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Segmentation algorithms for thermal images

A. Duarte^a, L. Carrão^{b,c}, M. Espanha^b, T. Viana^d, D. Freitas^d, P. Bártoło^{d,e,f}, P. Faria^{a,d},
H.A. Almeida^{a,d,*}

^a School of Technology and Management, Polytechnic Institute of Leiria

^b Department of Sport and Health, University of Lisbon, Faculty of Human Kinetics, CIPER

^c School of Health Sciences, Polytechnic Institute of Leiria

^d Centre for Rapid and Sustainable Product Development, Polytechnic Institute of Leiria

^e Manchester Institute of Biotechnology, University of Manchester, UK

^f School of Mechanical, Aerospace and Civil Engineering, University of Manchester, UK

Abstract

Biomedical techniques and applications are being developed and placed at the service of clinicians. An example is medical thermography, which is being used more often in the detection of certain diseases and also in pain distribution. Current thermography processing software has some limitations mainly because it is developed for general applications and does not allow the identification of a Region Of Interest (ROI) with a specific anatomic shape. Current commercial software usually uses regular prismatic shapes for the definition of these regions, such as, rectangles, squares, circles and/or ellipse that poorly define complex geometric regions. These shapes present limitations when they do not fit with the complex geometric shape of the area that is to be characterized, either by the exclusion or the inclusion of irrelevant data in the evaluation of the thermal images. This particular limitation is observed no matter how accurate the definition of the ROI is. In order to improve characterization of thermal images, a computational application was developed. The limitations of existing software applications was overcome by designing an application that allows choosing any ROI, independently of its geometric shape and optimize it for further processing. This research work presents several segmentation algorithms and a comparison of untreated and optimized ROI's.

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Keywords: Thermography; Infrared; Region of Interest; Image Segmentation; RGB colour model.

* Corresponding author. Tel.: +351 244 820 300; fax: +351 244 820 310

E-mail address: henrique.almeida@ipleiria.pt

1. Introduction

The last half-century has brought dramatic changes in the way human body is being investigated. Nowadays there are many different imaging techniques that open up greater opportunities for diagnosis [1].

Infrared (IR) thermography provides information on the thermal, metabolic, and vascular conditions of the human body that may be used to interpret the pathophysiologic information related to physical conditions. Studies and clinical observations have proven that IR thermography is a suitable indicator for distinguishing normal and abnormal physiologic progresses, particularly for diseases in its early phase [2]. Infrared thermography is also used in satellite imaging, movement detection, security, surveillance, etc. [4].

The accuracy of diagnosis depends on how well the segmentation of the Region of Interest (ROI) is performed [3]. Image segmentation is a fundamental step in thermal image analysis and different methods are being explored. In this paper we present a comparison of different ROIs using image segmentation algorithms. The use of segmentation algorithms helps to increase the accuracy of thermal image analysis.

This paper is organized as follows: in section 2 we present a general overview of thermography, in section 3 the identification of the ROI is discussed, section 4 presents the image segmentation algorithms. The case study is presented in section 5 before the results and concluding remarks in sections 6 and 7.

2. Thermography

Temperature distribution on the surface of an object can be determined using a method called thermal imaging, often also referenced as thermography [5].

Infrared energy is emitted by all materials above 0 °Kelvin (-273 °Celsius). IR radiation is part of the electromagnetic spectrum and occupies frequencies between visible light and radio waves. The IR part of the spectrum spans wavelengths from 0.7 micrometre (μm) to 1000 μm . Within this wave band, only frequencies of 0.7 μm to 20 μm are currently used for temperature measurement [6]. This energy is converted into electrical signals by the imaging sensor in the camera and displayed on a monitor as a colour or monochrome thermal image that represents the variations of the temperature values [7].

2.1. Background

Hippocrates was the first physician in the scientific literature that analysed the bodies heat by putting mud on the abdomen of a man and observed its change in colour while it dried with time [8]. Infrared thermography was discovered by Sir William Herschel around 1800. But it was only in the 1940's that the first applicable IR imaging system was developed. Infrared thermal imaging has been used in medicine since the early 1960's [9]. Significant improvement has been made over the last 20 years in the performance of IR imaging equipment, standardization of techniques and clinical protocols of thermal imaging.

2.2. Advantages

The main advantages of thermography are that it is non-invasive, noncontact, painless and not harmful either to the patients or the medical staff involved [10]. Modern thermal imaging cameras provide high speed and high resolution. Furthermore, the stability of the earlier cameras has improved dramatically and calibration of the image against a stable temperature reference can be achieved to ensure reliability. This is of particular importance when repeated acquisitions are made with this technique [1].

2.3. Disadvantages

One of the major problems of thermal images acquisition is the need of experience and specific algorithms to characterize them correctly. Moreover very accurate temperature measurements are hard to make due to changes in the emissivity of the material used and also because it is highly vulnerable to any external phenomena, such as, hair,

light or air flow, which can may introduce biases and/or may impair image quality [8]. Another major disadvantage of thermography is the relatively high cost of both the hardware and software, along with the personal training [6].

2.4. Clinical Applications

Thermography has been successfully used in diagnosis of breast cancer, diabetes neuropathy and peripheral vascular disorders. Additionally, it is been used to detect problems associated with gynaecology, kidney transplantation, dermatology, heart, neonatal physiology, fever screening and brain imaging [11].

3. Identifying the Region Of Interest

The first step in any thermography processing analysis is the definition of the ROI. Current commercial software usually uses regular prismatic shapes for the definition of these regions, such as, rectangles, squares, circles and/or ellipse that poorly identified certain anatomical regions. Figure 1 illustrates two typical geometric shapes for the definition of a certain ROI.

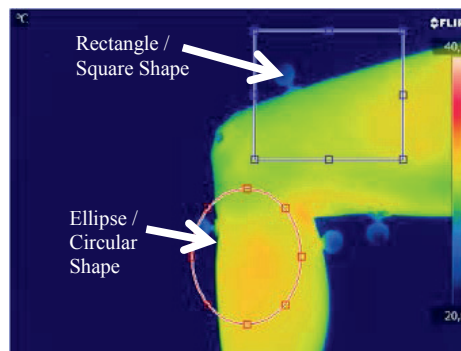


Fig. 1. Illustration of regular shapes for a certain Region of Interest.

These regular geometric shapes present limitations when they do not fit with the anatomical shape of the area that is to be characterized, either by the exclusion of relevant data or the inclusion of irrelevant data in the evaluation of the thermal images (Fig. 2). This can lead to the inclusion of errors or misunderstandings into the analysis of a certain thermal image.

In order to overcome the geometric limitations of inclusion of irrelevant data in the evaluation, image segmentation algorithms may be applied to the selected ROI's, optimizing the ROI by excluding the irrelevant data. The next section describes the several image segmentation algorithms explored.

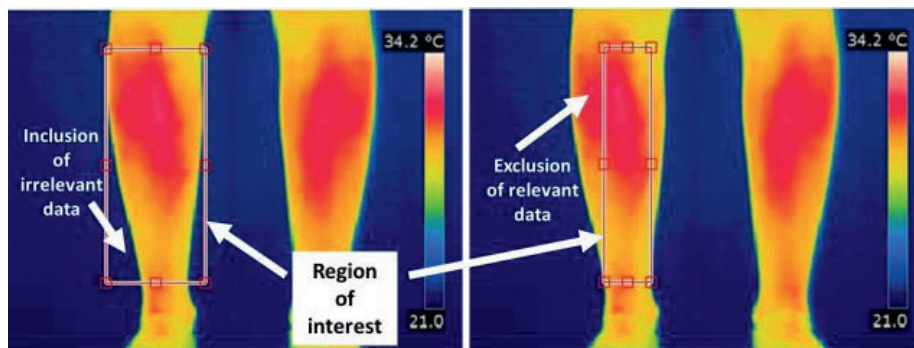


Fig. 2. Regions of Interest with the inclusion of irrelevant data or exclusion of relevant data.

4. Image Segmentation

Segmentation is performed by demarcating an object on an image using pixel-level or object-level properties of the object. These properties can be edges, texture, pixel intensity variation inside the object, shape, size and orientation [12].

The segmentation has two goals. The first is to decompose an image into regions for further analysis and the second is to perform a change of the representation of an image for faster analysis. Based on the application, a single or a combination of segmentation techniques can be applied to solve the problem effectively [4].

There are three types of segmentation techniques, namely Thresholding segmentation, Edge Detection segmentation and Region-based segmentation, which are described as follows.

4.1. Thresholding Segmentation

Thresholding segmentation algorithms define the boundaries of the images that contain solid objects on a contrast background. This technique gives a binary output from a grey scale image. This method of segmentation applies a single fixed criterion to all pixels in the image simultaneously [4]. The method consists of the selection of an adequate threshold value T , which is a converted binary image from a grey level image [13]. The advantage of getting a binary image is that it simplifies both the complexity of the data and the process of recognition and classification.

To describe it mathematically, a threshold image is defined with a pixel labelling where label 1 corresponds to the object and 0 corresponds to the background [14]. The threshold image can be defined as a function $f(x, y)$ whereas the threshold image $g(x, y)$ can be defined as follows:

$$g(x, y) = \begin{cases} 1, & f(x, y) > T \\ 0, & f(x, y) < T \end{cases} \quad (1)$$

4.2. Edge Detection Segmentation

This type of segmentation is based on the abstract level of edges and tries to capture the objects due to their closed outline in the image [15]. This technique detects both outlines and boundaries between objects and the background in the image [16]. Edges are considered to be the sign of lack of continuity and ending. As a result of this transformation, edge image is obtained without encountering any changes in physical qualities of the main image [17].

There are several types of edge detection techniques. The most traditional and used ones are Sobel, Roberts, Prewitt, Laplacian of Gaussian (LoG) and Canny, which are briefly described below.

4.2.1. Sobel

The Sobel edge detector computes the gradient by using the discrete differences between rows and columns of a 3x3 neighbourhood. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter [18]. The computation of the partial derivation in gradient may be approximated in digital images by using the masks shown in Table 1.

Table 1. Sobel Mask.

+1	+2	+1
0	0	0
-1	-2	-1

G_x

-1	0	+1
-2	0	+2
-1	0	+1

G_y

4.2.2. Roberts

In the Robert cross algorithm, both horizontal and vertical edges are calculated individually and put together to obtain the resulting edge detection [19]. This operator performs a simple, fast 2-D spatial gradient measurement of the image [16] and uses the following mask to approximate, digitally, the first derivatives as differences between adjacent pixels as shown in Table 2 [18].

Table 2. Roberts Mask.

+1	0
0	-1

G_x

0	+1
-1	0

G_y

4.2.3. Prewitt

The Prewitt edge detector gives an estimation of the magnitude and orientation of a certain edge [17]. Prewitt operator edge detection masks consider the one of the oldest and considered to be the best method for detecting edges in images. This technique uses the following mask to approximate digitally the first derivatives G_x and G_y as illustrated in Table 3 [18].

Table 3. Prewitt Mask.

-1	-1	-1
0	0	0
+1	+1	+1

G_x

-1	0	+1
-1	0	+1
-1	0	+1

G_y

4.2.4. Laplacian of Gaussian

The Laplacian method searches for zero crossings in the second derivative of the image to find edges. An edge has the one-dimensional shape of a ramp and calculating the derivative of the image can highlight its location [20]. The Laplacian is usually used to establish whether a pixel is on the dark or light side of an edge [16].

4.2.5. Canny

The Canny edge detection is a multistage algorithm used to detect a wide range of edges in an image. This detector finds edges by looking for a local maximum of the gradient of $f(x, y)$. The gradient is calculated by using the derivative of a Gaussian filter [18].

4.3. Region-based Segmentation

Region-based segmentation treats an image as the composition of a finite number of regions and performs regional statistics that are used for segmentation [21].

The watershed transform is a broadly used region-based technique for image segmentation. The intuitive idea underlying this method comes from geography. The topographic surface will slowly be flooded, from the lowest regions to the top of what lies in the image. When the "waters" merge they built "dams". These dividing lines resulting from these multiple floods are the watersheds. The watershed is applied to the image gradient and the watershed lines separate homogeneous regions, giving the desired segmentation result [22].

5. Material and Methods

5.1. Graphical User Interface and Thermal Imaging Acquisition

The Graphical User Interface (GUI) was developed in Matlab (MATrix LABoratory, Mathworks, Inc.). Regarding Infrared thermography, it was performed using a FLIR SC655 camera, mounted on a standard camera tripod located at 1.2 meters from the target. A resolution of the camera of 640×480 pixels was used. In this particular study the acquisitions were taken in a room where the temperature was maintained constant at 20°C with a humidity $\pm 50\%$.

5.2. Data Analysis

Measurements of 23 subjects of both genders were performed in both frontal and lateral views of the head. Descriptive statistics (means, standard deviations, range) of maximum, minimum and mean temperatures were used for basic data analysis. Data were tested for normality with the Shapiro-Wilk test and comparisons were computed using paired-samples t-tests (95% confidence interval - CI). Statistical analysis was performed using IBM SPSS Statistics 20 and the statistical significance was set at $p < 0.05$.

5.3. Identifying and Optimizing the Region of Interest

The proposed thermographic processing software allows the user to select any ROI independently of its geometric shape. It also contains a segmentation algorithm based on the Thresholding Segmentation method, which was considered to be the most accurate algorithm for our application. The segmentation algorithm optimizes the chosen region by removing areas that don't have any relevant statistic data in order to take into account only the temperature of the ROI that will be used in further characterization. The flowchart of the proposed algorithm is shown in Fig. 3.

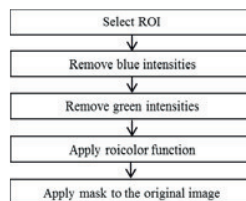


Fig. 3. Flowchart of the proposed algorithm.

The RGB image model (R for Red, G for Green and B for Blue) is considered the most appropriate for image processing. Colour is a powerful descriptor that simplifies object identification and extraction of a thermograph image [23]. In the RGB model, the images are segmented by a colour function. All fades of red comes under Red, fades of green under Green and so on. When detecting the Red regions, the Red regions are separated and all other fades are grouped together. The other colours are separated in a similar fashion [24].

The original thermal image is a $m \times n \times 3$ matrix. In this matrix the elements in $x(:, :, 1)$ are the red intensities, $x(:, :, 2)$ are the green intensities whereas the $x(:, :, 3)$ are the blue ones. It is a fact that the human skin tends to have predominance of red and non-predominance of blue [25], therefore the first step consists in applying the a zero function in the matrix to remove the blue intensities as shown in Fig. 4. a).

Then in the resulting image, the green intensities are eliminated, as illustrated in Fig. 4. b), by applying the same method explained above.

The next step was to apply the ROI colour method. This function selects a ROI based on a range of threshold index value. All values within that range are shown in white and values outside that range are shown in black. The final image is considered the mask. The optimal threshold value was found [0.1, 0.4]. The resultant mask is exemplified in Fig. 4. c).



Fig. 4.. Images obtained after remove blue intensities (a); after remove green intensities (b) and mask image used (c).

Finally, by using the Matlab function “*bsxfun*”, the two matrices (the original and the masked image) are multiplied element-by-element in order to obtain the optimized ROI. Figures 5. a) and 5. b) illustrate the images respectively, before and after optimization.

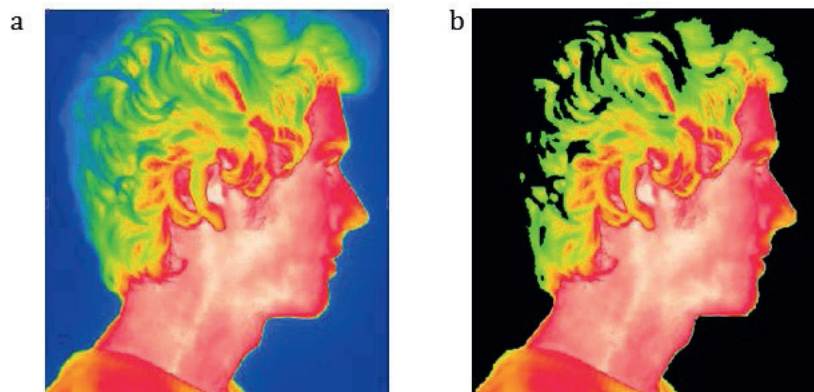


Fig. 5. Images before optimization (a); after optimization (b).

6. Results and Discussion

In order to perform this research work, 23 individuals of both genders were analysed. Head and neck thermograms in the frontal and lateral views were taken with the FLIR SC655 camera, making a total of 46 thermal scan images. Comparisons between the thermograms, from both frontal and lateral views before and after optimization, showed significant differences ($p \cong 0$), both in the minimum temperature and mean temperature ($p \cong 0$), but not in the maximum temperature. Tables 4 and 5 present the comparisons for the frontal and lateral views, respectively.

In Fig. 6, it is possible to observe that the mean difference is higher in the minimum temperature than in the mean temperatures and the differences between “before and after optimization” is more notorious in the frontal images.

In this study, it is possible to observe that the maximum temperature is not changed by the optimization; only the minimum and mean temperatures of the analysed images are influenced. Both values increased after optimization approximately 4 °C (for the minimum temperature) and 2.3 °C (for the mean temperature), which is explained by the optimization, which withdraws the values of lower temperatures that “pollute” the image, lowering the minimum

temperature and therefore influencing the average temperature of the analysed thermal images. When the optimization occurs, a more focused thermal image is obtained for examination and the minimum and average temperatures increase therefore representing a more accurate analysis.

Table 4. Mean, standard deviation, range and mean difference of the frontal images (with a rectangular shaped ROI) before and after optimization (N=23).

	Before Optimization	After Optimization	Mean Difference
Temperature (°C)	Mean (SD) Range	Mean (SD) Range	Mean (SD)
Maximum	39.64 (.59) 38.65-40.62	39.64 (.59) 38.65-40.62	0 (0)
Minimum	22.15 (.28) 21.41-22.60	26.42 (1.01) 24.00-27.90	4.27 (.74)*
Mean	32.82 (.84) 31.45-35.02	35.35 (.49) 34.47-36.21	2.53 (.35)*

* $p \cong 0$

Table 5. Mean, standard deviation, range and mean difference of the lateral images (with an ellipsoidal shaped ROI) before and after optimization (N=23).

	Before Optimization	After Optimization	Mean Difference
Temperature (°C)	Mean (SD) Range	Mean (SD) Range	Mean (SD)
Maximum	39.76 (.76) 38.14-40.80	39.76 (.76) 38.14-40.80	0 (0)
Minimum	22.26 (.40) 21.29-22.98	25.78 (1.21) 23.25-27.69	3.53 (0.81)*
Mean	32.09 (1.27) 30.20-34.47	34.19 (.84) 32.58-35.57	2.10 (.43)*

* $p \cong 0$

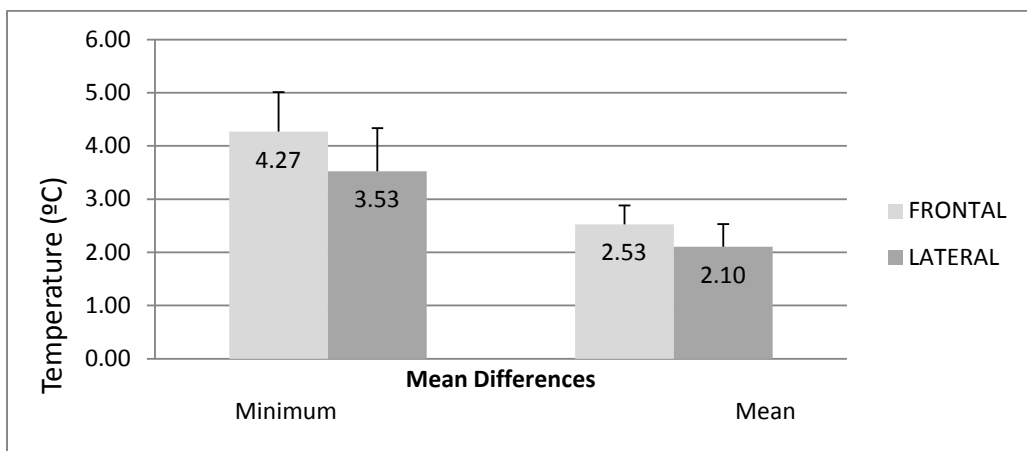


Fig. 6. Temperature mean differences and standard deviation before and after images optimization (frontal and lateral views).

7. Conclusions

Current thermography processing software has some limitations mainly because it is developed for general applications and does not allow the identification of a ROI with a specific anatomic shape. In order to improve thermal images characterization a computational application was developed. The limitations of existing software were overcome by designing an application that allows choosing any ROI, independently of its geometric shape and then optimize the ROI for further processing.

In this research work several segmentation algorithms were presented. A comparison of untreated ROI's and optimized ROI's are also presented. It is possible to observe that the maximum temperature does not change by the optimization however both the minimum and mean temperatures of the analysed images are influenced. When the optimization occurs, a more focal thermal image is obtained for examination and the minimum and average temperatures increased, therefore obtaining a more accurate thermal image for analysis.

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References

- [1] Ring F. Thermal Imaging Today and Its Relevance to Diabetes. *Journal of Diabetes Science and Technology*. 2010, 4:857-862.
- [2] Jin C, Yang Y, Xue Z, Liu K, Liu J. Automated Analysis Method for Screening Knee Osteoarthritis using Medical Infrared Thermography. *Journal of Medical and Biological Engineering*. 2013, 33.
- [3] Kapoor P, Prasad SVAV, Patni S. Image Segmentation and Asymmetry Analysis of Breast Thermograms for Tumor Detection. *International Journal of Computer Applications*. 2012, 50.
- [4] Sujji G, Lakshmi YVS, Wiselin G. MRI Brain Image Segmentation based on Thresholding. *International Journal of Advanced Computer Research*. 2013, 3(1):97-101.
- [5] Skala K, Lipić T, Sović I, Gjenero L, Grubišić I. 4D thermal imaging system for medical applications. *Periodicum Biologorum*. 2011, 407-416.
- [6] Pašagić V, Mužević M, Kelenc D. Infrared Thermography in Marine Applications. *Brodogradnja*. 2008, 123-130.
- [7] Hildebrandt C, Raschner C, Ammer K. An Overview of Recent Application of Medical Infrared Thermography in Sports Medicine in Austria. *Sensors* 2010. 2010, 4700-4715.
- [8] Szentkuti A, H. K, Grazio S. Infrared thermography and image analysis for biomedical use. *Periodicum Biologorum*. 2011, 385-392.
- [9] Ring E, Ammer K. The Technique of Infrared Imaging in Medicine. *Thermology International*. 2000, 10:7-14.
- [10] Nahm F. Infrared Thermography in Pain Medicine. *The Korean Journal of Pain*. 2013, 219-222.
- [11] Lahiri BB, Bagavathiappan S, Jayakumar T, Philip J. Medical applications of infrared thermography: A review. *Infrared Physics & Technology*. 2012, 55:221-235.
- [12] Ghosha P, Mitchell M, Gold J. Segmentation of thermographic images of hands using a genetic algorithm. In David Fofi KSN. *Image Processing: Machine Vision Applications.*: SPIE-IS&T; 2010.
- [13] Gonzalez R, Woods R. *Digital Image Processing*. 3rd ed.: Prentice Hall; 2008.
- [14] Akther M, Ahmed K, Hasan Z. Detection of Vehicle's Number Plate at Nighttime using Iterative Threshold Segmentation (ITS) Algorithm. *I.J. Image, Graphics and Signal Processing*. 2013, 5.
- [15] Deserno TM. *Biological and Medical Physics*, Biomedical Engineering Greenbaum E, editor.: Springer-Verlag Berlin Heidelberg; 2011.
- [16] Al-amri S, Kalyankar NV, S.D K. Image Segmentation by Using Edge Detection. *International Journal on Computer Science and Engineering*. 2010, 2:804-807.
- [17] Senthilkumaran N, Rajesh R. Edge Detection Techniques for Image Segmentation – A Survey of Soft Computing Approaches. *International Journal of Recent Trends in Engineering*. 2009, 1.
- [18] Acharjya P, Das R, Ghoshal D. Study and Comparison of Different Edge Detectors for Image Segmentation. *Global Journal of Computer Science and Technology*. 2012, 12.

- [19] Lakshmi S, Sankaranarayanan V. A study of Edge Detection Techniques for Segmentation Computing Approaches. In *Computer Aided Soft Computing Techniques for Imaging and Biomedical Applications*. 2010, 35-41.
- [20] Juneja M, Sandhu P. Performance Evaluation of Edge Detection Techniques for Images in Spatial Domain. *International Journal of Computer Theory and Engineering*. 2009, 1.
- [21] Tsai A, Yezzi A,J, Wells W, Tempany C, Tucker D, Fan A, et al. A shape-based approach to the segmentation of medical imagery using level sets. *IEEE Transactions on Medical Imaging*. 2003, 22.
- [22] Bala A. An Improved Watershed Image Segmentation Technique using MATLAB. *International Journal of Scientific & Engineering Research*. 2012, 3.
- [23] Selvarasu N, Nachiappan A, Nandhitha NM. Euclidean Distance Based Color Image Segmentation of Abnormality Detection from Pseudo Color Thermographs. *International Journal of Computer Theory and Engineering*. 2010, 2.
- [24] Manoj R, Thamarai M. A Survey of Segmentation in Mass Detection Algorithm for Mammography and Thermography. *International Journal of Advanced Electrical and Electronics Engineering (IJAEED)*. 2012, 1.