6)$$

Where N_f is the number of the frames in image. Substituting equations before leads to:

$$N_{op} = B_i^2 \times B_j^2 - 2 \times B_i^2 \times B_j - B_i \times B_j + B_i^2 + B_i \quad (7)$$

where B_i and B_j represent the dimension of the image B_f.

4 Generation of the AM

To find the elements of the recursive matrix, the frame is selected and compared, with the similarity of the frame neighbor pixels, with all reminder frames in the image. The matrix elements are evaluated by counting the numbers of the similar frames. That is, the frames that have the same neighbor pixels. The position in the matrix in which the result is located, represents the pixels gray level value. In other words, the first pixel value (gray level) in the similar frames represents row position in the RM. While the second pixel in these frames represent, the columns position in the AM. This processing which includes: the transformation of the image from the spatial domain to the AM domain makes the resultant AM unique for any image. Since the relation between the neighbors pixels different from an image to another even when the later image is distorted version of the original image. Thus, the value number of identical frames for any position in the AM is different. So that any element in the AM represents one of the implicit gray levels, relation and features associated with this image only.

Hence, the adaptive AM for any image can be summarized through the following programmable steps:

for (p = min (x (i, j) to max (x (i, j)))
for (l = min (x (i, j) to max (x (i, j)))

$$AM(x(i,j) = p, x(i, j+1) = l) = \sum_{j=0}^{B_j} \sum_{i=0}^{B_i - 1} 1$$

if(x (i,j) = p and x (i, j+1) = l respectively)

End
End

Where $x(i,j)$, represents the observed image, p and l are pixels values of a certain frame.

The AM also called the indirect method because of its representation of the image implicitly .The elements values in the resultant matrix are allocated mostly diagonal, few in the neighbor of this diagonal and a few of them in the corners of the matrix .The diagonal elements represents the relation between the identical neighbor high or low gray level pixel value, that is, relations elements represents the lowpass information of the image. This coincides with the normal distribution of the image in which its lowpassed filtered information has the prominence above the abrupt changing of the gray level values representing by highpass filtering. However, in the AM the elements that represent the features of the image appear as long as they are far from the diagonal of the AM from its tow sides. This is true because, these elements represent contours for the abrupt gray level changing for the different features areas in the image (highpass information). Finally, these features elements and the low information elements are associated with the selected image only and will be used as tools to recognize it from the other image.

5 AM of noisy images

As mentioned in the previous particle, the diagonal elements of the AM with, few rows below and above it represent the lowpass information of the image. As going far from the diagonal results in reaching to the elements of the AM, that represents the highpass informations (the abrupt change in the grayscale level) of the image.

According to this, it can be concluded that with the normal distribution of the grayscale levels of the image, the AM is mainly diagonal with, few above and below it. Become noisy (noise is also a high frequency component with small values) or the abrupt changes of the grayscale levels of the image increase the AM and will no longer be diagonal. In this case, the elements of the AM will be diagonal with elements spreads in the upper and lower triangles of the AM. The spread increases as the noise level or the abrupt changes of the image increases, this is shown in Fig. (2), which shows the RMs of Hand images with their noisy versions with different noise levels. It is clear from Fig. (2) that as the noise level increases the distribution of the AM will spread more out of the diagonal to cover the upper and lower triangles. In addition, the dimension of the RM of the noisy versions is larger than the dimensions of its correspondence of the original image.

For a binary image, the AM will be of size (2*2). This is apparent from range of the values of its pixels which is a monochrome (1 bit) having two values either 0 or 1,so the elements of the AM will distribute only on the four corners of the AM. This makes the AM a good tool to recognize the 1-bit binary image (monochrome) from the other types of images.

So it is strongly recommended to inspect the observed image to see whether it is the original image or the distorted version before denoising the observed image.

6 The Proposed Difference Matrix (DM)

The Difference Matrix (DM) is an ($n \times n$-1) matrix where n is the number of gray scale levels of the image. Its dimension equal to the maximum levels in the image. The first pixel in the DM comes from the first pixel from the original matrix minus the second pixel in the original matrix in a row. These pixels are overlapped until reaching the end of the first row. This operation is repeated until all the rows of the original matrix are completed.

The DM is needed because it is used to recognize types of noise in the images like Gaussian and speckle noise. Using of the DM needs an algorithm to recognize these noises. The following steps of the AM algorithm are used. The DM structure is shown in Fig. (3).

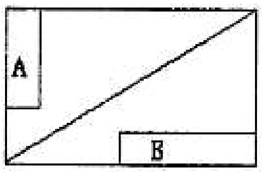
7 Noise Detection Using AM

1. Take the RM of the observed image in the spatial domain.

2. After the AM of the image is produced, observe the distribution of the elements of the AM. If the distribution is diagonal with few below and above it then it can be conclude that the observed image is noiseless (i.e. the observed image does not need denoising). In that case, the appearance of the image is not affected but this will be a wasted time. Hence, if the distribution of the AM is diagonal with elements spread in the upper and lower triangles of the AM. Then one can conclude that the observed image is noisy (i.e. the observed image does need denoising).

This inspection of the AM of the observed image can be achieved in two ways, the first is visually (i.e. by eye). The second way, which is more acceptable from the practical point of view, is mathematically. This can be implemented using the following proposed procedure:

1. Let AM denotes the Abstract Matrix of the image.
2. Let (A,B) a two dimensional matrices in the following form



3. If A and B are zero matrices then the observed image is noiseless.
4. If A and B or one of them is non-zero matrices then the observed image is noisy.

8 Noise identification with original image

The following algorithm is used to identify each type of noise using original image:

1. Take the number of pixels that equal (0) (black) before and after adding the noise (name it **num1** and **num2**).
2. If the num1 equal num2 then we find a speckle noise in the image.
3. Find the difference between the absolute value of the number of one's before adding a noise and the absolute value of the number of one's after adding a noise.
4. If the difference is between a range taken then this indicate a salt and pepper noise.
5. If the conditions in steps 2 and 4 are not true then there is a Gaussian noise in the image.

9. Adaptive Noise identification

The following algorithm is used to identify each type of noise with out using original image (adaptive algorithm):

1. Take the noisy image, if there is a white pixel (255) a(i,j) and all the a rounded pixels: a(i,j-1), a(i,j+1), a(i-1,j-1), a(i-1,j), a(i-1,j+1), a(i+1,j-1), a(i+1,j) and a(i+1,j+1) are darkness in a range less than (100) then there is a salt noise.
2. Take the noisy image, if there is a black pixel 0) a(i,j) and all the a rounded pixels: a(i,j-1), a(i,j+1), a(i-1,j-1), a(i-1,j), a(i-1,j+1), a(i+1,j-1), a(i+1,j) and a(i+1,j+1) are lightness in a range grater than (150) (by test) then there is a pepper noise.
3. Take a DM to the AM of the noisy image.
4. If the number of zeros in the right diagonal of the DM is less than (87) (by test), so there is Gaussian noise.
5. Other wise there is a speckle noise in the noisy image.

10 Experimental Results

An image (128×128) is used with other (99) images. The AM for these images are generated, the RM of the images, their noisy versions with different noise levels (1, 2, 3, ... SNR). These (100) images are tested to the identification noise algorithms. With original image, the result of identification was (100%). Without original image, salt-and-pepper algorithm gives (100%) result while with speckle, noise gives (94%) result and with Gaussian, noise gives (86%) results. Fig. (4) gives an example. These algorithms are generated for each image Table (1) represents an example for these algorithms.

11 Conclusions

In this paper a methods for detecting the noise in images is proposed, called the AM and the DM. It is implemented in the spatial domain. Its generation is very fast and can be generated for each image. The assumption for this method in that the images are smooth (grayscale levels of the image changes gradually). We found that this method does not give accurate results if the images have very sharp grayscale levels changes (non-smooth images). Because in this case we cannot recognize between the noise and the high frequency components of the image. In addition, in this paper we define methods for identifies different type of noise with and without original images using AM, DM (for Gaussian and speckle noises) and image properties (for salt and pepper noise). The results are more efficient if the original image is existed.

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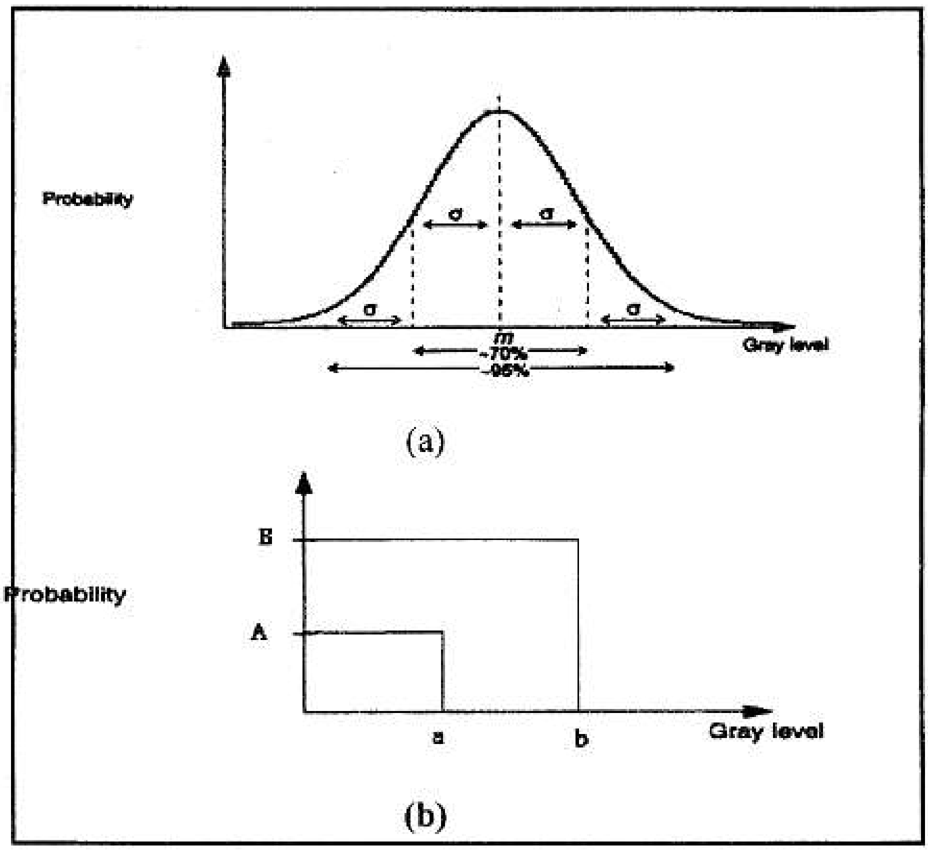

Figure (1): a) Gaussian distribution, b) Salt and pepper distribution.

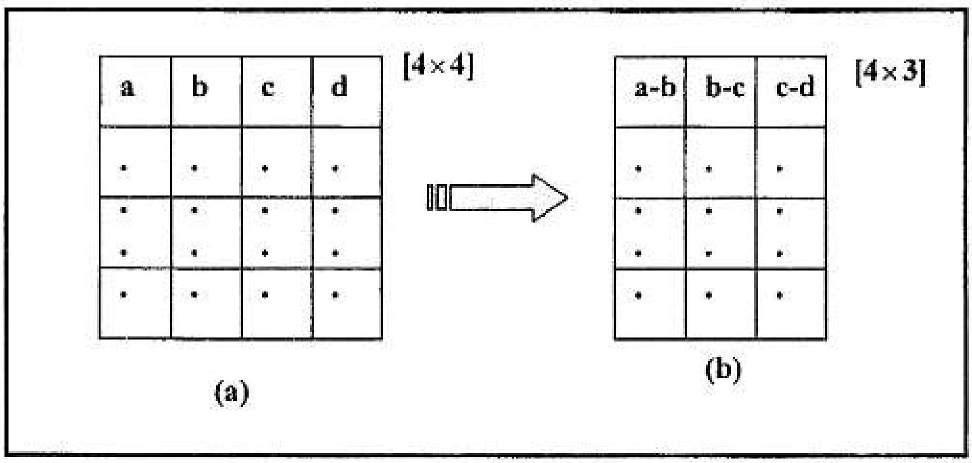

Figure (3): (a) Original matrix, (b) DM for matrix (a).

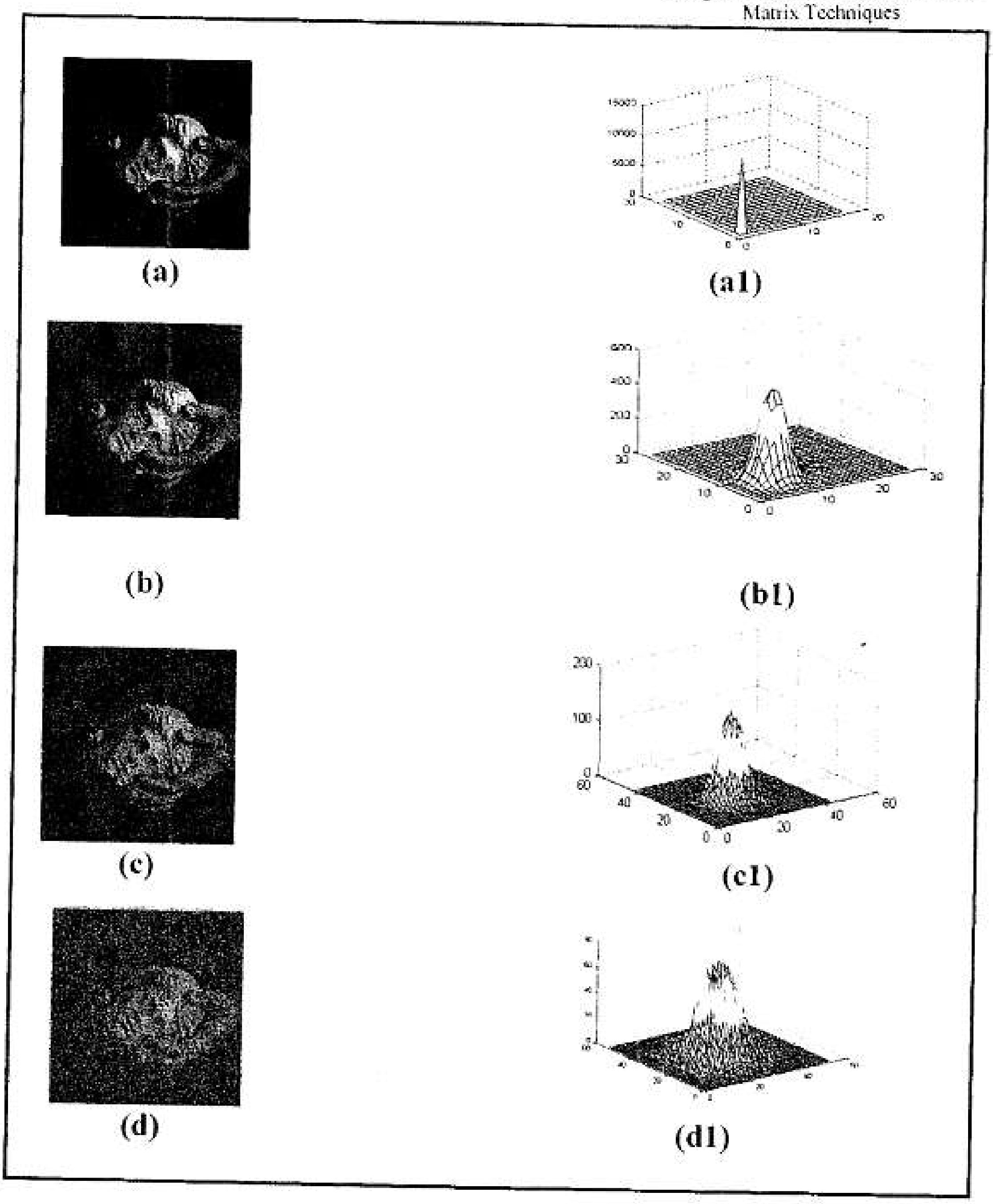

Figure (2): Shows the RMs for different noise levels: (a) the original image (a1) it's RM (b) the noisy image (7 dB SNR) (b1) its RM (c) noisy image (3 dB SNR) (c1) it's RM (d) noisy image (1 dB SNR) with (d1) it's RM.

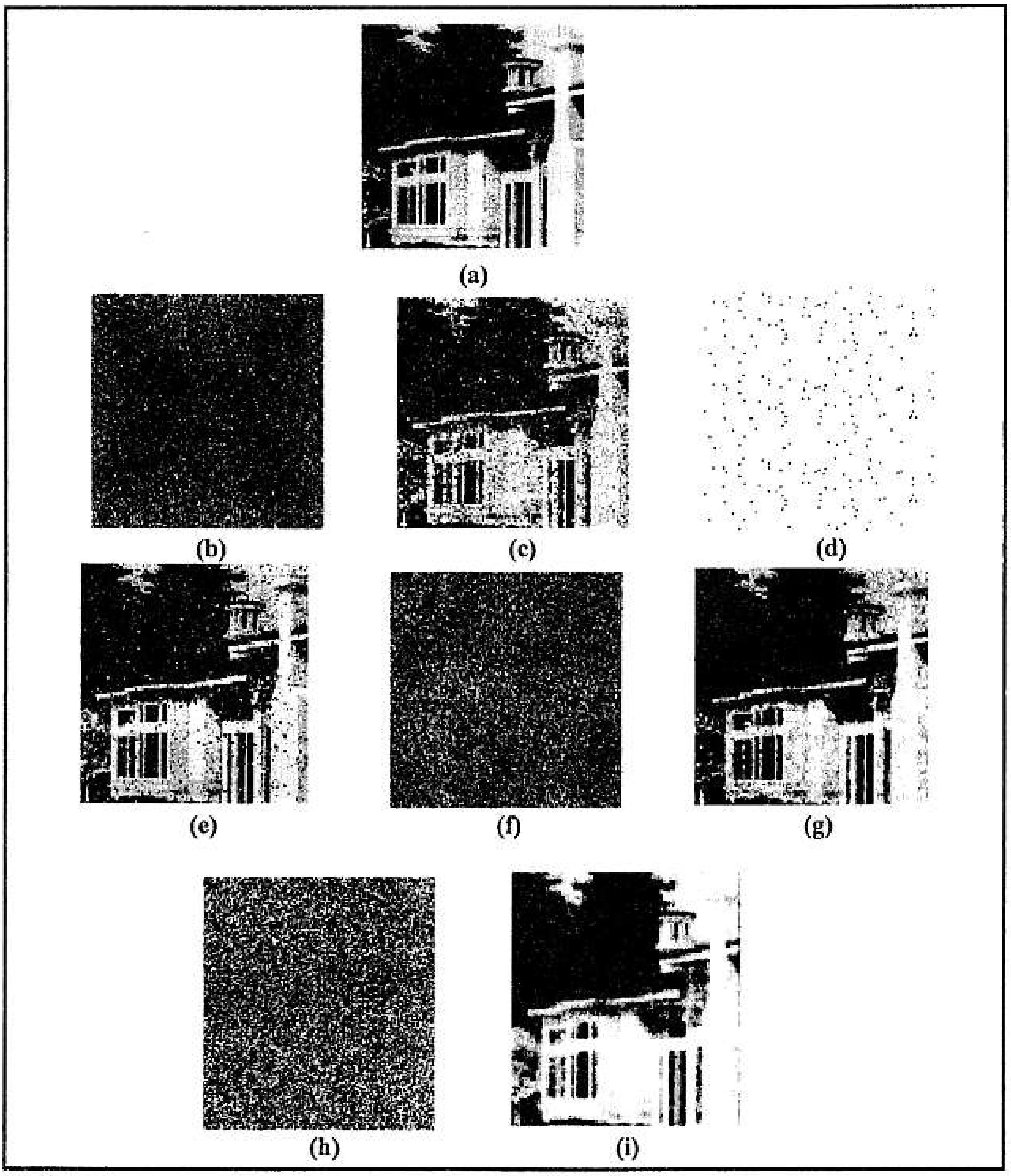

Figure (4): The effect of noise in several images: a) Original image, b) Gaussian noise– mean =0; σ =20, c) Original image with added Gaussian noise, d) salt and pepper noise with σ =20, e) Original image with added salt and pepper noise f) Speckle noise - with variance = 0.04, mean = 0, g) Original image with added Speckle noise, h) Uniform noise, s= -50; t = +50, i) Original image with added Uniform noise.

	Image name	**speckle noise**	**S&P noise**	**Gaussian noise**
With org. image	Flower	Speakle	S&P	Gaussian
Without org. image	Flower	Speakle	S&P	**Speakle**
With org. image	Butterfly	Speakle	S&P	Gaussian
Without org. image	Butterfly	Speakle	S&P	Gaussian

Table (1): With and without original images algorithms results.