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# STATISTICAL DESCRIPTION OF WAVELET COEFFICIENTS OF THERMOGRAPHS FOR QUANTITATIVE CHARACTERIZATION OF BREAST CANCER

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## ABSTRACT

High mortality rate of breast cancer can be avoided if it is detected at the early stage. Clinical infrared thermography is a non-contact, non-invasive, non-hazardous diagnostic technique that can detect cancer even at the earlier stages of formation. It maps the temperature variations into thermographs. Thermographs are then given to thermologists for interpretation. However manual interpretation of thermographs is subjective in nature. Hence it is necessary to develop effective automated analysis for thermograph interpretation and classification. This paper presents an effective wavelet based technique for detecting the presence of thermographs. Based on the nature of temperature variation, Haar, Biorthogonal and Reverse Biorthogonal wavelets are chosen for analysis. It is found that Haar wavelets provide better results when compared to the other wavelets.

**Keywords**
Breast cancer, thermographs, Discrete Wavelet Transform, Haar, Biorthogonal and Reverse Biorthogonal wavelet

## 1. INTRODUCTION

High mortality rate of breast cancer is due to lack of diagnostic techniques to detect cancer at the early stage. Moreover conventional diagnostic techniques may become hazardous and painful if done repeatedly. Mortality rate can be greatly reduced if breast cancer is detected at an early stage so that treatment can cure it. Hence a non-contact, non-invasive, non-hazardous diagnostic technique that can detect cancer even at the earlier stages of formation can highly reduce the mortality rate. Clinical infrared thermography is a non-hazardous, non-painful, non-contact technique that can detect cancer at the earlier stages. It captures and maps the temperature of the test region as thermographs. A thermograph is a 2 dimensional radiance function where g(x,y) denotes the radiance and x,y denotes the spatial co-ordinates. Clinical thermography is applicable for early detection of breast cancer because for the formation of tumor cells, it requires large amount of nutrients and hence causes heavy blood flow in that region. The sudden inrush of blood affects the temperature of the region. Hence as infrared thermography captures these temperature variations, it is capable of early detection of breast cancer.

Thermographs are then given to thermologists for interpretation. Thermologists make a decision based on the temperature variations. A thermograph with uniform and symmetric temperature distribution indicates absence of abnormality. On the other hand, if the temperature distribution is asymmetric and if there is an abrupt variation in temperature, it indicates the presence of abnormality i.e. tumor. However manual interpretation of thermograph is not that easy. The variation in temperature may not be significant and hence not visible to human eye. Moreover, fibroadenoma, the non-dangerous lumps in breast also causes temperature variations. Hence there is a possibility for misinterpretation of thermographs. Also manual interpretation is subjective in nature. Thermologists' fatigue may result in false alarm rate or may have very poor success rate. Hence it is necessary to develop efficient, automated software that can identify and differentiate breast cancer from fibroadenoma. The steps involved in the development of the software are Acquisition of thermographs, Development of effective feature extraction technique for identifying the abnormality, Identification of suitable feature descriptors for abnormality quantification, development of Artificial Neural Network (ANN) for decision making. This paper reports the developed feature extraction technique and explores the suitability of commonly used statistical parameters for describing the abnormality.

This paper is organized as follows. Section 2 reviews the use of Infrared thermography as a medical diagnostic tool. Section 3 gives an overview of different wavelet transform packets. Section 4 deals with data acquisition and interpretation. Section 5 deals with Results and Discussion and Section 6 conclude the work.

## 2. REVIEW OF INFRARED THERMOGRAPHY IN MEDICAL DIAGNOSIS

Infrared thermography, a successful Non Destructive Testing (NDT) Technique is recently accepted as a successful medical diagnostic procedure. It is based on a careful analysis of skin surface temperatures as a reflection of normal or abnormal human physiology (Gray, 1995). Infrared or thermal images are produced with Infrared camera. Based on these thermal images, accurate temperature measurements can be made to detect even the smallest temperature differences when looking at human bodies. Over the years thermal images taken using infrared cameras, liquid crystal thermography, and infrared tympanic thermometer have proven the human body is symmetrical right to left, extremities are cooler, and injuries to nerves, tendons, and muscles produce differentiating temperatures (Green, 1987, Harway, 1986). Human body temperature is a complex phenomenon. Man is homoeothermic, and produces heat, which must be lost to the environment. The interface between that heat production and the environment is the skin. This dynamic organ is constantly adjusting to balance the internal and external conditions, while meeting the physiologic demands of the body. Digital infrared thermography is a totally non-invasive clinical imaging procedure for detecting and monitoring a number of diseases and physical injuries, by showing the thermal abnormalities present in the body (Sherman et al, 1997, Seok Won Kim et al, 2004). Content-based image retrieval system was developed for thermal medical image retrieval. Fractal encoding technique was developed to increase the linear size for fragments of the traced thermal medical images (Feldman and Nickoloff, 1984). Computerized technique based on image processing of thermographs was achieved. However noise in thermographs was removed by wavelet based noise removal techniques (Uematsu et al, 1988).

From the literature survey it is understood that thermographs can be taken of the whole body or just areas being investigated. It diagnoses abnormal areas in the body by measuring heat emitted from the skin surface and expressing the measurements into a thermal map. For a normal person under healthy condition, thermographs depicted uniform and symmetrical pattern. On the other hand abnormality manifests itself either as hot spots or as cold spots. Hot spots correspond to the region of maximum intensity and cold spots correspond to the region minimum intensity and hence the temperature. Several image-processing algorithms were developed for computer-based assessment of medical thermographs. However these techniques are application specific and are developed for that particular group of thermographs.

## 3. OVERVIEW OF WAVELET TRANSFORMS

An image is a two dimensional function along the spatial coordinates x,y and f(x,y) is the amplitude along the spatial coordinates. Let f(x,y) be the two dimensional function in the two variables x and y (Mallat, 1989). Wavelet transform on the image produces four subband image coefficients. They are the approximation, horizontal detail coefficients, vertical detail coefficients and diagonal detail coefficients. Let f(t) be any square integrable function. The continuous-time wavelet transform of f(t) with respect to a wavelet $\Psi(t)$ is defined as

$$W(a,b) \equiv \int_{-\infty}^{+\infty} f(t)\,(1/\sqrt{a})\Psi^*((t-b)/a)dt \qquad (1)$$

where a and b are real and * denotes complex conjugation, a is referred to as scale or dilation variable and b represents time shift or translation [8]. CWT provides a redundant representation of the signal in the sense that the entire support of W(a,b) need not be used to recover the original signal f(t). A new non-redundant wavelet representation is of the form

$$f(t) = \Sigma_{-\infty}^{+\infty}\Sigma_{-\infty}^{+\infty}\, d(k,l)2^{-k/2}\Psi\,(2^{-k}t-l) \qquad (2)$$

This equation does not involve a continuum of dilations and translations; instead it uses discrete values of these parameters. The two dimensional sequence d (k,l) is called as the Discrete Wavelet Transform. The discretization is only in the a and b variables. The Haar basis is obtained with a multiresolution of piecewise constant functions. The scaling faction is $\phi = 1_{[0,1]}$. The filter h[n] is given by

$$H[n]=\{2^{-1/2} \quad \text{if } n = 0,1 \qquad (3)$$
$$0 \text{ otherwise}$$

The above equation has two non-zero coefficients equal to $2^{-1/2}$ at n=0 and n=1. The Haar wavelet is

$$\Psi(t) = \begin{cases} -1 & \text{if } 0 \leq t < 1/2 \\ 1 & \text{if } 1/2 \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

Biorthogonal Wavelets are families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function. In the biorthogonal case, rather than having one scaling and wavelet function, there are two scaling functions, that may generate different multiresolution analysis, and accordingly two different wavelet functions (Salem et al, 2009). The decomposition and wavelet functions of Biorthogonal wavelet and Reverse biorthogonal wavelet 1.5 [10] is shown in Figure 1-2.

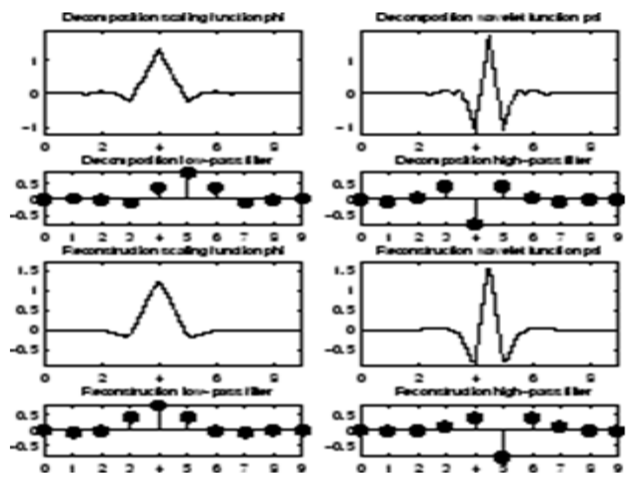

Figure 1: Decomposition scaling and wavelet functions of biorthogonal wavelet 4.4

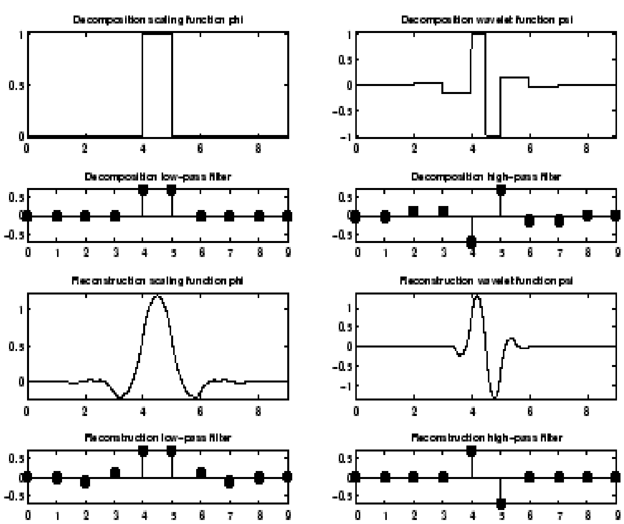


Figure 2: Decomposition scaling and wavelet functions of Reverse biorthogonal wavelet 1.5

## 4. DATA ACQUISITION AND INTERPRETATION

Over 30 samples of breast thermographs were collected from the patients. From the collected samples it is found that in normal region, the temperature distribution is uniform. In the affected region, there is an increase in temperature as these regions have heavy blood flow. The temperature profile of the thermographs along the row in the affected region shows the following variations at the affected region. The temperature varies abruptly from low to high is retained for some region and then changes from high to low. The profiles of four different patients named as cancer1.jpg, cancer2.jpg, cancer4.jpg and cancer5.jpg are shown in Figures 3-6.

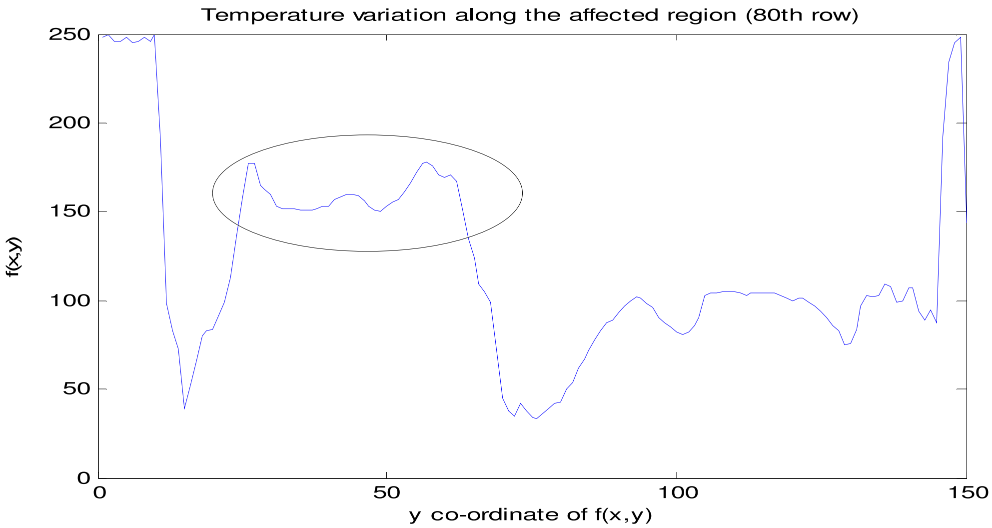


Figure 3: Variation of intensity along the cancer affected region in cancer1.jpg

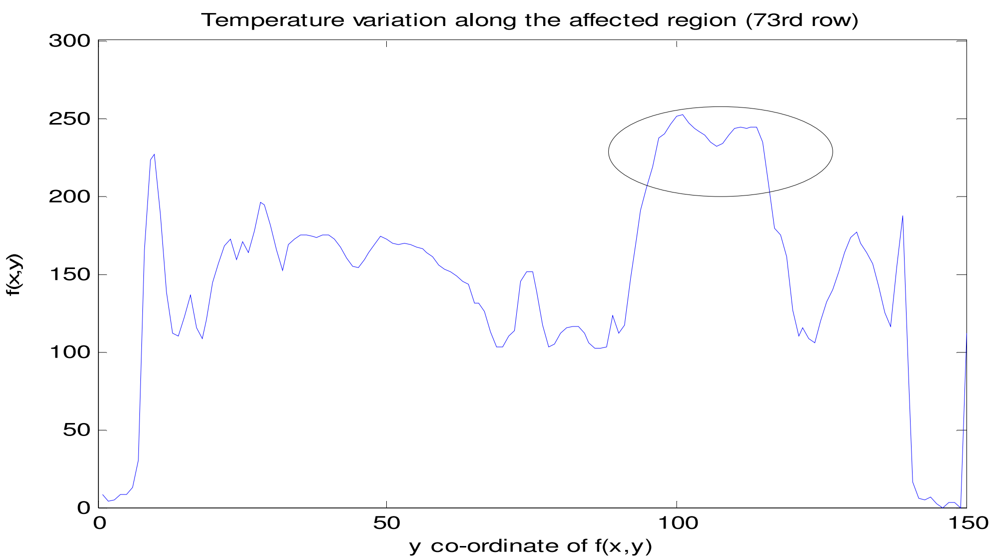


Figure 4: Variation of intensity along the cancer affected region in cancer2.jpg

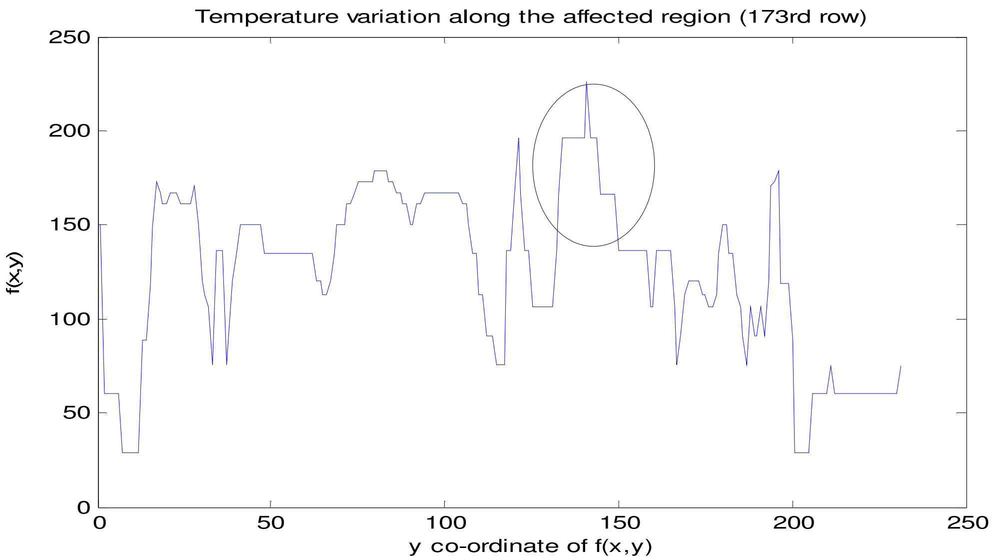


Figure 5: Variation of intensity along the cancer affected region in cancer4.jpg

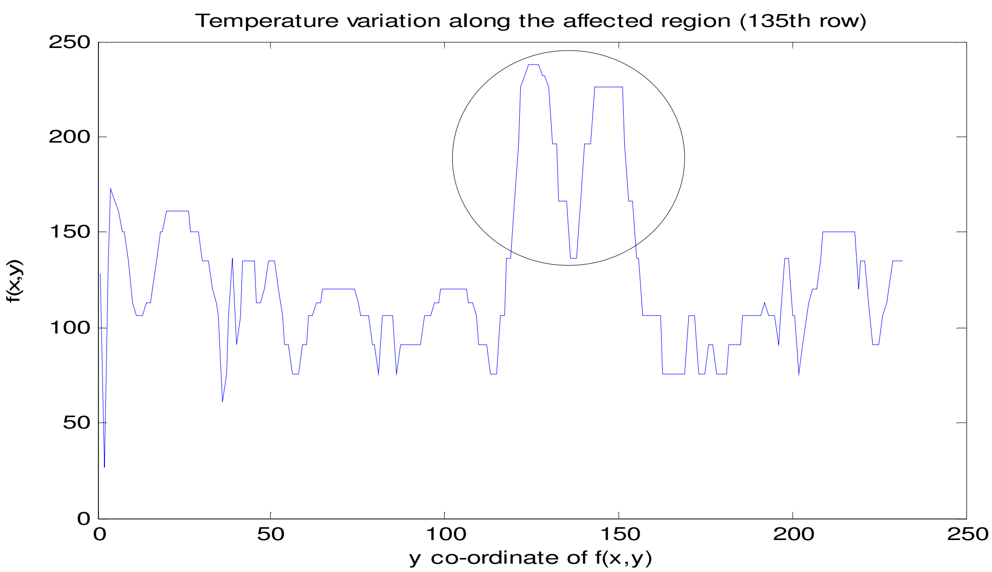


Figure 6: Variation of intensity along the cancer affected region in cancer5.jpg

An appropriate wavelet function has to be chosen to clearly identify and represent the region of interest. The best choice would be to choose wavelet transforms that have similar characteristics as that of the temperature variation in the cancer affected region. From the literature it is found that Haar wavelets, Biorthogonal wavelets and Reverse biorthogonal wavelets have the similar shape characteristics. Hence these two wavelets are applied on the thermographs.

After extracting the wavelet coefficients these wavelet coefficients can then be given directly to train the network. But this process is computationally complex due to the size of the image and also noise if present greatly affects the performance of the system. Hence the coefficients have to be generalized without compromising the uniqueness of the values due to abnormality. Statistical parameters are the best choice for representing these coefficients. Of the different parameters, mean and standard deviation are chosen. The basis for the selection is that mean and standard deviation clearly describe the size and shape of the variations. The absolute difference between the affected and the unaffected regions are found as the direction of variation is insignificant for the analysis. The methodology adopted for automated analysis is as shown in Figure 7.

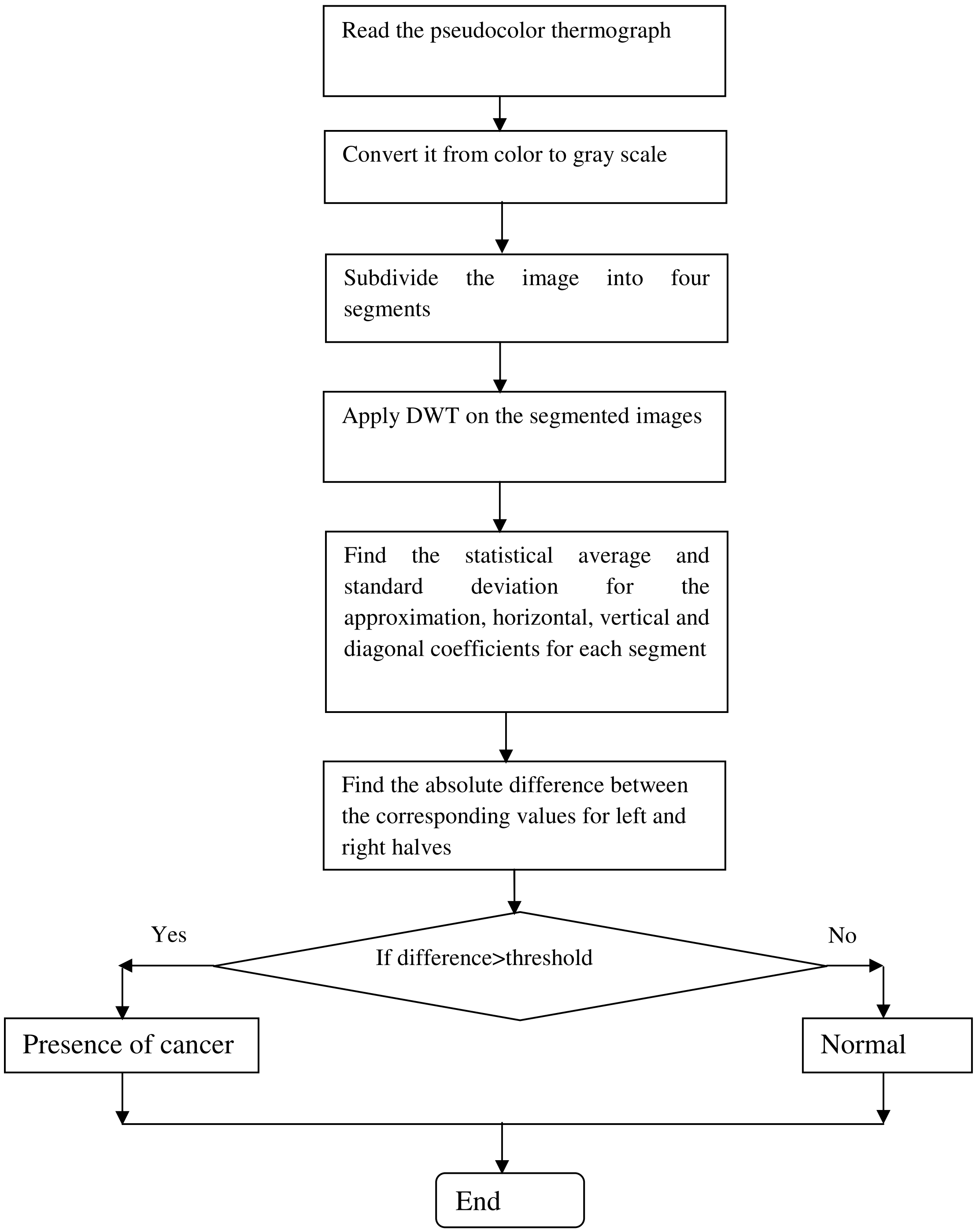


Figure 7: Discrete Wavelet transform based methodology for abnormality extraction

## 5. RESULTS AND DISCUSSION

Four different thermographs depicting cancer are considered. Discrete wavelet Transform is applied on the four subdivisions of each thermograph. Three different wavelets namely Haar, Bi-orthogonal wavelet 4.4 and Rbio1.5 (Reverse Biorthogonal wavelets) were used. The absolute difference between the mean and the standard deviation for the corresponding left and right segments were computed. The absolute difference between the unaffected right and left halves was insignificant. On the other hand, the absolute difference is significant between the unaffected right side and the affected left side of the subdivided thermographs and the readings are tabulated from Tables 1-3. From Tables 1-3 it is understood that absolute difference in mean and standard deviation for Haar coefficients is significant when compared to other wavelets. Also it is found that the difference is significant for approximation coefficients when compared to detailed coefficients because approximation coefficients denote the low resolution region (spread of the cancer region) whereas the detailed coefficients provide the information about the edges where the temperature varies abruptly.

Table 1: Absolute difference between Mean and standard Deviation using Haar Wavelet

| Type of the image | Mean | | | | Standard deviation | | | |
|---|---|---|---|---|---|---|---|---|
| | Approximation coefficient | Horizontal detail | Vertical detail | Diagonal detail | Approximation coefficient | Horizontal detail | Vertical detail | Diagonal detail |
| Cancer1.bmp | 0.4569 | 0.0031 | 0.0223 | 0.0004 | 0.0684 | 0.0106 | 0.0007 | 0.0027 |
| Cancer2.bmp | 0.0941 | 0.0025 | 0.0156 | 0.0000 | 0.0673 | 0.0088 | 0.0125 | 0.0018 |
| Cancer4.bmp | 0.2191 | 0.0008 | 0.0034 | 0.0003 | 0.0278 | 0.0013 | 0.0017 | 0.0014 |
| Cancer5.bmp | 0.1101 | 0.0014 | 0.0053 | 0.0012 | 0.0797 | 0.0047 | 0.0162 | 0.0002 |
| Cancer6.bmp | 0.0739 | 0.0005 | 0.0022 | 0.0016 | 0.0908 | 0.0011 | 0.0110 | 0.0006 |

Table 2: Absolute difference between Mean and standard Deviation using Bi-orthogonal wavelet 4.4

| Type of the image | Mean | | | | Standard deviation | | | |
|---|---|---|---|---|---|---|---|---|
| | Approximation coefficient | Horizontal detail | Vertical detail | Diagonal detail | Approximation coefficient | Horizontal detail | Vertical detail | Diagonal detail |
| Cancer1.bmp | 0.4476 | 0.0001 | 0.0025 | 0.0003 | 0.0632 | 0.0047 | 0.0047 | 0.0014 |
| Cancer2.bmp | 0.0933 | 0.0000 | 0.0020 | 0.0001 | 0.0647 | 0.0038 | 0.0016 | 0.0019 |
| Cancer4.bmp | 0.2159 | 0.0002 | 0.0004 | 0.0003 | 0.0199 | 0.0004 | 0.0026 | 0.0001 |
| Cancer5.bmp | 0.0995 | 0.0008 | 0.0011 | 0.0008 | 0.0531 | 0.0002 | 0.0125 | 0.0029 |
| Cancer6.bmp | 0.0872 | 0.0003 | 0.0019 | 0.0005 | 0.0850 | 0.0007 | 0.0024 | 0.0015 |

Table 3: Absolute difference between Mean and standard Deviation using Rbio1.5

| Type of the image | Mean | | | | Standard deviation | | | |
|---|---|---|---|---|---|---|---|---|
| | Approximation coefficient | Horizontal detail | Vertical detail | Diagonal detail | Approximation coefficient | Horizontal detail | Vertical detail | Diagonal detail |
| Cancer1.bmp | 0.4291 | 0.0001 | 0.0015 | 0.0002 | 0.0651 | 0.0051 | 0.0059 | 0.0021 |
| Cancer2.bmp | 0.1006 | 0.0000 | 0.0019 | 0.0001 | 0.0649 | 0.0036 | 0.0068 | 0.0031 |
| Cancer4.bmp | 0.2191 | 0.0003 | 0.0006 | 0.0002 | 0.0192 | 0.0001 | 0.0013 | 0.0004 |
| Cancer5.bmp | 0.0990 | 0.0008 | 0.0011 | 0.0007 | 0.0595 | 0.0014 | 0.0194 | 0.0014 |
| Cancer6.bmp | 0.0812 | 0.0003 | 0.0020 | 0.0005 | 0.0865 | 0.0018 | 0.0019 | 0.0018 |

## 6. CONCLUSION

In order to determine an automated abnormality classification algorithm, it is first essential to determine an effective set of input feature vectors that best describe the abnormality. In this paper, statistical descriptors for wavelet coefficients of thermographs are chosen for quantitatively characterizing the abnormality region. Also instead of choosing a wavelet based on trial and error method, the choice of the wavelet is based on the shape of the variation of temperature in the abnormality. From the results it is found that approximation coefficients of Haar wavelet provide significant results when compared to the detailed coefficients and other wavelets. Hence absolute difference in mean and standard deviation between the affected and the unaffected regions can be used for representing the abnormality region. In future, Artificial Neural network based classifier can be developed for classifying the abnormality region.

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