

Merging Ultrasound Images Based on Up and Down Motion Blur Technique

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Abstract: Merging digital images is an essential step in digital image processing, as it allows information from two or more images to be combined into one image to obtain a highquality and clear image. This work simulates the case of motion blur with a different block size of 11,9,,7,5,3 pixels. The point spread function is programmed to obtain a linear blur motion. I used to simulate motion blur for half of the image in two parts (the top half and the bottom half). We relied on the traditional methods used to combine distorted grayscale images, such as addition and multiplication, and the proposed new techniques depend on weights, which are the standard deviation. The added, distorted, and common edges of the original image, the upper blurry half, the lower blurry half, and the merged image were detected. Different thresholds are used to compare edges visually and by identifying added, deleted and common edges, we can determine the best fusion method.

Keywords: Ultrasound image fusion, motion blur, edge detection, medical image processing, MATLAB, digital image fusion.

1.1 Introduction

Fusion is the technique to merging two or more images to obtain one image with complete information [1].

The importance of details being of high quality, high efficiency, and high clarity eliminating repetition and randomness in the data to obtain high-quality data [2].

Fusion is many applications such as Remote sensing (satellite images) works to merge images of different spatial and spectral resolution, also used in the medical imaging Magnetic Resonance Imaging and Computed Tomography, where it, such as tissues and bones, to obtain a complete image of information, monitoring, merging multi-exposure images, and Multi focus images, etc[3].

Multi-focus images Fusion, where an image in which one part is distorted and the other is clear, is combined with another image in which one part is clear and the other is distorted. They are combined to obtain an image that is better than the original image in terms of quality and clarity. It is used because it is difficult to design a device that works to give complete information as well. It will be a high cost [4].

1.2 level of image fusion

There are three levels of fusion:

1.2.1 Pixel Level Fusion

It is one of the most basic method of image fusion, the mathematical operations dealing with the pixel values of the input images. This technique concentrates on each part of image and produces good results if the image has high brightness and contrast [5].

1.2.2 Feature level fusion is often used in applications such as object recognition, face recognition and video surveillance, and can improve the accuracy and efficiency of these systems by providing a more complete and dependable representation of data [6].

1.2.3 Region Level Fusion

Region-based merging occurs based on image blocks in pixels. Region -based fusion is the highest technology for multi-stage representation and measuring according to each area in the image. It involves dividing input images into regions based on their visual characteristics, such as color, and then fusion the corresponding regions to create a new image [6].

1.4 Medical fusion applications

Among the medical applications of fusion is ultrasound:

1.4.1 Ultrasound Imaging

It is a sound wave with frequencies higher than the upper audible limit of human hearing, humans can hear sound in the frequency range between 20 to 20,000 Hz (20 KHz) [7]. Ultrasound is used in many different fields; Ultrasound devices are used to detect movement organs in real time. Ultrasound imaging is often used in medicine, non-destructive testing of products and structures, and is used to detect invisible defects. Industrially, it is used for cleaning, mixing, and accelerating chemical processes. Ultrasound uses higher frequencies than Doppler imaging.

Ultrasound is an imaging technique where high-frequency sound waves are used to create an image. The ultrasound wave is produced by a probe using impact[8].

Two basic principles about how ultrasound is generated and image formation must be understood. The first is the piezoelectric effect, which explains how the ceramic crystals in the

transducer generate ultrasound waves. An electric current passes through a cable to the transducer and is applied to the crystals, causing them to deform and vibrate. This vibration is produced by the ultrasound beam. The frequency of the ultrasound produced is predefined by the crystals in the transducer [9].

The second main principle is the pulsed echo principle, which explains how an image is created. Ultrasound is produced in pulses, not continuously, because the same crystals are used to generate and receive sound waves, and they cannot do both at the same time. In the time between pulses, the ultrasound beam enters the patient and is bounced or reflected back to the transducer. These reflected sound waves, or echoes, cause the crystals in the transducer to deform again and produce an electrical signal that is then converted into an image displayed on a screen. The transducer generally emits ultrasound only 1% of the time; The rest of the time is spent receiving the returning echoes [10].

Generate the ultrasound wave:

1. By using piezoelectric elements that generate an ultrasound wave in response to an electrical pulse.
2. The ultrasound wave then travels through a medium such as the human body.
3. Some of its energy gets reflected back toward the Interactions of ultrasound waves with Tissues:

When an ultrasound waves travels through a medium, it causes expansion and compression of the medium. Ultrasound waves interact with tissue in these five basic manners: 1- Reflection

1. Transmission
2. Scattering
3. Attenuation
4. Refraction

Probe: It is a device that produces sound waves that bounce off body tissues and create echoes. The transducer also receives the echoes and sends them to a computer that uses it to create an image called an ultrasound. The transducer, or probe, is the main part of the ultrasound machine. Some types of sensors [11].

Types of Probes:

1. Convex Sensors (3.5MHz) The convex transducer for 2D and 3D imaging has a wide area and its center frequency is 2.5MHz - 7.5MHz. It is used for abdominal examinations [11].
2. Linear Sensors (7.5MHz) The 2D imaging linear transducer has a wide area and its center frequency is 2.5MHz - 12MHz. You can use this power adapter for different. Applications, for example: vascular examination, angiography, breast and thyroid
3. Sector probe (2.5 MHz) used in cardiac and abdominal applications. Brain diagnosis.
4. Vaginal probes (6.5 MHz) used to examine the uterus, ovaries, tubes, and cervix Pelvic area.
5. Rectal probes (6.5 MHz) designed to allow ultrasound examination of deep areas of the rectum and anus

1.5 Literature Review

G.D. Stetten et al (2002) [12] , The technique combines a flat-panel monitor with a half-silvered mirror such that the image on the monitor is reflected precisely at the proper location within the patient. In this way, the ultrasound image is superimposed in real time on the view of the patient along with the operator's hands and any invasive tools in the field of view. Instead of looking away at an ultrasound monitor, the operator can manipulate needles and scalpels with direct

hand-eye coordination. Invasive tools are visible up to where they enter the skin, permitting natural visual extrapolation to targets in the ultrasound slice. Tomographic reflection is independent of viewer location, requires no special apparatus to be worn by the operator, nor any registration of the patient. Hind Dadoun et al (2021) [13], make use of this method to generate a training data set with segmentation masks of the region of interest (ROI) and train a U-Net to perform the same task in a supervised way, thus considerably reducing computational time of the method, one hundred and sixty times faster. These images are then processed with existing inpainting methods to remove annotations present inside the fan area. To the best of our knowledge, this is the first parametric approach to quickly detect the fan in an ultrasound image without any other information than the image itself. The goal of the research is to fusion distorted medical digital images with motion blur technique as a simulator of the distorted image, with the aim of improving its quality and clarity and highlighting the fine details that may be hidden due to the distortion, as well as evaluating the quality of medical images based on the edge detection.

Materials and Methods

2.1 Methodology and algorithms

In this chapter, we will discuss the techniques that were adopted in the work, including merging techniques (addition, Multiplication, real standard deviation), as well as learning about motion blur technology and the quality standards that include the edge detection standard, where the programs were developed and built based on the MATLAB 2021 program [13].

2.2 Motion Blur Method

Motion blur is one of the most prevalent types of image distortion that occurs in dynamic scene duo to camera shake or object motion. Its strength depends on by exposure time as well as the speed of the object close to the camera. It uses in cinematic productions, and in amateur videos. The point spread function (PSF) can be simulated in continuous spatial coordinates, using principles of geometric optics or physical optics to simulate motion blur in computer. There are three primary causes of motion blur, the first of which occurs when the camera is steady while objects are moving in the scene. The second factor is when the camera moves but the object does not. Motion distortion can also occur when both the camera and the subject are in motion simultaneously. Since 1976, a large number of researchers have created algorithms for estimating linear motion blur coefficients.

Where H is the function of blurring or PSF that transform a source image in accordance with equ. (2.1) [14].

$$(i, j) = \begin{cases} \frac{1}{L}, & \sqrt{i^2 + j^2} \leq L \\ 0, & \text{otherwise} \end{cases} \quad \begin{matrix} i \\ j \end{matrix} \quad \text{-- and --} = -\tan(\phi) \quad (2.1)$$

Where (L) the length of motion and (ϕ) the direction of motion. The general form of the motion blur function is given as follows.

$$G(i, j) = F(i, j) * H(i, j) \quad (2.2)$$

Where $G(i, j)$ is image blur, $F(i, j)$ is the source image, and $H(i, j)$ represents the blur function. In this thesis, the length of the movement was estimated in a horizontal direction, and it changes according to the block size (3, 5, 7, 9, and 11) with a fixed theta direction of movement.

2.3 The Adopted Fusion Methods

2.3.1 Mathematical Fusion Methods

Mathematical operations are a traditional and uncomplicated method of image processing by using a set of mathematical and logical processes for two, or more images. The operators are applied pixel by pixel, which means that the pixel value in the resultant image relies solely on the values of pixel units in the input images, which usually should be the same size. The main advantages of mathematical operations are very simple and fast, as well as having a wide range of applications. Two methods of fusion were used which are addition and multiplication method [15].

➤ The Addition Method

The fused images are calculated by a simple averaging of pixels from two images resulted by motion blur technique, each pixel of each image is considered in this method. It is a rapid technique for combining images while preserving image details as well as it enhances image brightness and highlights details, making it especially helpful for low-contrast images. It can also be combined with other methods to produce more sophisticated fusion technologies. If the images were captured with the same type of sensor and have a high level of brightness and contrast, the fusion will produce favorable results. The image fusion technique was applied by Addition two images as in the relationship[16] :

$$C_{Add}(i, j) = \sum_{i=1}^m \sum_{j=1}^n \frac{I_A(i, j)}{2} + \frac{I_B(i, j)}{2} \quad (2.3)$$

Where C_{Add} is the fused image, I_A , I_B are reference source images and, m , n is number of row and columns of images.

➤ The Multiplication Method

To illustrate the combined spectral properties of both groups, the multiplier model was used to create two data sets by taking the square root of a merged data set. The model incorporates multiplication to reduce the likelihood of color distortion. Multiplicative transformation was recanted to be able to fuse the two different images; it is given as follow[17]:

$$C_{MLT}(i, j) = \sqrt{\sum_{i=1}^m \sum_{j=1}^n I_A(i, j) \times I_B(i, j)} \quad (2.4)$$

Where C_{MLT} is the fused image I_A , I_B are reference source images and, m , n is number of row and columns of images. In general, multiplication image fusion is an effective technique for combining images that keeps image features and can be particularly useful for high contrast images and detecting changes. It can be used for image enhancement and combined with other techniques to produce more complex fusion methods, sharper edges, etc. and the resulting images keep all data and improve accuracy.

2.3.2 Statistical Fusion Methods

Statistical methods are techniques for analyzing data and extracting results from it. Descriptive statistics which are a type of statistical method used to summarize and describe data. This involves utilizing measures such as the mean, median, mode, range, and standard deviation to provide an overview of the data. Presentation of data in a visual format such as graphs, charts, and tables to help identify patterns and relationships. There are many other statistical methods used in various fields. The advantages of image merging include statistically improved image quality. It can combine multiple images to create a single image with high quality and clarity.

Increased information content, reduced noise, and improved accuracy [18].

➤ Weighted Statistical Fused Image Techniques

The fused image of this method is produced through the weighted statistical average of the pixel's intensity from each input image. It involves assigning weights to each image based on its quality and relevance to the final image, and then using these weights to combine the images, which are fundamental fusion algorithms. The process of merging images can be denoted as following [19]:

$$(i,j) = P_1 I_A(i,j) + P_2 I_B(i,j) \quad (2.5)$$

Assuming that the source images are denoted as I_A and I_B both of size $i \times j$, the resulting fused image is described as C , where I and j are the image's pixel rows and columns, respectively. The selection of weighted factor values P_1 and P_2

is a critical aspect of the algorithm, these values can be set based on human experience or determined dynamically? Typically, the weighted factors are calculated using the following equation:

$$P_1 = \frac{I_A(i,j)}{I_A(i,j) + I_B(i,j)}; P_2 = (1 - P_1) \quad (2.6)$$

Where p_1, p_2 are weighted factors and I_A, I_B are reference source images.

• The Real Standard Deviation

This criterion is applied to measure contrast. A high contrast in the fused image indicates a high standard deviation. The higher its value, the better its efficiency. The standard deviation is an important criterion to determine the detail quantity in the chosen image. The standard deviation calculation is as follows [20]:

$$\sigma_{I_A, B}(i,j) = \sqrt{\frac{\sum_{i=1}^m \sum_{j=1}^n (I(i,j) - \mu)^2}{m \cdot n}} \quad (2.7)$$

Where m is the number of rows, n defines the number of columns, $I(i,j)$ show combined image, μ indicates mean, and $\sigma_{I_A}, \sigma_{I_B}$ standard deviation for refer image

$$P_1 = \frac{\sigma_{I_A}(i,j)}{\sigma_{I_A}(i,j) + \sigma_{I_B}(i,j)}; P_2 = (1 - P_1) \quad (2.8)$$

Calculate fused image with the following equation:

$$I_{F-real\ std} = P_1 I_{Up} + (1 - P_1) I_{Down} \quad (2.9)$$

2.4 Edges Detection

Edge detection is a method in image processing that is employed to find the edges or boundaries of objects present in an image. Image edges are areas with high intensity contrasts and intensity changes from one pixel to the next. The goal of edge detection is to significantly decrease the quantity of data and eliminate irrelevant details, while keeping the crucial structural characteristics of an image. Edge detection is one of the major applications of convolution, for image segmentation and data mining in areas such as image processing, biomedical imaging, robotics and autonomous vehicles [21]

There are several ways to detect edges; including Laplacian-based methods calculate image density to determine the points where the density changes abruptly. Gradient-based methods compute the gradient of image intensity to determine the points at which the intensity changes rapidly. Gradient-based methods include the Sobel operator, the Prewitt operator, and the Canny edge detector. In this work, we will look at the Sobel coefficient.

Sobel is an edge detection algorithm used in image processing and computer vision. It uses a pair of 3×3 convolution kernels to calculate the gradient of the image in the x and y directions, and then combines them to get the amount and direction of the gradient. The edges are then detected by locating pixels with a higher gradient size. The Sobel operator kernel is designed to

approximate the derivative of the image intensity function in the x and y directions. The x-kernel and the y-kernel [22]:

$$\text{Mask } |G_x| = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \text{ and } \text{mask } |G_y| = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad (2.25)$$

These masks can then be combined together to find the absolute magnitude of the gradient at each point. The gradient magnitude is given by [23]:

$$\text{Mask } |G| = \sqrt{(G_x^2 + G_y^2)} \quad (2.26)$$

The Sobel operator utilizes a mathematical convolution of an image by applying a small and separable filter that contains integer values in both directions. To compute the gradient of the x-direction, the image is convoluted with the x kernel, and to compute the gradient in the y-direction, it is convoluted with the y kernel. The magnitude and direction of the gradient are calculated. So, it is simple in mathematical calculations, detector determine the direction that exhibits a high increase from a brighter to a darker hue, as well as the speed of transformation along that direction. The main advantage of the Sobel filter is its simplicity, it allows the observer to examine the light and color changes in the image in detail, and it processes and understands the image better. The disadvantage is the signal-to-noise ratio [24,25,26,27,28].

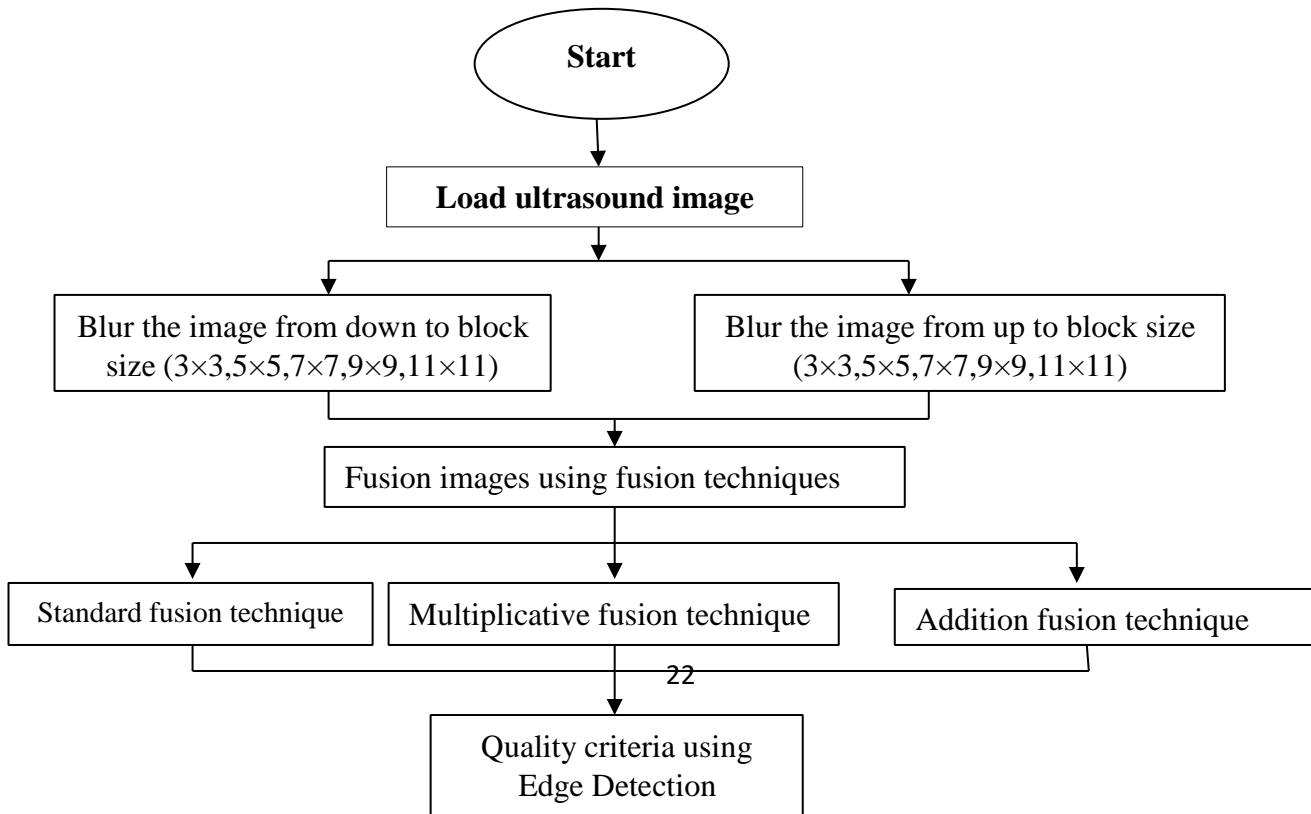
2.5 Adopted Algorithms

In this study, number of algorithms was programmed as follows:

3. Practical Part

3.1 Introduction

In this chapter, the work plan that was approved will be presented, which includes the approval of a laboratory image taken from Yarmouk Teaching Hospital - Baghdad. Ultrasound images depend on the difference in skin depth. Figure (4-6a) shows a breast ultrasound image with a size of 284 x 187 pixels. Figure (4-6c). The image used in the study was 24 bits deep. Superficial structures such as the breast were imaged at a higher frequency (7-18 MHz), to provide better axial and lateral resolution. The program was built and developed using software computing, and quantitative analysis was performed. A Dell laptop, CPU i7, 8G RAM, and a Sonar device, E Healthcare 9900 Innovation Drive, Wauwatosa, WI53226, U.S.A. The programs were built and developed using MATLAB 2021. The practical part included two parts: The first part is blurring the image. The medical image was scanned from the top once and from the bottom a second time with a different block size (3x3, 5x5, 7x7, 9x9, and 11x11). Two distorted images were merged from the top and bottom for each block size. The practical part included two parts: **The first part** is blurring the image. Medical from the top once and from the bottom a second time in a motion blur method with a different block size (3x3, 5x5, 7x7, 9x9, 11x11). Each two distorted images were merged from the top and bottom for each block size, relying on a number of merging techniques (mathematical, representational, and statistical). As for **the second part**: included evaluating the quality of work based on the standard of quality and efficiency, edge detecting.



4.1 Results and Discussion

In this chapter, the most important results obtained will be presented, discussed, and the work will be evaluated based on efficiency measures. We relied on an ultrasound image obtained from Yarmouk Governmental Hospital - Baghdad. The image was a person's abdominal muscles, with a size of 527 x 104 pixels and a depth of 24 bits. They are imaged at a higher frequency (7-18 MHz), to provide better axial and lateral resolution. The image is distorted from half to the top and from half to the bottom with different block sizes (3x3, 5x5, 7x7, 9x9, and 11x11) using motion blur technique. Then the images were merged based on the traditional and proposed merging technique, where the images were merged based on the weights method. The merging methods included mathematical (addition and multiplication) and statistical techniques included the standard deviation method. The results were evaluated before and after the merging process based on the efficiency and quality metrics of edge detection. The programs were built and developed based on the MATLAB 2021a program

4.2 Image adopted in this study

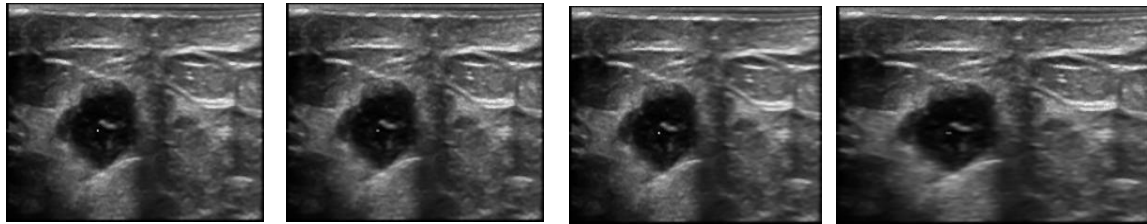
An ultrasound image was relied upon, as shown in the figure (4-1).



Figure (4-1): ultrasound image adopted

4.3 Results of blurred images

The results of the images resulting from applying the motion blur technique will be displayed in an up and down direction and for a block size (3×3, 5×5, 7×7, 9×9, and 11×11).



3×3up

3×3 down

5×5 up

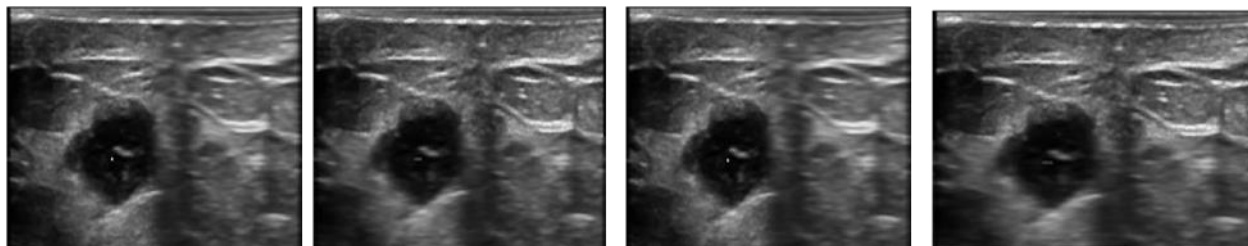
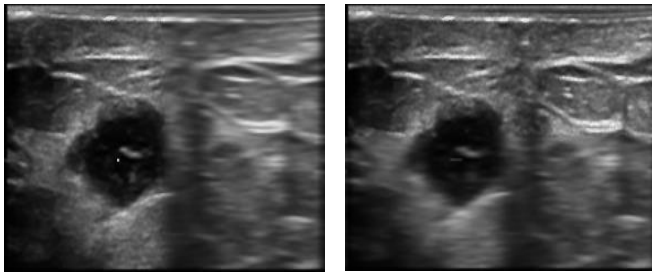
5×5 down

7×7 up

7×7 down

9×9 up

9×9 down



Origion Image

First Image

Second Image

Fused Image

Fused Image

Fused Image



11×11 up

11×11 down

Figure (4-2): Images result from motion blur

4.4 Results of the Fusion Process

The resulting images of the figure (4-2) were merged using fusion techniques (addition, multiplication, standard deviation), where half the image blurred up was merged with the half the image blurred down for the same block size, and the resulting images were evaluated before and after the merging based on Edge detection was calculated according to five thresholds whose values are (0.01, 0.02,

0.03, 0.04, 0.09), as in the figure shown in Figure (4-3),(4-4), (4-5). (4-6) and (47).

Add multi std

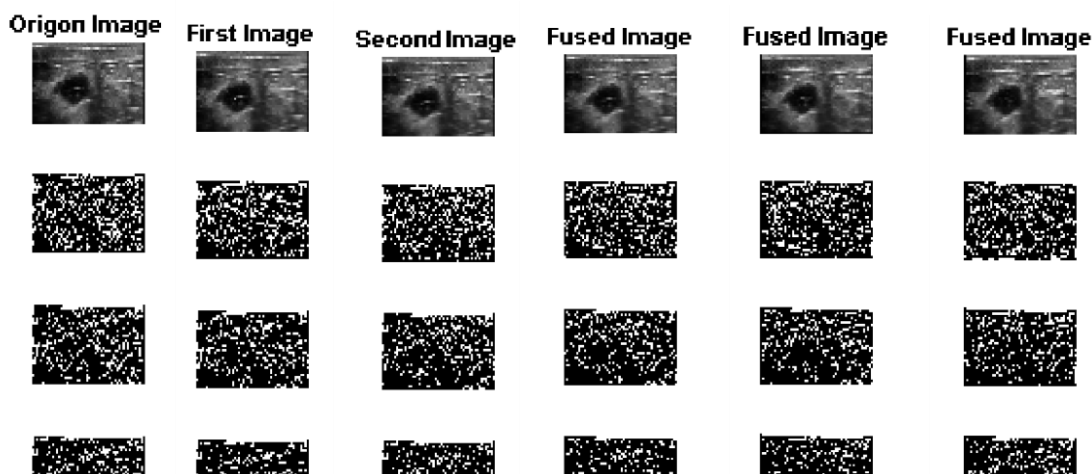
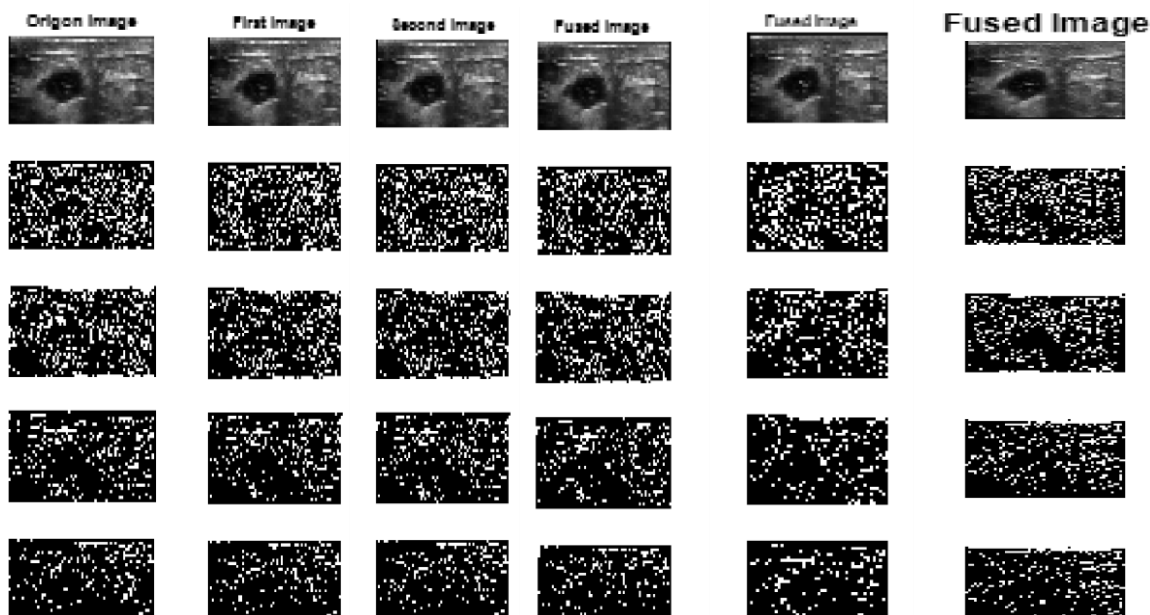
Figure (4-3): Results of merging (3×3) and edge detection for blurred images

From the figure (4-3), notice that the merging process based on addition is better than the multiplication and standard deviation techniques, as notice that the number of edges was more.

Add multi std

Figure (4-4): Results of merging (5×5) and edge detection for blurred images

From the figure (4-4), notice that the merging process based on multiplicative is better than the add and standard deviation techniques, as notice that the number of edges was more.



Add multi std

Figure (4-5): Results of merging (7×7) and edge detection for blurred images

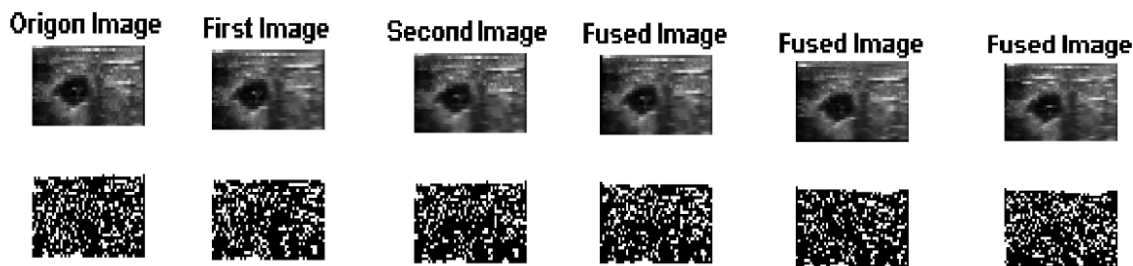
From the figure (4-5), notice that the merging process based on multiplicative is better than the add and standard deviation techniques, as notice that the number of edges was more.

Add multi std

Add multi std

Figure (4-6): Results of merging (9×9) and edge detection for blurred images

From the figure (4-6), notice that the merging process based on multiplicative and std are better than the add technique, as notice that the number of edges was more.



From the figure (4-7), notice that results were almost similar among all the adopted merging techniques in terms of the number of edges

5.1 conclusion

From the results we can conclude the following points:

1. Simulate a gray-gray blur image using a smooth linear motion blur type with a block size of (3, 5, 7, 9, 11) pixels. Using the linear trend from above and below, and combining them using integration methods (addition, multiplication, and standard deviation), we conclude the following:
2. The best methods of integration are mathematical methods. Depending on the quality standards edge detection
3. Images resulting from fusion methods are better in terms of efficiency, accuracy, clarity of information and details, and are also more balanced in terms of contrast and color. Each image has a blending technique that works well.
4. Image merging methods overcome blurring of all degrees in the image, so that the resulting image is improved and of high quality regardless of the degree of blurring.
5. Edge detection achieved a high rating in evaluating image quality by detecting added, deleted and shared edges and determining the best merging method.

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