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Consideration for segmentation based on radiometric data processing, towards the research of quantitative medical thermography

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Abstract — **Medical thermography is considered an auxiliary technique in preventive medicine, treatment monitoring, and surgery. However, the true value of thermography lies in quantitative studies so that the information presented to the human eye can be maximized. To this end, it is essential to preserve the radiometric data that may provide information to quantitative studies, e.g., temperature difference analysis, segmentation, contrast adjustments, artifact removal, etc. However, certain thermographic equipment may not be radiometric so only a mapped thermal image known as a false color image can be obtained. Therefore, the radiometric aspect must be considered to perform quantitative studies. This paper presents the comparison between processing radiometric data matrices and false color images. The methods employed were segmentation of the region of interest (RoI) and contrast adjustment once segmented. The segmentation method is based on thresholding, in which an optimal threshold was found to be approximately 0.8 for radiometric arrays and 0.6 for grayscale images that were not transformed from an RGB image. In conclusion, using radiometric data arrays has advantages over using RGB images as input information. Moreover, medical thermography should not only consider a qualitative aspect when it comes to diagnostics, but the validation of thermography lies in quantitative studies based on radiometric input.**

Keywords — Medical thermography, IR radiometric processing.

I. Introduction

Quantitative thermography uses radiometric information from thermograms. Thermograms are obtained by measuring the infrared (IR) energy of the object or patient. The measured temperature reflects the temperature of the skin surface because of metabolism [1]. Commonly, thermograms are represented as a graphic image in false colors (not representative of the true color) or grayscale. Color mapping corresponds to the temperature distribution of the skin surface [2,3]. When the thermogram is presented as an image, the temperature is a qualitative representation of the metabolic processes of the patient. However, it is the radiometric information that preserves the temperature data that a quantitative study can provide [4].

Quantitative thermography fundamentally aims to adjust the thermal image in such a way that it maximizes the information presented to the human eye, however, on the other hand, the radiometric information can be used for device calibration, training of disease classification systems, and segmentation of the RoI for thermal interference removal [5]. These quantitative studies can provide information for the diagnosis of abnormalities such as thermal distribution changes, temperature asymmetries, or internal inflammation [6].

In recent years, medical thermography has generated interest as an auxiliary method to classical medical imaging techniques. Different applications have been explored from preventive medicine, treatment monitoring, and even surgery. However, care must be taken to preserve the signals coming from the sensors so that the images can be reconstructed later without losing the temperature property. Thermography measurements determine a relative temperature because it is an indirect measurement [7]. The predicted temperature is based on the measurement of surface IR energy. Even when attempting to measure absolute temperature with state-of-the-art equipment, a typical error of ±2°C for microbolometers (the fundamental unit of IR sensors) must be considered [8]. Several studies do not consider the error carry-over and even less the radiometric data are preserved, i.e., the reference is the commonly reconstructed image with a contrasting color mapping for the eye [7,9]. Ignoring the treatment of radiometric data and relying on medical intuition solely on thermal images could be considered a misconception.

In this paper, a comparative study between radiometric data processing and RGB images is presented, so the hypothesis suggests processing the signals extracted from the sensor prior to the reconstruction of an RGB image is preferred, since a false color image may require advanced processing techniques for a problem that can be straightforward using signals directly from the sensor. The methodology is based on segmenting the RoI of the hand or foot with prospects for studies of degenerative diseases such as diabetes or arthritis. Once segmented, the contrast between the warmer and colder regions was maximized. Furthermore, the technique was validated with Fisher's criteria and Bhattacharyya's distance to quantitatively study the likelihood between segmentations based on different kinds of input data (i.e., radiometric, grayscale images, and false color images).

II. METHODS

A. Sensor Characteristics

Radiometric information is employed for quantitative analysis, because each pixel contains a correlated temperature that allows for processing such as temperature correction, drift errors, etc. However, not all thermal equipment is radiometric. Consequently, the only information they can provide is a false-color mapped image along with a scale whose temperature is not absolute. Even with the scale or contrast in the temperature distribution, a quantitative study of the temperature difference cannot be performed, so it is not recommended to take accuracy for granted [8,10].

The sensor used in this study is the Lepton 2.5 LWIR radiometric model (Flir, OR, USA). Table 1 summarizes the thermal imager characteristics [11].

Table 1: Lepton 2.5 LWIR thermal imager characteristics.

Characteristics	Range	Units
IR sensor resolution	80 x 60	Pixel
Pixel size	17	µm
Thermal Sensitivity	≤ 50	mK
Infrared Spectral Band	8 – 14	µm
Refresh rate	8.6	FPS

The information provided by the sensor is a matrix of size 80 x 60 with double-type values. The data contained are 14-bit elements, however, it was previously characterized to obtain a thermogram of temperatures in [ref Rafa].

B. Data asset

The data used were a set of thermograms obtained from the hands of volunteers with no history of pathology [12] and from the feet of patients with a history of diabetic foot [13].

The hand samples were taken in an uncontrolled environment to induce thermal interference to test the robustness of the algorithm. The foot samples were taken in a controlled environment with a relative humidity of 50% at room temperature; the purpose of these samples is to contrast possible areas with abnormal temperature distribution. Fig. 1 represents the most representative samples as jet-scale mapping images (red to blue).

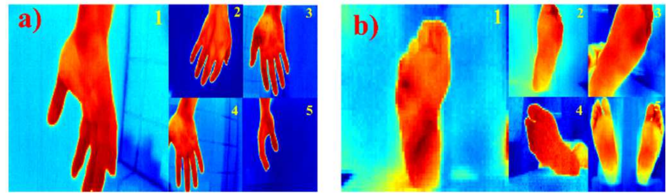

Fig. 1: a) image of the thermogram of the hand in uncontrolled conditions. It is possible to observe temperature changes in the ceiling panels and homogeneous distribution on the hand. b) image of the thermogram of the foot with significant thermal interferences on the surrounding. Each image is numbered from 1 to 5 which corresponds to the number of samples.

C. Data processing

Although the input data are temperature thermograms, it is also possible to input a grayscale image prior to reconstructing an RGB image. This is because the transformation to the grayscale domain of an image can distort the original information. Fig. 2 shows the comparison between a grayscale image reconstructed from radiometric information and an RGB image subjected to grayscale transformation based on the weighted method.

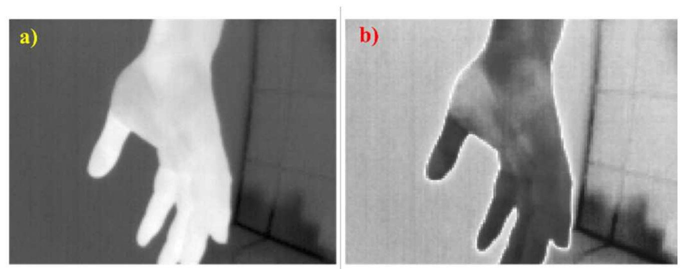

Fig. 2: a) grayscale image mapped from radiometric information, b) RGB image transformed by the weighted method in which the RGB triplet is mapped in shades of gray with an 8-bit scale (0-255 values).

Even using the signals provided by the sensor prior to image reconstruction and display can save a few steps as illustrated in Fig. 3.

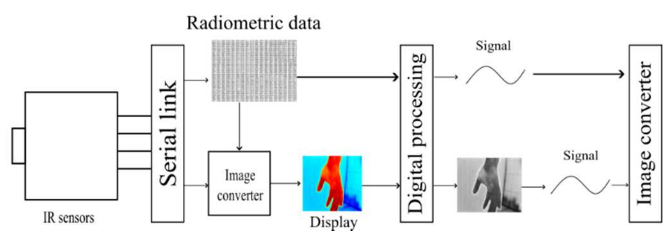

Fig. 3: Schematic of signal processing from the IR sensor. Radiometric information can be treated with digital processing techniques for segmentation and contrast adjustment prior to image display. Using an RGB image as input information may not only lead to errors but also extra steps.

Image segmentation in medical thermography is essential for the training of classifiers whose perspective is a medical diagnosis. Any thermal interference can generate measurement errors, and in the worst case a false diagnosis. The algorithm used for this study was presented in [14,15]. The idea is to delimit an area of interest as a function of temperature intensity in such a way that the abnormal temperature distribution is visible to the human eye and also to obtain a mask whose coordinates allow obtaining the temperatures of interest whose perspective is quantitative thermography studies. Fig. 4

presents the flow chart of the segmentation process and the contrast enhancement based on the normalization of the radiometric data.

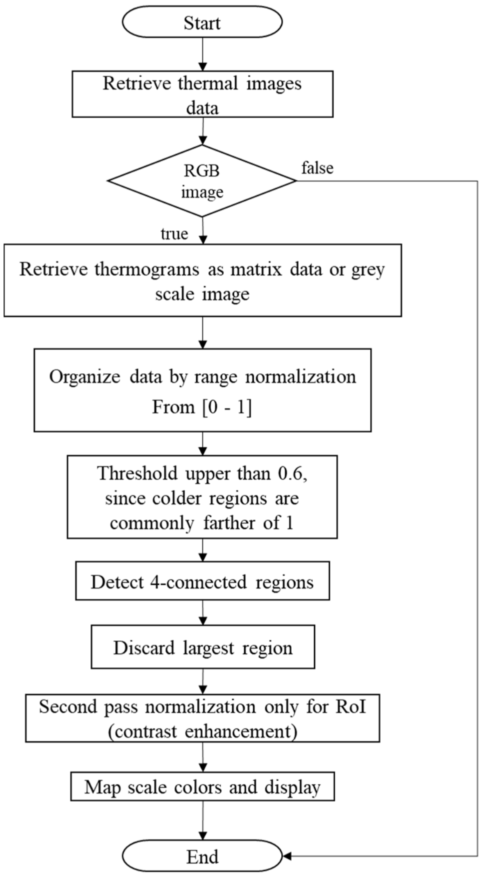

Fig. 4: RoI segmentation and contrast processing flowchart

D. *Likelihood validation*

One way to validate segmentation performance is through statistical metrics that quantitatively test the difference or similarity between the original image and the segmented image. Typically, a base of images segmented by an expert is required such that they would be used as a reference. In these cases, methods such as the Jaccard index could be effective. However, in a scenario where a relatively large set of images is involved, it may be impractical and time-consuming to manually segment each image.

Since this study does not have a base of segmented images, Bhattacharyya distance and Fisher's criterion methods were implemented. The Bhattacharyya distance measures the similarity between two probabilistic distributions in such a way that the similarity between the scene and the segmented region is compared (see equation. 1) [16]. The farther the result is from zero, the more accurate the segmentation is.

Let p be the original image and q the segmented image with a normal distribution of values. The Bhattacharyya distance is defined as:

$$D_B(p,q) = \frac{1}{4}\frac{\left(\mu_p - \mu_q\right)^2}{\sigma_p^2 + \sigma_q^2} + \frac{1}{2}\ln\left(\frac{\sigma_p^2 + \sigma_q^2}{2\sigma_p\sigma_q}\right) \qquad (1)$$

Where μ_p y μ_q are the means of the p and q distributions respectively, y σ_p^2 y σ_q^2 are the variance of the distributions p and q respectively.

On the other hand, the Fisher criteria is a simplification of the Bhattacharyya distance. The Fisher criteria, or Fisher discriminant, maximizes the separation function between two classes given the projection of the class means and minimizes the function by the variance between classes (see equation 2) [17]. Like the Bhattacharyya distance, it is not a bounded coefficient, but the result is values that tend to move away from zero [ref]. These methods are known as blind validation since there is no reference (e.g., an image segmented by an expert) but the classification of the distributions of the images.

$$F_c(p,q) = \frac{\left(\mu_p - \mu_q\right)^2}{\sigma_p^2 + \sigma_q^2} \qquad (2)$$

Ambos criterios podrían ser indicadores del rendimiento que tiene este método de segmentación a partir de información radiométrica. Si bien, el discriminante de Fisher puede distinguir la separación entre dos clases, la distancia de Bhattacharyya se ha implementado en estudios de segmentación [16].

III. Results

Fig. 5 illustrates the comparison between an image of the foot reconstructed in grayscale and an image based on the weighted method, in which the distortion of the original mapping is observed.

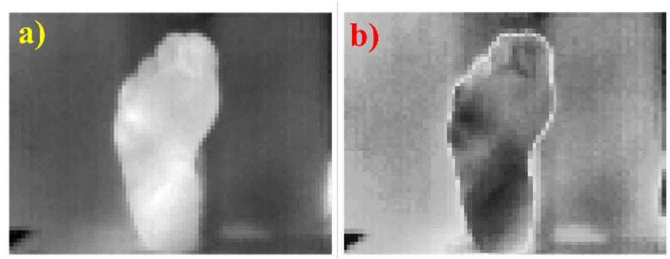

Fig. 5: a) grayscale image reconstructed from radiometric signals in which the foot (RoI) is observed with high contrast to the scene, b) grayscale transformed RGB image in which a thermal contour and a higher temperature homogeneity between the foot and the scene are observed.

Fig. 6 shows the results of using the segmentation algorithm on RGB images converted to grayscale. The result of the process is presented in a jet color scale (red to blue).

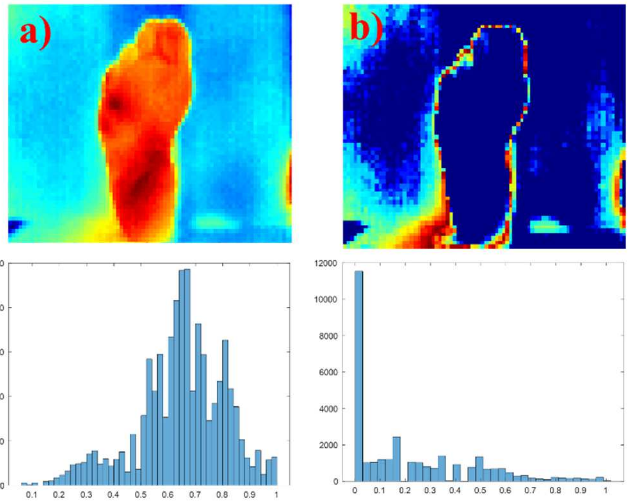

Fig. 6: a) original thermal image with its respective normalized histogram, b) reconstructed image with segmentation errors with its respective histogram.

Fig. 7 shows the results of hand imaging for the purpose of testing thermal interference near the RoI.

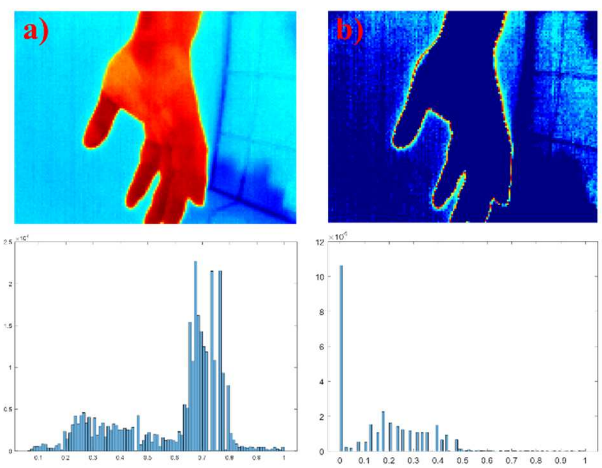

Fig. 7: a) thermal image of the hand with its respective histogram, b) segmented image with errors in which it is observed that the thermal interferences in the panel continue in the result.

However, Fig. 8 shows the correct segmentation with temperature contrast when the input information is radiometric data.

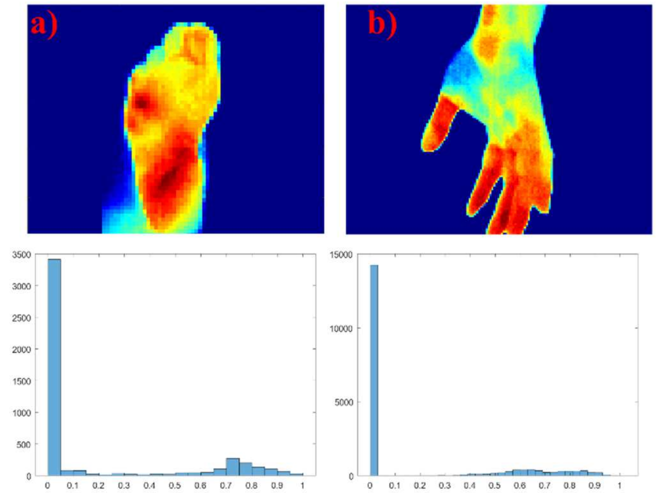

Fig. 8: segmented images whose input information were the radiometric data matrices, a) segmented image of the foot in which most of the interferences located at the periphery of the image have been removed (see Fig. 6 a)), b) segmented image of the hand without thermal interferences contrast adjustment.

From the histograms of the segmented images, it can be seen that the RoI tends to have values greater than 0.5, even commonly close to 1 because it is the region with the highest temperature. That is why the threshold setting can be approximately between 0.6 for non-RGB gray images to 0.8 in the case of matrices of radiometric values. Fig. 9 shows the histograms of the normalized radiometric data.

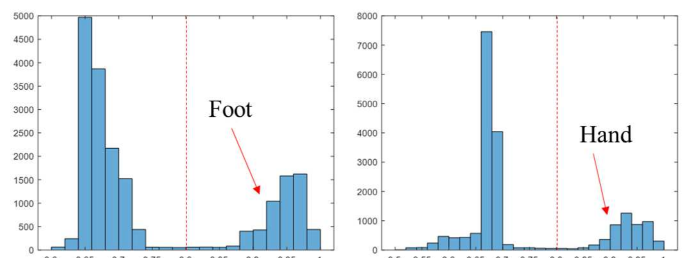

Fig. 9: histogramas de las matrices de datos radiometricos normalizados entre [0 - 1].

Fig. 10 shows the grayscale images (not RGB) together with the histograms in case only this information is available from the equipment.

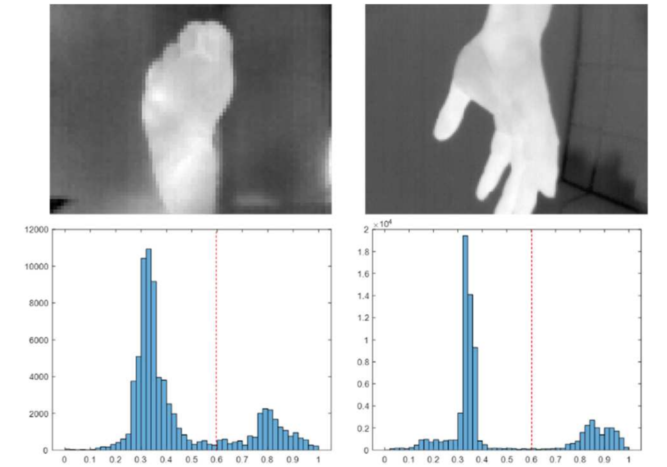

Fig. 10: non-RGB grayscale images reconstructed from radiometric data. These images can be used for segmentation and contrast adjustment in the same way that a data matrix can be used. However, the adjustment threshold is different.

Fig. 11 shows the results of the blind validation, to quantitatively support the performance of the method proposed in this study.

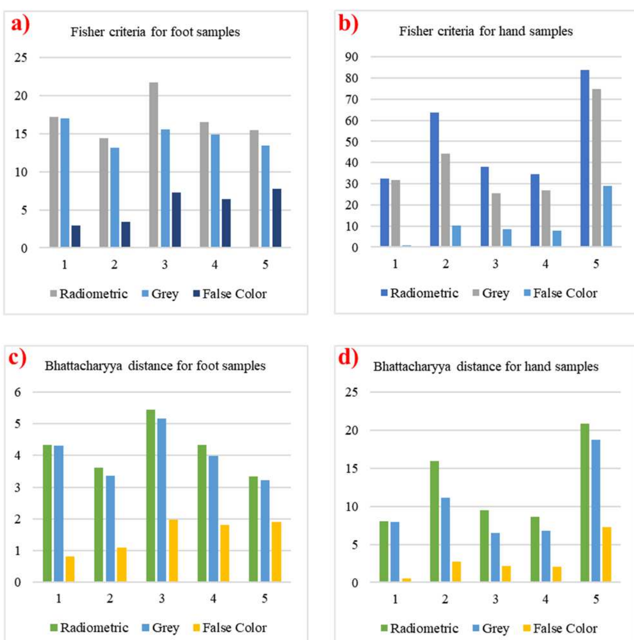

Fig. 11: validation methods results, the numbering of each sample corresponds to the numeration in Fig. 1; a) Fisher's criteria for foot samples, b) Fisher's criteria for hand samples, c) Bhachattaryya distance for foot samples, d) Bhachattaryya distance for hand samples.

IV. Discussion

Segmentation and contrast adjustment algorithms can be successful when the input information is radiometric data or non-transformed grayscale images of an RGB image. Digital image processing commonly requires images to be in grayscale, however transforming an RGB image by various methods (e.g. weighted method) can distort the intensities of objects in the scene. This error induces interferences in the image that make processing difficult.

On the other hand, using only radiometric information matrices to process the sensor signals can save some steps. Using a grayscale image can also yield favorable results, however, this path involves generating an image from the sensor signals, deconstructing it into a signal, and reconstructing it again as an image.

Whether radiometric data or gray images are used, the threshold for separating the RoI from the scene may differ between the type of input data. Commonly in medical thermography, the RoI is centered as the larger area concerning the surrounding thermal interference. However, the scene usually has a larger number of pixels but with values smaller than 0.5 because they are usually colder than the RoI (foot or hand). These considerations only work for segmenting limb members (hands or feet) that have an insulating wall or object as the scene. This segmentation and contrast adjustment algorithm does not work with breast images so other processing techniques are required.

On the other hand, the results presented in Fig. 11 indicate similarities between using radiometric data and grayscale images. However, in all cases, it is observed that the implementation of radiometric information tends to be slightly higher than using gray images. Finally, the indicators show that the implementation of false color images is far from correct segmentation.

V. Conclusions

Medical thermography has experienced significant development in recent years as an auxiliary tool in preventive medicine, treatment monitoring, and even surgery. In addition, radiometric data must be retained for signal processing and information for further quantitative thermography studies. An RGB image alone cannot provide quantitative but qualitative information. Even when attempting to correlate color intensities to temperature, images may present color distortions due to mapping (see Fig. 5).

Segmentation, contrast adjustment, and acquisition of metadata can be performed with radiometric information. The idea of using radiometric data is to be able to segment by exploiting the temperature difference between the RoI and the scene so that the algorithm does not conform to anatomical shapes. For this purpose, discrimination thresholds were used, with values of approximately 0.6 for the gray images (not RGB) and 0.8 for the radiometric value matrices. The difference in thresholds is because the radiometric data were normalized from the sensor signal, whereas in the image the threshold is crossed. Because an image was reconstructed before being treated as a signal, the threshold is lowered. After segmentation, the RoI-only contrast can be adjusted depending on the required study. In addition, some steps can be saved by taking advantage of IR sensor signals before thermal image reconstruction. Likewise, the use of radiometric information for image segmentation was proven to have a slight advantage over the implementation of grayscale images. However, its implementation is not discarded since it is also adaptable with this method but requires extra steps.

In conclusion, radiometric signal processing may represent an advantage over the use of thermal imaging (RGB images) when the objective is to segment the upper and lower extremities whose scenario is usually colder than the human body. Otherwise, the use of grayscale-transformed RGB images may not segment correctly and thus require more robust digital image processing techniques.

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