Qualitative Measures of Breast Thermograms Towards Abnormality Prediction

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***Abstract*— Reported reviews in the existing literature reveals that there is no significant work on the quality of thermal medical images. In the present scope, we briefed an overview on the quality measures of thermograms that should consider during processing and analysis of thermal medical images. Our analysis shows the effect of image qualities on the processing of breast thermograms using correlation coefficient of feature vectors. Features of left and right breast should be more correlated for normal thermograms than the abnormal one. The fact is based on the asymmetry analysis of breast thermograms. Based on the correlation coefficient the analysis is conducted in this present work. The result of analysis validates that image qualities are an important factor during thermogram analysis.**

Keywords—Breast Thermograms; Image quality; edge-density; contrast, Entropy.

I. Introduction

Significant technological advancement in medical systems has increased the interest of automation of such systems [1]. Most of the technologies used for abnormality prediction are based on image analysis & processing. Ultrasound imaging, MRI imaging, Mammography, Tomography, Microscopic imaging, Thermal imaging are such example. Automation of these said techniques implicitly depends upon the automation of image processing & analysis. Automation has been implemented so far are specific to imaging devices, its resolution, experts' work in detection of contour manually for proper segmentation of ROI [1]. Algorithm design for automatic prediction also depends upon the quality of images. Variability in acquisition method, in camera handling, introduces variation in quality of images such as varying brightness or orientation in the images. Due to these different elements, proposed algorithms work correctly for a given type of medical imaging with a specific quality [1]. Apparently, algorithms work good for the specific quality of images. Predicting the performances of proposed algorithms in different image sets prior implementation, a quantitative measure of image qualities may require. Based on this analysis, quality of a dataset can also be predicted, so that more or less all algorithms shows a significant accuracy.

Thermal imaging used to record temperature distribution of human skin for several decades. The temperature distribution carries information regarding clinical activities [2]. Temperature information is also considered as a good predictor of any abnormalities in human. Malignances, inflammation & infection such abnormalities increased the localized temperatures [3]. The increase in localized temperature change the symmetrical pattern & produce hot-spot in the concerned thermogram [3]. This characteristic of thermal imaging already proved its efficacy in the prediction of breast abnormality [3] [4] [5]. To assess the effect of image quality on different algorithms image qualities should be defined first. Comparatively least significant work is done in quality assessment of thermal imaging as well as thermal medical imaging.

This literature first focus on the basic image qualities such as entropy, edge-density, contrast, etc. Other thermal image qualities also analyzed to verify the effect of image qualities. Such as, FISH algorithm [6] is used to assess the image sharpness. Analysis showed image sharpness is more important compare to other image qualities. For analysis, the effect of image quality, the correlation between the features of left & right breast is examined. The analysis is stood on the fact that correlation between left & right breast is less in abnormal breast thermograms as compared to normal breast thermograms. Classifiers employed in the automatic detection of abnormality using breast thermograms is also based on the correlation of these features [7] [8] [9].

A. Review work related to proposed method & contributions

A good amount of work related to image quality based performance prediction is done for face recognition system [10] [11] [12]. Model designing for performance prediction of face recognition system is the ultimate goal of this type of quality assessment. Limited reporting of quality based prediction in thermal medical images are available in the relevant literature. Dennis G. Fryback et al. [13] address the importance of technical quality of medical imaging in performance of diagnostic imaging. They present a hierarchical model of efficacy in the assessing the efficacy of imaging. In this structure level 1 consist of technical quality of the images.

In radiology imaging, assessment of image quality is important as quality depends upon the radiation dose to the patients. C.J. Martin et al. [14] describe the relation between the image quality and radiation dose. They also mentioned the need of quality assessment and adequate quality of medical images.

Several works are done on the effect of bio-medical image acquisition on the analysis & processing of images. Robert Koprowski et. al. [1] provide a good qualitative assessment on bio-medical image acquisition. Image quality primarily depends upon the image acquisition. Koprowski et. al. describe the effect of image acquisition on image quality for different medical imaging method. The author gives error rate for each imaging system with respect to its application based on image quality. In this literature, thermal imaging is considered. This literature [1] showed that camera operation and patient position degrade the quality of images. The degradation cause error rate of 31% in the performance of thermogram processing algorithm. These factors cannot be handled during acquisition. Quality assessment of thermograms can provide measures of quality that should consider during capturing and database creation. Quality assessment of thermograms is the first step towards prediction of algorithm performance. Qualities that effect the most should be taken care first. So, define the most significant qualities is a vital work. This literature focuses on the quality of thermograms that effect the classifier output. only Breast thermograms are considered in this literature. The contributions and advantages of this article are summarized as follows:

1. Defining the thermal image qualities that have an importance in breast thermogram analysis.
2. Evaluating the effect of each image quality on each features mostly used for breast thermogram analysis.

The rest of the paper is organized as the following: Section II describes the method of analysis. Section III describes the outcomes of the analysis. Finally, we conclude in section V.

II. METHODOLOGY

This paper focuses on the analysis of different image quality of breast thermograms. The analysis based on the correlation of different features of breast thermograms used previously for abnormality detection. Asymmetry analysis between left and right breast signify the breast pathology. Asymmetry between both the breasts indicates abnormality. Both the breast will have symmetry for normal patients. Automatic abnormality detection algorithms consist of primarily following steps: Data acquisition, pre-processing, feature extraction and lastly Classification [7] [8] [9]. Classification of breast thermograms is based on the underlying asymmetry between left & right breast. Left & right breast persist considerable asymmetry compared with Normal breast thermograms. This asymmetry analysis is the key component of the algorithm for automatic classification of abnormal and normal breast. Algorithm efficiency mostly represented by the classifier's output. The definition says that classifier classifies groups that are previously labeled by analyzing the features. Features are the utmost element of classifier so of algorithm performance. This paper illustrates that quality of images can make a difference in nature of features as well as in classifier's output. Classifier's output is nothing but the interpretation of the correlation between features of distinct classes. So, we can concluded that abnormality detection using breast thermograms relies on the correlation between the features of left & right breast. These features are more correlated for normal patients than patients with abnormality. The correlation between the left & right breast features suffered from the bad quality of images. This has been shown here using considerable analysis, in the later section. The image qualities of breast thermograms, which have more impact on the algorithm performance also distinguish in the result section with proper numeric. The method of analysis, step by step is described in this section.

A. *Features of Breast Thermograms*

Thermal imaging, unlike other medical imaging, does not carry any anatomical information human body. It just restrains the temperature pattern of the captured part of human body [2] [3], [19]. Intensity value of a thermal image pixel is nothing but the heat information of that point. This is the reason behind the more use of statistical features than the structural feature in asymmetry analysis of breast. A review work of Usha rani Gogoi et al. [16] on the analysis of breast thermograms enlighten the same fact in their work. They have also provided knowledge of relevant literatures where statistical features are mostly considered for abnormal breast prediction. Statistical features are therefore used in this literature for the similar reason.

Statistical features are categorized into two groups, one is first order statistical feature, and the other one is second order statistical features. The first order statistical features that are computed from the intensity histogram are: Mean, Variance, Standard Deviation, Skewness, Kurtosis, and Entropy. These features do not consider the pixels relationship to its neighbor pixels. The second order statistical features deal with the relative positions of the gray levels within an image as well as consider the relationship between a pixel and its neighbor. Gray level Co-occurrence matrix, mostly used as a second order statistical feature for breast thermograms. GLCM is a presentation of occurrence of different combinations of pixel gray levels in an image. The Co-occurrence matrix based features describe in [15] [16] are: Energy, Contrast, Entropy, Dissimilarity. These statistical features are studied in our previous published work [17], to find most discriminating features in analyzing breast thermograms. By analyzing the features of left and right breast of 10 healthy and 10 unhealthy breast thermograms, first order features are considered as most discriminating features in said literature. Second order features are not so effective as first order features in classifying abnormal and normal breast. An asymmetry is found as well in features of co-occurrence matrix but not decisive [17]. Based on this analysis the following features are used in this literature to find out the effect of image quality: Mean, Skewness, Kurtosis, Entropy (first order statistical features).

B. *Image quality of Thermograms*

Image quality is a measure of degradation in the image. Noise, blurring, fading, blocking artifacts are the reason of degradation in the image. These are introduced to the image during compression, image acquisition, storage, etc. Rather than this thermal images have some added features, unlike other visual images. Thermal images have a lack of texture and relatively small contrast. It is already assessed from the statistics of infrared images [18]. In this paper, we consider the following principal qualities of thermal images: pseudo Signal-to-Noise ratio, contrast, blur, sharpness, entropy, image information capacity, and edge-density.

1) Edge-density:

Segmentation is one of the important steps of thermal image processing in medicine. Hot-spot in breast thermograms signifies abnormality [3]. So, segmentation of hot-spot is an important task in breast thermogram analysis. Edge density of an image always considered as an important quality regarding proper segmentation of images [20]. Edge-density gives important information about edges of an image. For any region 'R' with the top-left and bottom-right corners given by (x_1, y_1) and (x_2, y_2) respectively, and the edge magnitude of the pixels within r given by e (x, y). The edge magnitude of the region r is given by the equation:

$$Edge\ density = \frac{1}{A_R}\sum_{u=x_1}^{x_2}\sum_{v=y_1}^{y_2} e(x,y) \quad (1)$$

2) Contrast:

Nigel J. W. Morris [18] showed that joint statistics of the wavelet co-efficient are very similar to those reported for visible images but on a smaller scale. The reason given by them is, a relatively low contrast of thermal image comparing visible images. Low contrast images also result poor edges. Contrast of thermograms considers as an important quality. Contrast is defined as the difference between each pixel intensity to the mean intensity of the image. Contrast of an image having size M by N with mean intensity I_{mean} can be defined as following:

$$Contrast = \sqrt{{}^{1}\!/_{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(I_{ij} - I_{mean})} \quad (2)$$

3) Image entropy

Image entropy is one of the mostly used quality measure. Image entropy, a measure of information content, can be found on the histogram of pixels' color. This is defined as follows:

$$Entropy = -\sum_{i=1}^{B} P_i \log(P_i) \quad (3)$$

P_i represents the probability for a pixel whose color falls into the i^{th} bin and B is the total number of bins.

These three measures are common quality measures for any image. The following measures are specific to thermal image. In this literature, all the measures are analyzed for each feature and based on these qualities that effect the algorithm performance are distinguished.

4) Pseudo Signal-to-noise ratio:

Xu Chun-mei et al.[21] proposed a new measure namely Pseudo Signal-to-noise ratio specific for Thermal image. 'A' can be assumed as an original image, and the original image signal cannot be obtained. 'A'' considered as the image that is captured and composed of original image and noise signal. The captured image can be filtered to get an image 'A"',can be thought as an original image without noise. Using these A" and A' image, Xu Chun-mei et al. calculated the Pseudo signal-to-noise ratio. It is not the true performance but describes the influence of noise on signal at a certain extent by showing the true ratio.

Thermal image noise is characterized by two noise combination, 1/f noise, and white noise. 1/f noise and white noise are uncorrelated. Considering these facts, Xu Chun-mei et al. defined the given noise as an additive function as follows:

$$A^{'} = A^{"} + n + m.A^{"} \quad (4)$$

f(x,y) is actual radiated picture, f '(x, y) is an ideal picture, n(x, y) is white noise, m·f '(x, y) is 1/f noise. Before separate noise picture and signal picture with small wave space, the 1/f noise can be removed, and the resultant image can be defined as follows:

$$A^{'} = A^{"} + n^{'} \quad (5)$$

n' is represent as a pseudo noise can be evaluate as follows:

$$n^{'} = A^{'} - A^{"} \quad (6)$$

The pseudo signal power will be:

$$S_P = \sum_{i=1}^{N}\sum_{j=1}^{M} A^{"2}(i,j) \quad (7)$$

The pseudo noise power will be:

$$N_P = \sum_{i=1}^{N}\sum_{j=1}^{M} n^{2}(i,j) \quad (8)$$

The pseudo signal-to-noise performance equation given in [21] is:

$$Pseudo\,SNR = 10\log\left(\frac{S_P}{N_P}\right) \quad (9)$$

5) Information capacity of image

Xu Chun-mei et al.[21] defines image information capacity of an image is also an essential quality of thermal image. This quality also has a good significance in medical imaging as information capacity defines the distribution of image intensity. Proposed Information capacity measure is based on the two-dimensional histogram of image intensities. One dimensional histogram shows the statistics of image intensity. Two-dimensional histogram also shows the same with accounting the relationship between the different image elements. It contains moderate statistical quantity and coherent merits, as it is used to analyze macro coherent of statistic quality. Based on this two-dimensional histogram, Xu Chun-mei et al. defines the image information capacity in [21] as follows:

$$C_{image} = \log_2\left[1 + \sum_{w} Norm_{\log}(G_1 + G_2)\right] \quad (10)$$

Where, $Norm_{\log}(G_1+G_2)$ defined as follows,

$$Norm_{\log}(G_1 + G_2) = \log[1 + num(G_1 + G_2)] / \log[1 + \max(num(G_1 + G_2))] \quad (11)$$

$Num(G_1+G_2)$ is the two-dimensional histogram & $Norm_{\log}(G_1+G_2)$ is logarithmic normalized two-dimensional histogram. All the element contained in two-dimensional histogram represent as *w*.

6) Entropy of energy spectrum

An image can be perceived as a distribution of frequency spectrum. High-frequency component represents the articulation of an image. A number of high-frequency component describe the quality of an image. Xu Chun-mei et al.[21] introduced entropy of energy spectrum to analyze the frequency spectrum of thermal image. The entropy of energy spectrum defined by them as follows:

$$E = -\sum_{i=1}^{N}\sum_{j=1}^{M} E(u,v)\ln E(u,v) \quad (12)$$

The energy spectrum E(u,v) can be calculated as follows, where F(u,v) is the two-dimensional Fourier transform of the image.

$$E(u,v) = \left[Re\left[\frac{F(u,v)}{\sum_{i=1}^{N}\sum_{j=1}^{M} f(i,j)}\right]\right]^2 + \left[\mathrm{Im}\left[\frac{F(u,v)}{\sum_{i=1}^{N}\sum_{j=1}^{M} f(i,j)}\right]\right]^2 \quad (13)$$

7) Sharpness

Sharpness is an also considered as a quality factor of image. Several algorithms are there to measure the image sharpness. FISH (Fast Image Sharpness) is a proposed algorithm to measure sharpness [6]. It is based on the wavelet transform of images. FISH consider that the image sharpness can be measured from the high frequency of images. FISH decompose the image into three levels of DWT transform using Cohen-Daubechies-Fauraue 9/7 filters. Steps for calculating FISH score is clearly discussed in [6].

C. Analysis

Analysis to perceive the impact of above-said image qualities on the algorithm performance, correlation between a feature of left and right breast is used. Breast thermogram is a representation of heat pattern of breast. Abnormality in breast gives a rise in the temperature of breast. That will result in hotspots in breast that will change the symmetric temperature pattern of breast. So, asymmetry in left and right breast signifies abnormality. In other words, features of left & right breast of normal breast thermograms are more correlated than abnormal breast thermograms. This literature is based on this correlation.

Considering Q = $\{q_1, q_2, \ldots, q_6\}$ & F = $\{f_1, f_2, f_3, f_4\}$ are the quality vector consisting six qualities and feature vector consisting four features respectively. Correlation of feature of left & right breasts is defined as $C(L_f, R_f)$. L_f, R_f are defined as a feature of given number of images. According to the asymmetry analysis of breast thermograms, good quality thermograms should satisfy the following equation:

$$C_N(L_{f_i}, R_{f_i}) > C_A(L_{f_i}, R_{f_i}), \quad \forall_i \; where\; i \in F \quad (14)$$

Where, C_N & C_A represent the left & right breast correlation of normal and abnormal thermograms respectively. For each quality q_i, a given dataset can be grouped into two categories based on a threshold, τ. The value of q_i greater than τ considered as good quality. One group consists *M* number of images and $q_{ij} > \tau, \forall_j$ where, $j \in M$. The other group of *N* number images and $q_{ix} < \tau, \forall x$ where, $x \in N$. The quality q_i, have a considerable impact on the breast thermograms if the two groups satisfy the following equations.

$$C_N(L_{f_{kM}}, R_{f_{kM}}) < C_A(L_{f_{kM}}, R_{f_{kM}}), \forall_k \; where\; k \in F \quad (15)$$

Where, L_{kM} & R_{kM} represent the left & right breast vector for feature f_k of M number of samples. Each quality is analyzed in this described way, and the result shows the impact of each quality on the algorithm performance. The result of this analysis is shown in result and discussion section. The threshold value, τ defines the quality range. Any threshold value selection method can be used to define τ.

TABLE I. CORREALATION OF LEFT AND RIGHT BREAST OF THE GROUPS PARTITIONED BASED ON IMAGE QUALITY

Features / Image Qualities		Mean		Skewness		Kurtosis		Entropy	
		Correlation of left & right Normal breast	*Correlation of left & right Abnormal breast*	*Correlation of left & right Normal breast*	*Correlation of left & right Abnormal breast*	*Correlation of left & right Normal breast*	*Correlation of left & right Abnormal breast*	*Correlation of left & right Normal breast*	*Correlatio n of left & right Abnormal breast*
Edge-density	$>\tau$	**0.1308**	**0.0521**	0.1513	0.2421	**0.2092**	**0.0360**	0.2458	0.3612
	$<\tau$	**0.0946**	**0.4858**	0.5947	0.0384	**0.6659**	**0.2186**	0.8560	0.1169
Contrast	$>\tau$	**0.0773**	**0.0641**	**0.2477**	**0.0813**	0.1844	0.1767	**0.4879**	**0.1635**
	$<\tau$	**0.1979**	**0.4837**	**0.2829**	**0.3250**	0.6788	0.2939	**0.4607**	**0.5491**
Entropy	$>\tau$	**0.5213**	**0.3422**	**0.6652**	**0.1866**	**0.4456**	**0.3138**	**0.8269**	**0.1555**
	$<\tau$	**0.6696**	**0.4186**	**0.2972**	**0.3985**	**0.1955**	**0.3917**	**0.3182**	**0.2512**
Pseudo-SNR	$>\tau$	0.2608	0.3487	0.0169	0.3675	0.1264	0.2765	0.2220	0.6355
	$<\tau$	0.2277	0.0813	0.1592	0.1338	0.3884	0.0122	0.7245	0.0317
Image Information Capacity	$>\tau$	**0.6040**	**0.1269**	0.1456	0.14768	0.1132	0.2782	**0.4107**	**0.1847**
	$<\tau$	**0.2190**	**0.0942**	0.1025	0.0163	0.3981	0.0033	**0.5691**	**0.4071**
Energy-entropy	$>\tau$	**0.4685**	**0.0859**	**0.6111**	**0.5548**	0.3405	0.4949	**0.3309**	**0.1654**
	$<\tau$	**0.3613**	**0.2400**	**0.2503**	**0.1899**	0.4448	0.1485	**0.3059**	**0.8303**
FISH	$>\tau$	**0.5503**	**0.0481**	**0.3656**	**0.2299**	**0.3245**	**0.1673**	**0.7468**	**0.1344**
	$<\tau$	**0.1882**	**0.1240**	**0.3428**	**0.3659**	**0.0336**	**0.6404**	**0.3675**	**0.2214**

III. RESULT AND DISCUSSIONS

A. *Database preparation*

The proposed segmentation technique in our work was tested on one thermal medical image datasets, which were created and collected from Regional Cancer Center (RCC), Govind Ballav Pant Hospital (GBP), Agartala, Tripura, India respectively [17]. The dataset contains both breast thermograms of normal and abnormal patients. A total number of 70 breast thermograms are used in this literature. Among them, 40 breast thermograms are of abnormal patients and the rest of normal patients. Camera used for this dataset preparation is FLIR T650sc. Breast thermograms are cropped into same sized left and right breast for asymmetry analysis. This step is required for any other breast datasets.

B. *Effect of qualities on correlation of features*

Features of Left & right breast thermograms will have small correlation coefficient as a prediction of abnormality. Correlation coefficient is a predictor of performance of the classifier. Correlated features of different class, if fed into the classifier, degrade classifier's performance. Good quality images should satisfy (14). Table-I shows the effect of previously described image qualities on the asymmetry analysis of breast thermograms. For each image quality, q_i two groups are considered. Two groups signify by $>\tau$ and $<\tau$. For the quality values directly proportional to the quality, $>\tau$ will signify the group with good quality and $<\tau$ will signify group with less quality. Abnormal and normal breast thermograms having good quality will satisfy (15).

Table I shows the correlation coefficient of left and right breast features for each image quality. $>\tau$ and $<\tau$ defines the groups based on quality values and threshold. Only for image quality entropy, $<\tau$ defines a group of good image quality, as small entropy represent the good quality image.

Significant image quality effects on the features are shown in bold script in Table I. Among all the image qualities; it is apparent that except Pseudo SNR and image information capacity other image qualities have a good impact on the features of breast thermograms. FISH that measure the sharpness of images effect all the features.

From Table I it is more evident that image quality is an important factor in analysis and processing of images. this information will be useful in creating datasets medical thermograms, in designing of automatic algorithms for detecting abnormality using breast thermograms. This analysis also is an important step in designing a prediction algorithm that predicts an algorithm performance based on image quality prior implementation.

IV. CONCLUSION

There prevails a lack of work in the field of quality assessment of medical thermal images. The fact that image quality effect the analysis and processing of images are proved here with considerable experiments and results. The analysis is based on simple implementation. Image qualities that should be considered during database design and analysis of datasets are obtained from this analysis. Contrast, sharpness, entropy, edge clarity are found important qualities of breast thermograms. Measure of image qualities is the most significant work regarding this analysis. Qualities effected by image acquisition, only considered in this literature. So, there is the limitation of this work that the other qualities that can be affected by camera parameter, lighting conditions are not accommodate in this work. Other image qualities other than these can be analyzed in the same way. The work can further extend by considering other features in the future scope.

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