Comparative Evaluation of Medical Thermal Image Enhancement Techniques for Breast Cancer Detection

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Abstract. Thermography is a potential medical imaging modality due to its capability in providing additional physiological information. Medical thermal images obtained from infrared thermography systems incorporate valuable temperature properties and profiles, which could indicate underlying abnormalities. The quality of thermal images is often degraded due to noise, which affects the measurement processes in medical imaging. Contrast stretching and image filtering techniques are normally adopted in medical image enhancement processes. In this study, a comparative evaluation of contrast stretching and image filtering on individual channels of true color thermal images was conducted. Their individual performances were quantitatively measured using mean square error (MSE) and peak signal to noise ratio (PSNR). The results obtained showed that contrast stretching altered the temperature profile of the original image while image filtering appeared to enhance the original image with no changes in its profile. Further measurement of both MSE and PSNR showed that the Wiener filtering method outperformed other filters with an average MSE value of 0.0045 and PSNR value of 78.739 dB. Various segmentation methods applied to both filtered and contrast stretched images proved that the filtering method is preferable for in-depth analysis.

Keywords: *contrast stretching; filtering; image enhancement; medical thermal image; thermography technique.*

1 Introduction

In general, thermal images obtained from infrared thermal imaging systems provide not only the visual information of the image but also the surface temperature data of a particular object [1-3]. In some infrared applications, such as security and surveillance, the display of the targeted object is more important than an accurate temperature display on the image [4]. However, in medical thermography, each temperature point is crucial and needs to be conserved, because they indicate physiological changes that occur underneath the skin

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[5,6]. Thus, color contour image representation is usually preferred for an effective interpretation. However, the quality of thermal images is often degraded due to radiation from the surroundings, limited aperture, pixel reading procedure and radial distortion due to non-linear image points with respect to the optical center [7-9]. Hence, image enhancement is usually performed to enhance blurred images and reduce noise [10].

Initially, images were processed into grayscale thermal images due to the limitations of the infrared system [11,12]. As the infrared imaging technology has further developed in the last decade, researchers have started to analyze thermal images in true-color, red-green-blue format (RGB) [13,14]. However, in contrast to the ubiquitous studies on other medical imaging techniques, studies on medical thermal image enhancement have hardly been done. In previous studies, researchers have stated that image filtering is a root process method in medical image processing that benefits the post-processing tasks. They concluded that bilateral median filtering produces better enhancement of the image in comparison to Gaussian filtering [15]. Agaian and Roopaei have proposed a simple enhancement technique on thermal images based on filtering and stretching and also proved that their proposed method yielded a better output image compared to other methods [4]. Zadeh and others analyzed the asymmetrical properties of both breasts in their study, in which they used a 6x6 Gaussian filter to reduce noise levels after discovering that the segmented thermal images were contaminated [16].

Conventional histogram equalization, or contrast stretching, has also been investigated as an enhancement technique frequently applied in medical image processing. This is due to its capability of highly enhancing the contrast of blurred images for better target detection and segmentation [17]. Recently, some new improvement techniques on histogram equalization have been proposed [18]. Advanced fuzzy-based contrast stretching was used by previous scholars for medical image enhancement, who showed that the performance was better when using histogram equalization alone [19]. However, most of the proposed methods impose additional processing time and load. Hence, the combination of image processing methods used depends on the specific aim of the study, while considering whether factors such as computational time and processing load will affect the overall processing performance.

Thus, the objective of this study was to conduct a comparative evaluation of multiple enhancement techniques on symptomatic thermal images and quantitatively measure their individual performances. Based on a review of previous image enhancement works, the histogram equalization method was chosen as the contrast stretching technique, while three different image filtering methods – namely Wiener filter, Gaussian filter and median filter – were used as image filtering techniques. The final enhanced images were evaluated using different segmentation methods developed for the post-processing stage to verify their performance.

2 Methods and Material

2.1 Image Acquisition

Thermal images were acquired using an Epidermal Thermal Imaging Professional (ETIP) infrared imaging camera system, model 7640 P-Series (Infrared Camera Incorporation, Texas USA). The camera was fixed-mounted on the flexible metal bar and connected to the display monitor as shown in Figure 1. The distance of the camera to the sample, $\boldsymbol{x}$, was set to 100±2cm in order to minimize variation in measured temperature. To stabilize the system, initialization of the camera was carried out prior to screening. The room's temperature was controlled in a range of 20-22 °C and all available sources of light in the room were switched off before and during the screening process to minimize variation in the room's temperature.

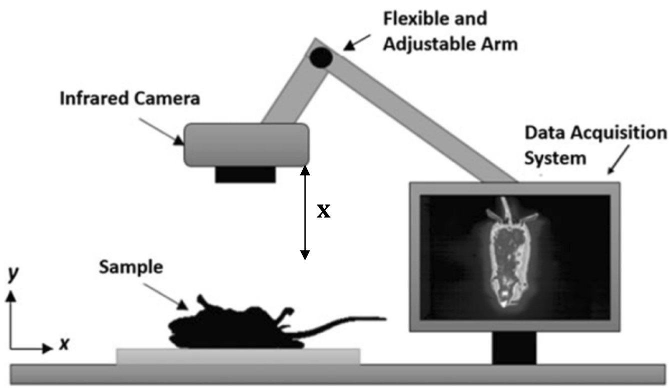

Figure 1 Experimental setup for acquiring thermal images.

Sample images were taken from carcinogen-induced Sprague-Dawley rats palpated with extruded lump after 6 weeks of the induction process. The use of animal models in this study was approved by the institutional review board of Universiti Kebangsaan Malaysia, Animal Ethics Committee (UKMAEC), Selangor. The entire experiment was conducted in the Animal Laboratory, Faculty of Bioscience and Medical Engineering, Universiti Teknologi Malaysia (FBME, UTM), Johor, Malaysia. A strict set of protocols was developed and followed before, during and after the screening processes.

2.2 Image Enhancement

The use of additive color composite channelization was proposed to preserve the original surface temperature profiles of the thermal images. It uses three different light sources and converts them into an individual color channel that carries only an 8-bit data string compared to RGB images with a 24-bit data string. Two enhancement methods, namely contrast stretch and filtering were applied to the thermal images, after which a visual comparison between the enhanced thermal images and the initial images was made.

2.3 Contrast Stretching Method: Histogram Equalization

Histogram equalization is a contrast stretching technique that is widely used in medical image pre-processing [17,20]. Higher histogram equalization is accomplished when there is an effective spreading out of the most frequent intensity values as derived from Eq. (1) [18,21]:

$$p_n = \frac{Number\ of\ pixel\ with\ intensity\ n}{Total\ number\ of\ image\ pixels}\ , n = 0,1,2 \ldots\ldots, L-1 \quad (1)$$

where p is the normalized histogram with a bin for each possible image intensity with an m_r by m_c matrix of integer pixel intensities ranging from 0 to L-1. Subsequently, the histogram-equalized image can be obtained using Eq. (2):

$$g_{i,j} = floor\ ((L-1) \sum_{n=0}^{i,j} p_n \quad (2)$$

where *floor* refers to the nearest integer part of a real number.

2.4 Image Filtering Techniques

2.4.1 Wiener Filtering

Wiener filtering works based on the statistical characteristics of the image within the filtering window in order to filter out noise from the corrupted image to estimate the underlying region of interest. Original thermal images can be modeled in Eq. (3) as follows:

$$y(i,j) = x(i,j) + n(i,j) \quad (3)$$

where *y(i,j)* is the original thermal image with noise, *x(i,j)* is the noise-free thermal image and *n(i,j)* is additive noise. Wiener filtering will remove the noise and produce a linear estimation of *x(i,j)* with minimized mean squared error [11].

2.4.2 Gaussian Filtering

Gaussian filtering is designed to disallow overshoot to a step function input while minimizing the rise and fall time. This particular filtering method is also known as a smoothing filter in two-dimensional convolution operation, which is used to remove noise and prevent image blur and can be expressed as Eq. (4) [23]:

$$g(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{4}$$

with x and y representing the pixel coordinates and σ is the standard deviation which controls the Gaussian bell shape [21].

2.4.3 Median Filtering

Median filtering is a non-linear filter that is used to reduce noise in an image with a better output compared to mean filtering since it preserves more details of the original image. This method changes the image intensity mean value when the spatial noise distribution of the image is asymmetrical within the window by reducing its variances and finally determines which pixels have the median brightness value [21,22].

2.5 Assessment of Thermal Image Enhancement Techniques

The mean squared error (MSE) and peak to noise ratio (PSNR) values of all images were calculated to quantitatively measure the performance of each enhancement technique adopted in this study. A lower MSE means less error, while a higher PSNR means that the clean signal is much stronger than the noise. Hence, the best enhancement technique is the one with the lowest MSE (Eq.(5)) and the highest PSNR values (Eq.(6)) [21,24].

$$MSE = \frac{1}{MxN}\sum_{i=1}^{m}\sum_{j=1}^{n}[x(i,j) - y(i,j)]^2 \tag{5}$$

$$PSNR = 20log_{10}\left[\frac{(2^n-1)}{\sqrt{MSE}}\right] dB \tag{6}$$

where *x(i,j)* and *y(i,j)* are the images before and after filtering, respectively; *MxN* is the size of the image; and *n* is the number of bits that is used to represent the pixels of the image.

3 Results and Discussions

3.1 Additive Color Composite Channelization

The output images for additive color composite channelization are shown in Figure 2. All individual color channel images were used in the image enhancement process, regardless of the visual assessment, and their output images were then quantitatively measured for further evaluation.

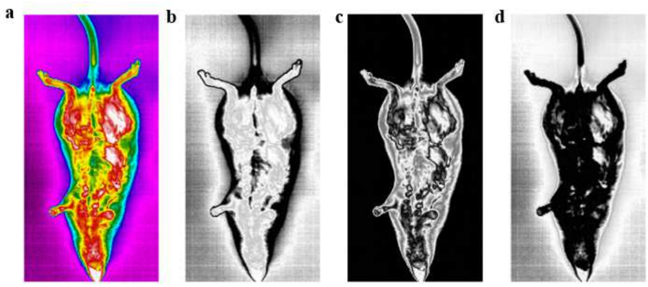

Figure 2 Output individual image after color channelization: (a) original thermal image, (b) red channel, (c) green channel and (d) blue channel.

3.2 Contrast Stretching Technique

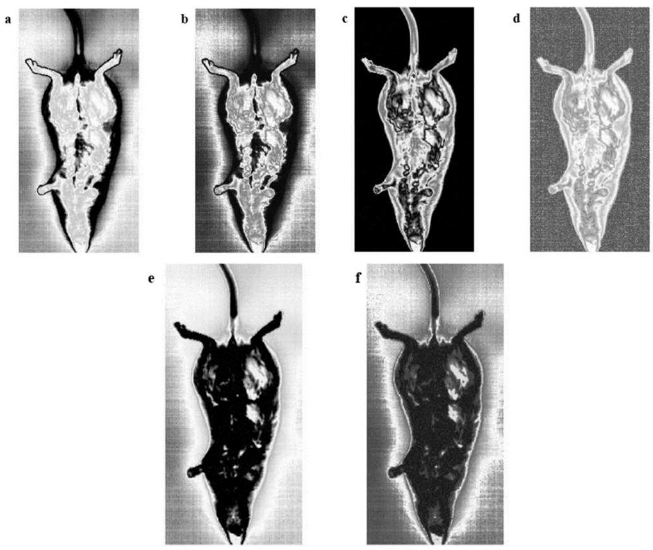

Figure 3 Original image and its corresponding image output using contrast stretching in different color channels: (a) red channel, (b) contrast stretched red channel, (c) green channel, (d) contrast stretched green channel, (e) blue channel and (f) contrast stretched blue channel.

After the contrast stretching method had been applied, the original thermal images were transformed into an intensity image format. It was found that the warmer areas – represented by the lightest areas in the original format – had been poorly retained. This causes undesired loss of visual data and changes the original surface profile of the image by enhancing the unwanted image background, as can be seen in Figure 3. Likewise, although a good histogram equalization result was obtained, as shown in Figure 4, this indicator cannot be used as a good measure for image enhancement in thermography since some important small bins of the histogram have been eliminated. Unlike in other medical imaging techniques, such as X-ray imagery, uniform histogram distribution by contrast enhancement is preferred to enhance the region of interest. Both MSE and PSNR calculations show that the histogram equalization method produced extremely high MSE and lower PSNR values, as shown in Table 1. Hence, this method will increase the complexity in the next step that needs to be performed, i.e. segmenting the region of interest.

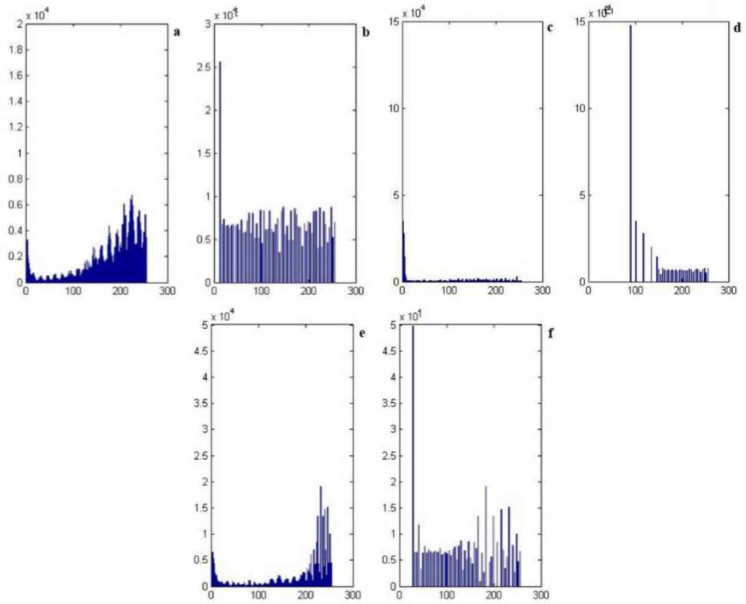

Figure 4 Histogram equalization result of thermal images in Figure 2 a) red channel, (b) contrast stretched red channel (c) green channel, (d) contrast stretched green channel, (e) blue channel and (f) contrast stretched blue channel.

Table 1 MSE and PSNR values of histogram equalization method applied to red, green and blue color channel.

	Red Channel	Green Channel	Blue Channel
MSE	774.411	1041.706	201.303
PSNR	19.241	17.953	25.092

3.3 3.3 Image Filtering Techniques

Figures 5, 6 and 7 show the results of the thermal image after it was filtered using the Wiener, Gaussian and median filtering methods. Based on visual comparison, the temperature profile of all individual channels was retained without causing any obvious changes to their original profiles. Therefore, a quantitative measurement based on MSE and PSNR calculation was carried out to evaluate which method best fit the thermal image enhancement process.

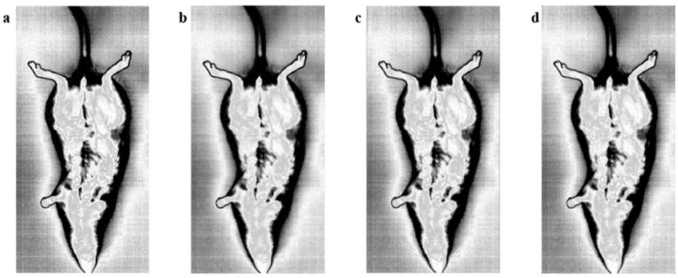

Figure 5 (a) Original red channel image and its corresponding image output using different filtering methods: (b) Wiener filtered image, (c) Gaussian filtered image, and (d) Median filtered image.

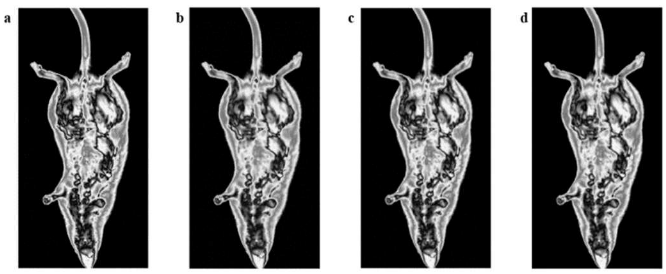

Figure 6 (a) Original green channel image and its corresponding image output using different filtering methods: (b) Wiener filtered image, (c) Gaussian filtered image, and (d) Median filtered image.

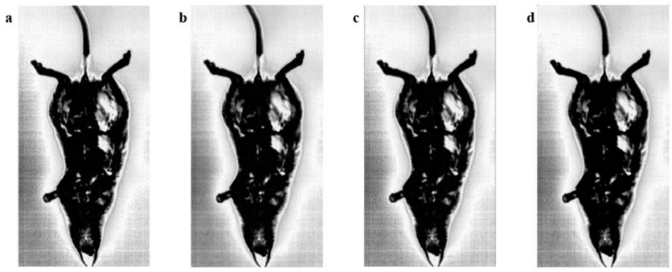

Figure 7 (a) Original green channel image and its corresponding image output using different filtering methods: (b) Wiener filtered image, (c) Gaussian filtered image, and (d) Median filtered image.

Tables 2 and 3 present the result for the MSE and PSNR calculations respectively. Based on the results obtained, it can be seen that different filtering methods resulted in a significant enhancement for different color channels. Median filter was shown to be the best method for enhancing the red channel image compared to the other filter types, with an MSE value of 0.003 with a PSNR value of 73.325 dB, while the Gaussian filter more optimally reduced noise in the green channel image compared to the median and Wiener filters, with a MSE value of 0.00002 and a high PSNR value of 94.226 dB. In addition, the Wiener filtering method was seen to produce a highly enhanced image for the blue channel image as well, with an MSE value of 0.0002 and a PSNR value of 93.657 dB. In terms of overall performance, the Wiener filter was shown to provide the best filtering results, with the lowest average MSE (0.0045) and the highest average PSNR (78.739 dB) for all channels, with a minimal MSE and acceptable high PSNR values for each channel, without causing surface profile temperature changes to the original image compared to the contrast stretching method.

Table 2 MSE values of three different filters applied to individual channels of thermal image.

Image Type / MSE	Wiener	Gaussian	Median
Red Channel (RC)	0.0115	0.1769	0.003
Green Channel (GC)	0.002	0.00002	0.4857
Blue Channel (BC)	0.0002	0.2157	0.2267

Table 3 PSNR values of three different filters applied to individual channels of thermal image.

Image Type / MSE	Wiener	Gaussian	Median
Red Channel (RC)	67.5242	55.6525	73.3245
Green Channel (GC)	75.0372	94.2264	51.2669
Blue Channel (BC)	93.6565	54.793	54.5769

For verification, all enhanced color channels were recombined to form an RGB enhanced image. Figure 8 shows the final output of both histogram equalization and the selected Wiener filtering. Preliminary segmentation methods were then applied to both final images and their visual performance was observed.

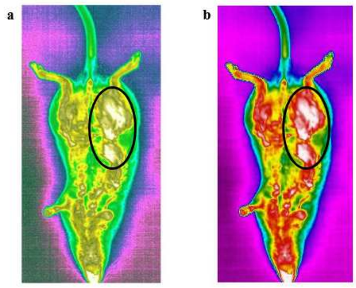

Figure 8 Enhanced image output with highlighted symptomatic area using (a) histogram equalization and (b) Wiener filter.

It can be seen in Figure 9(a-b) that when segmentation method 1 was applied to both enhanced images, the filtered image was shown to have clear subject segmentation as well as symptomatic region segmentation, while the contrast stretched image appears to retain most of the unwanted background image. Similarly, Figure 9(c-d) shows that the filtered image captures the optimum symptomatic region area, while the contrast stretched image was shown to capture only a small part of this region due to changes occurring in the overall temperature profile during the enhancement process. Hence, it was verified that for medical thermal image enhancement, filtering has better performance in suppressing noise while preserving the temperature profile data.

Figure 9 Segmentation method 1 on enhanced images using: (a) histogram equalization and (b) Wiener filter, segmentation method 2 on enhanced images using (c) histogram equalization and (d) Wiener filter.

4 Conclusion

In this study, two enhancement techniques on medical thermal images were compared based on overall MSE and PSNR results. It was shown that image filtering has better performance than contrast stretching in enhancing medical thermal images since it retains the temperature profile of the original thermal image. Further assessment of different filter types showed that the Wiener filter produced the best enhancement of the thermal images compared to the other filtering methods. Despite this, it was also seen that median and Gaussian filtering resulted in optimal image enhancement for the red channel and the green channel images, respectively. Both final enhanced images were treated with different segmentation methods, which showed that the filtered images had clearer segmentation regions compared to the contrast stretched images. Hence, depending on the specific application, an enhancement method can be individually selected based on color channel or using a general filter for all channels in order to reduce the total time taken and processing load for achieving high accuracy enhanced thermal images. For future improvement, a combination of multiple enhancement techniques on each color channel could be investigated to produce higher quality enhanced true-color medical thermal images.

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