



## Automated Segmentation of Skin Lesion Images using Dominant Intensity Pixel: A Boundary Detection Technique

M.Mohamed Sathik

Associate Professor,

Department of Computer Science and Engineering,  
Sathakathullah Appa College, Tirunelveli, India.

[mmdsadiq@gmail.com](mailto:mmdsadiq@gmail.com)

S.Arumugam

Chief Executive Officer,

Nandha Engineering College,  
Erode, Tamilnadu, India

S.Zulaikha Beevi\*

Associate Professor,

Information Technology,

National College of Engineering,, Tirunelveli, India.

[zulaikha23@gmail.com](mailto:zulaikha23@gmail.com)

**Abstract:** Dermoscopy is one of the major imaging modalities used in the diagnosis of melanoma and other pigmented skin lesions. Automated segmentation of dermoscopy images is an important step for computer-aided diagnosis of melanoma. In this paper, we investigate how to use the dominant intensity pixel present in the border of the pigmented lesions to improve the segmentation of dermoscopy images. The algorithm groups the dominant intensity image pixels with homogeneous properties, and merges the pixel groups into a few super-regions. The optimal lesion skin boundary is chosen from the set of all region boundaries, where the optimality is determined from the color and texture properties of the regions. We test our method on many dermoscopy images and compare the automatically generated segmentation with dermatologist-determined segmentation. The results demonstrate the advantage of incorporating intensity specific constraints into the segmentation process. The medical images, while acquisition is generally bound to contain noise. The preprocessing stage employs background noise reduction techniques to filter noise. The algorithm converts an image to a binary image, based on threshold, and finds edges in the image using dominant intensity and traces the object boundary in the image. The algorithm was applied on many noisy clinical skin images containing lesions. The proposed segmentation algorithm successfully detects the border of noisy clinical skin images and makes them accessible for further analysis and research.

**Keywords:** Border detection, dermoscopy, Image Segmentation, Skin Lesion

### I. INTRODUCTION

Skin cancers are one of the most common forms of cancers in humans. Skin cancers can be classified into melanoma and non-melanoma. Although melanomas are much less common than non-melanomas, they account for most of the mortality from skin cancers [2]. Automatic image segmentation applied to the detection of this kind of lesions could result in the detection of the disease at an early stage and a subsequently increment in the likelihood that the patient will survive. Although color is the most important information in this kind of images, it is not the only source of knowledge available. Because these types of pigmented lesions are rich in color and texture. Studies have shown that dermoscopy can improve the diagnostic accuracy of dermatologists by as much as 30% over clinical examination [1]. This improvement in diagnostic accuracy, however, is seen primarily when dermoscopy is used by a trained expert, or when the user applies specific diagnostic algorithms that are often not practical in the clinical setting. Based on this, there has been increasing interest in computer aided analysis of dermoscopy images. The first step of such analysis is the segmentation of pigmented lesions from the surrounding skin. The resulting border structure not only provides a basis

for calculation of important clinical features such as lesion size and border regularity, but it is also crucial for

extraction of discriminating dermoscopic features such as atypical pigment networks and radial streaming. It has also been demonstrated that dermoscopy may actually lower the diagnostic accuracy in the hands of inexperienced dermatologists [4]. Therefore, in order to minimize the diagnostic errors that result from the difficulty and subjectivity of visual interpretation, the development of computerized image analysis techniques is of paramount importance [5]. Automated border detection is often the first step in the automated or semi-automated analysis of dermoscopy images [6, 7, 8, 9, 10]. It is crucial for the image analysis for two main reasons. First, the border structure provides important information for accurate diagnosis, as many clinical features, such as asymmetry, border irregularity, and abrupt border cutoff, are calculated directly from the border. Second, the extraction of other important clinical features such as atypical pigment networks, globules, and blue-white areas, critically depends on the accuracy of border detection. Automated border detection is a challenging task due to several reasons: (i) low distinction between the lesion and the surrounding skin, (ii) irregular and imprecise lesion borders, (iii) artifacts such as black frames, skin lines, hairs, and air bubbles, (iv) speckled coloring inside the lesion. Once a dermoscopic image is

selected, the system should provide an automatic segmentation of the lesion, which aims at identifying the lesion and separate it from the background. Edge detection is the process of contour extraction of different objects from background, and it is very important to image understanding and computer vision. Edge location errors, false edges, and broken or missing edge fragments are often problems with edge detection [11]. Automated border detection is crucial for the image analysis for two main reasons. First, the border structure provides important information for accurate diagnosis, as many clinical features such as asymmetry, border irregularity, and abrupt border cut off are calculated directly from the border. Second, the extraction of other important clinical features such as an a typical pigment network, globules, and blue-white areas, critically depends on the accuracy of border detection. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. All of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics.

This paper is organized as follows. Section II is for the purpose of providing some information about edge detection for Image Segmentation. Section III is focused on showing the proposed approaches using edge detection and also focused on implementation of various images using this Boundary Detection Methods. Section IV presents the result and discussion and section V focuses conclusion.

## II. RELATED WORKS

Different image features such as shape, color, texture and brightness have been employed to perform skin lesion segmentation. For this purpose, numerous methods have been proposed. Edge detection techniques transform images to edge images benefiting from the changes of grey tones in the images. Edges are 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 [12]. Objects consist of numerous parts of different color levels. In an image with different grey levels, despite an obvious change in the grey levels of the object, the shape of the image can be distinguished in Figure 1.

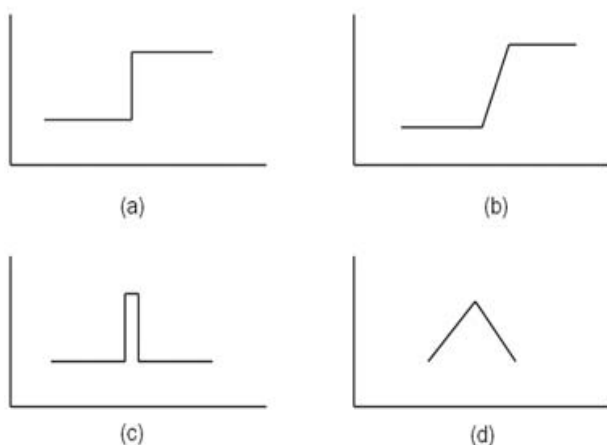


Figure. 1. Type of Edges (a) Step Edge (b) Ramp Edge (c) Line Edge (d) Roof Edge

Roberto Rodríguez et al. developed a segmentation algorithm where the entropy is used as stopping criterion in the segmentation process by using recursively the mean shift filtering [13]. Teresa Mendonca et al. performed the segmentation by Manual Segmentation by a non-specialist (M) and by three automatic methods: Robust adaptive contour - Robust Snakes (RS), Vector valued active contours - Level Sets (LS) and Adaptive Thresholding (AT) [2].

Active contours are a popular approach to estimate the organs boundaries in medical applications. Two types of algorithms have been proposed: parametric active contours which adapt a deformable curve until it fits the object boundary and geometric active contours based on level set theory. The geometric models are able to perform topological changes e.g., curve splitting. Despite all the research efforts in this area, most of the algorithms require an initialization of the contour model close to the object boundary since the contour is attracted towards spurious features (outliers) belonging to other objects or produced by the image texture. Recent approaches to overcome this difficulty are the gradient vector flow algorithm based on anisotropic diffusion and the robust algorithms (adaptive snakes and shape-probability data association model)[2].

Chunming Li, Chenyang Xu, Changfeng Gui, and Martin D. Fox, presented a new variational formulation for geometric active contours that forces the level set function to be close to a signed distance function, and therefore completely eliminates the need of the costly re-initialization procedure. Their variational formulation consists of an internal energy term that penalizes the deviation of the level set function from a signed distance function, and an external energy term that drives the motion of the zero level set toward the desired image features, such as object boundaries [14].

The medical images generally are bound to contain noise while acquisition. In this paper, we have developed a segmentation method using dominant intensity pixel for border detection of real skin lesions for noisy skin lesion images and also noiseless skin lesion images. and compared with variational formulation for geometric active contours for detecting, the desired image features, such as object boundaries by Chunming Li et al[14].

## III. PROPOSED METHODOLOGY

This paper proposes an image segmentation algorithm to extract the true border that reveals the global structure irregularity, which may suggest excessive cell growth or regression of a melanoma. This algorithm is applied to the image containing the lesion, where the RGB image is converted to grayscale intensity image by eliminating the hue and saturation information while retaining the luminance and adds salt and pepper noise to the image and uses background noise reduction techniques to filter noise. The algorithm converts an image to a binary image, based on threshold, and find edges in the image using dominant intensity pixel and traces edge that is the object in the image.

### A. Preprocessing

Usually, the medical images obtained from sensors are bound to contain noise and blurred edges. The process of segmentation is made more intricate, owing to the presence of these artefact in medical images. Consequently,

denoising images prior to segmentation perhaps produce better segmentation accuracy. Recently, Alessandro Foi *et al* [15] presented an efficient denoising algorithm, which is used in the proposed approach. Initially, the input noisy medical images are denoised using the above-mentioned denoising algorithm. A brief description of the denoising strategy employed in the proposed approach is provided in the subsequent subsection.

#### (a) Pointwise SA-DCT Denoising

Since noise is an inevitable one in image acquisition, denoising plays an important role in increasing the quality of the image. Noise removal has been widely studied as a primary low-level image processing procedure and copious amount of denoising schemes have been proposed. In our approach, we employed an efficient Pointwise Shape Adaptive DCT denoising algorithm [21] In order to preserve the image local structures in a better way, within the transform support. In this way, it ensures that data are represented sparsely in the transform domain, significantly improving the effectiveness of thresholding. Before we proceed further, it is worth mentioning that the approach can be interpreted as a special kind of local model selection which is adaptive with respect both to the scale and to the order of the utilized model. Shape-adapted orthogonal polynomials are the most obvious choice for the local transform, as they are more consistent with the polynomial modeling used to determine its support. However, in practice, cosine bases are known to be more adequate for the modeling of natural images. In particular, when image processing applications are of concern, the use of computationally efficient transforms is paramount and, thus, the low-complexity SA-DCT and high robustness to noise.

#### B. Dominant Intensity Pixel Identification

Literature reveals many edge detectors based on gradients, filters, derivatives etc. A simple method to find dominant pixels has been introduced in [13] based on various matrix rotation operations. The dominant pixels thus obtained represent the core structure or the border of the image. The steps involved in obtaining dominant pixels are as follows.

- Step-1: Read the given color image (i).
- Step-2: Apply the symmetric filter to smoothen the image.
- Step-3: Apply rotation operations.
- Step-4: Obtain dominant pixels by image differencing.
- Step-5: Dominant pixel enhancement by thresholding.
- Step-6: Dominant pixel linking and smoothing to obtain boundary.
- Step-7: Creating new matrix to get rid off distortion outside the boundary
- Step-8: Getting edge map of the color image-an output image

#### C. Rotation Operations

The image, represented as a matrix, can be rotated by blocks of images. The image is dividing into number of blocks of size  $(2n+1) \times (2n+1)$ , where  $n \geq 1$ . In this case, the parameters to be specified are angle of rotation  $\Theta$ , and direction (clockwise or anti-clockwise). The value of  $\Theta$  can be 45°, 90°, 135° or 180°. The rotations are performed keeping the intensity value of the centre pixel unchanged and value of "n". The best results are obtained for  $n=1$  or 2 i.e., dividing the image into blocks of 3x3 and 5x5 each. This way or rotating the image matrix guarantees the variation of pixels from neighbouring data i.e., the intensity values of an image thereby

the sharp variations as well as minute transitions can be captured effectively.

#### D. Difference Images

Once the dominant color pixel is obtained, the distances between every single pixel of the image and each of the reference color is calculated. We have chosen the distance metric. This measure has been extensively tested and outperformed other existing color difference formulae [4]. As a consequence, the CIE 2000 is color difference formula. Then, a new set of images is built, where each pixel value will be the color difference to the dominant color. In order to obtain a better visualization, we invert this image, that is, those pixels whose values are similar to the reference ones, will appear light in a dark background. These inverted images are called the distance images.

#### E. Edge Enhancement by Thresholding

The dominant pixels obtained are distributed over an intensity range. For better visualization of these dominant pixels, single level thresholding is used. The pixels after thresholding are termed as enhanced dominant pixels. The thresholding is carried out as given in equation below.

$$i(x, y) = \begin{cases} 0, & i(x, y) \leq T \\ 255, & \text{otherwise} \end{cases} \quad (1)$$

#### F. Edge linking and smoothing

Edge linking is carried out to enhance the dominant pixels. After linking, certain pixels are left isolated. Such isolated pixels are removed using average or median filtering.

## IV. RESULTS AND DISCUSSION

In this section, the results of the proposed method are presented. Both synthetic and real world images are used to show the effectiveness of the proposed method. An image segmentation algorithm to extract the true border that reveals the global structure irregularity, which may suggest excessive cell growth or regression of a melanoma, has been implemented using matlab. Our aim is to select an image and the system should provide an automatic boundary of the lesion, which aims at identifying the lesion and separate it from the background. If the image is having noise, the proposed algorithms detect the boundary of the skin lesion without any distortion. This is the effectiveness of our algorithm. We employed the point and shape noise removal algorithm in the preprocessing. The algorithm will have to be able to remove noise and other undesired features in the image, and to correctly segment the lesion. The algorithm should work well even when the transition between lesion and surrounding skin is too smooth. The segmentation stage is not a straightforward task due to the great variety of lesions, skin types, presence of hair and so forth. The proposed segmentation algorithm works well even in the presence of noise and hair, to detect the border of the lesion, which helps the medical practitioners in diagnosis. The proposed approach with noiseless image is shown in figure 2.

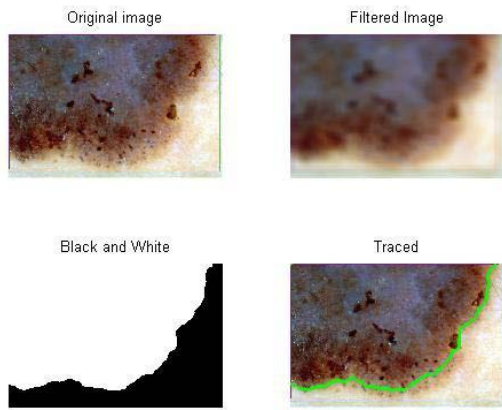


Figure 2. Demonstration of border detection for Skin lesion that shows original image, filtered image, black and white and boundary traced image without noise.

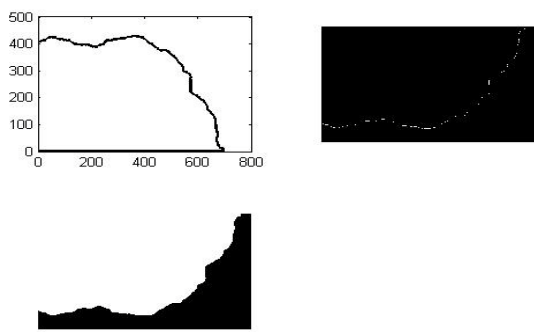


Figure 3. Implementation of the border detection on black and white images without noise

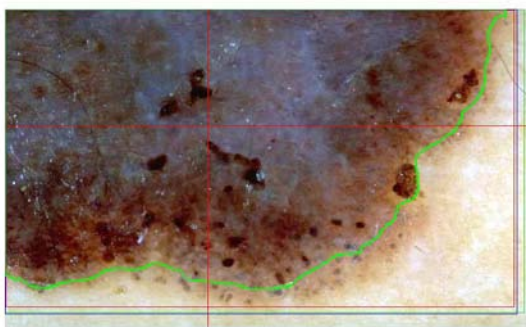


Figure 4. Image with boundary and geometric center without noise

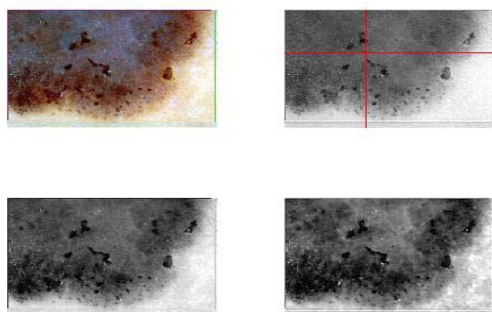


Figure 5. Original image, grey image with geometric center, segmented image level 1 and level 2

The proposed image is added with 2% salt and pepper noise. This image is tested with our proposed algorithm. The boundary detection is very effective without any distortion on the boundary. The figure shows.

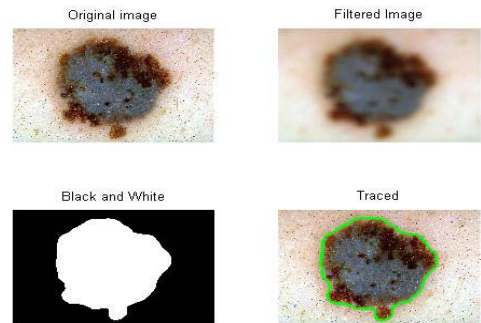


Figure 6. Demonstration of border detection for Skin lesion that shows original image, filtered image, black and white and boundary traced image with 2% noise.

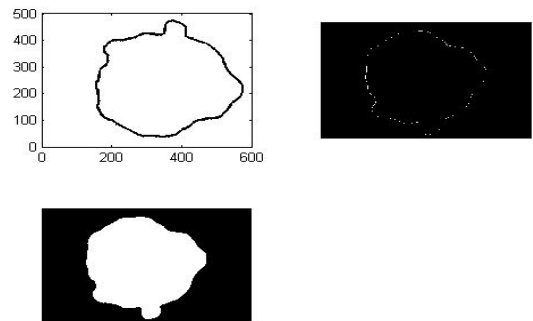


Figure 7. Implementation of the border detection on black and white images with 2% noise

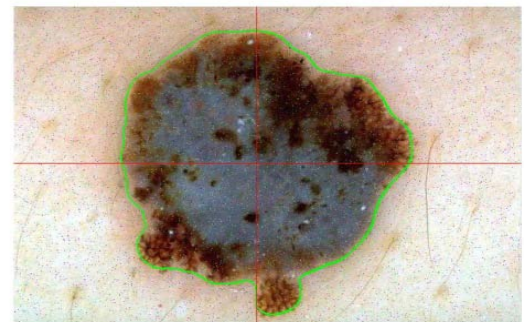


Figure 8. Image with boundary and geometric center with noise

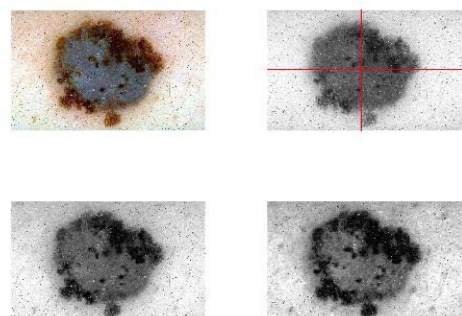


Figure 9. Original image, grey image with geometric centre, segmented image level 1 and level 2 with noise

Similarly the proposed algorithm is applied on the same image with 4% noise. The result shows the effective edge map on the skin lesion images. The employed shape and adaptive denoising algorithm is applied on the skin lesion image. Here also the edge map is very strength than the previous results. The figure shows the result.

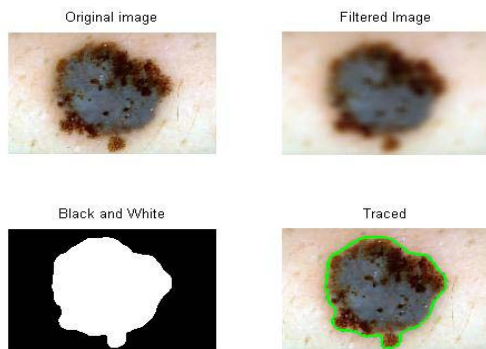


Figure 10. Implementation of preprocessed image, filtered image, black and white image and boundary traced image on 4% salt and pepper noise added image.

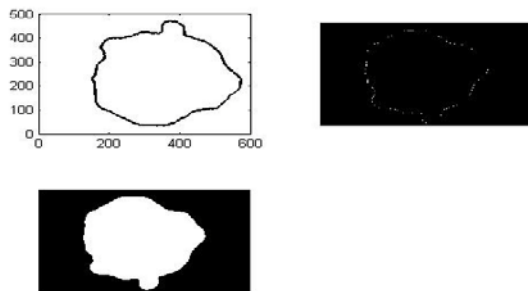


Figure 11. Implementation of the border detection on noisy black and white image

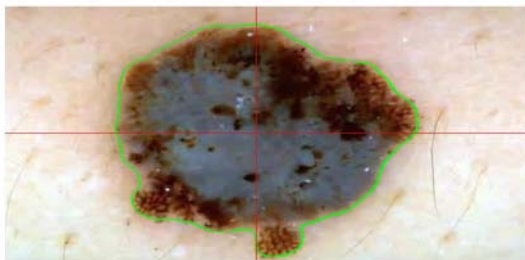


Figure 12. Image with geometric centre and boundary

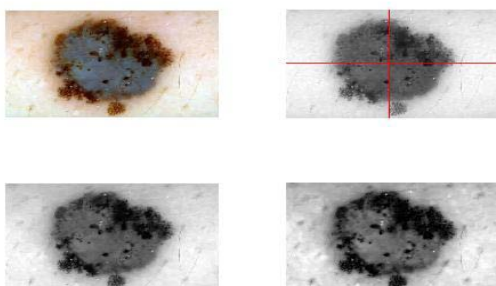


Figure 12. Constructed image, grey image with geometric centre, segmented image with level 1 and level 2 on noisy image.

## V. CONCLUSION

In this paper, we have proposed a new effective segmentation algorithm using dominant intensity pixel for border detection on real noisy and noiseless skin lesions for skin lesion diagnosis. To verify the capability of the segmentation algorithm in detecting the borders of the lesions for skin lesion diagnosis, the algorithm was applied on diversity of clinical skin image containing lesions with and without noise. The experimental results demonstrated the successful border detection of real skin lesions by the proposed segmentation algorithm for clinical skin images and make them accessible for further analysis and research. We conclude that, the proposed algorithm segments the lesion from the image even in the presence of noise for a variety of lesions, and skin types.

## VI. REFERENCES

- [1] D.S. Rigel, R.J. Friedman, and A.W. Kopf, "The incidence of malignant melanoma in the United States: Issues as we approach the 21st century," *J Am Acad Dermatol.*, vol. 34, pp. 839–847, 1996
- [2] L. Xua, M. Jackowska, A. Goshtasby\*, D. Rosemanb, S. Binesb, C. Yuc, A. Dhawand, A. Huntleye, "Segmentation of skin cancer images," *Image and Vision Computing* 17 65–74 (1999).
- [3] Arthur Tenenhaus<sup>1</sup>, Alex Nkengne<sup>2</sup>, Jean-François Horn<sup>3,4</sup>, Camille Serruys<sup>3,4</sup>, Alain Giron<sup>3,4</sup> and Bernard Fertil<sup>5</sup> "Detection of melanoma from dermoscopic images of naevi acquired under uncontrolled conditions", Author manuscript, published in *Skin Research and Technology* Vol. 16, N° 1 (2009) pp. 85-97
- [4] Binder M, Schwarz M, Winkler A et al. *Epiluminescence Microscopy. A Useful Tool for the Diagnosis of Pigmented Skin Lesions for Formally Trained Dermatologists.* *Archives of Dermatology* 1995; 131(3): 286-291.
- [5] Fleming MG, Steger C, Zhang J et al. *Techniques for a Structural Analysis of Dermoscopic Imagery.* *Computerized Medical Imaging and Graphics* 1998; 22(5): 375-389.
- [6] Schmid P. *Segmentation of Digitized Dermoscopic Images by Two-Dimensional Color Clustering.* *IEEE Trans. on Medical Imaging* 1999; 18(2): 164-171.
- [7] Erkol B, Moss RH, Stanley RJ, Stoecker WV, Hvatum E. *Automatic Lesion Boundary Detection in Dermoscopy Images Using Gradient Vector Flow Snakes.* *Skin Research and Technology* 2005; 11(1): 17-26.
- [8] Iyatomi H, Oka H, Saito M et al. *Quantitative Assessment of Tumor Extraction from Dermoscopy Images and Evaluation of Computer-based Extraction Methods for Automatic Melanoma Diagnostic System.* *Melanoma Research* 2006; 16(2): 183-190.
- [9] Celebi ME, Aslandogan YA, Stoecker WV et al. *Unsupervised Border Detection in Dermoscopy Images.* *Skin Research and Technology* 2007; 13(4): 454-462.
- [10] Celebi ME, Kingravi HA, Iyatomi H et al. *Border Detection in Dermoscopy Images Using Statistical Region Merging.* *Skin Research and Technology* 2008; 14(3): 347-353.

- [11] LI Xue-wei, ZHANG Xin-rong, “ A Perceptual Color Edge Detection Algorithm”, 2008 International Conference on Computer Science and Software Engineering, pp.297-300
- [12] Ibrahiem M. M. El Emary, “On the Application of Artificial Neural Networks in Analyzing and Classifying the Human Chromosomes”, Journal of Computer Science, vol.2 (1), 2006, pp.72-75.
- [13] Roberto Rodríguez\* and Ana G. Suarez, “A new algorithm for image segmentation by using iteratively the mean shift filtering”, Scientific Research and Essay Vol. 1 (2), pp.043-048, November 2006
- [14] Chunming Li, Chenyang Xu , Changfeng Gui, and Martin D. Fox , “Level Set Evolution Without Re-initialization: A New Variational Formulation”, Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05)
- [15] Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian, “Pointwise Shape Adaptive DCT for High Quality Denoising and Deblocking of Grayscale and Color Images”, IEEE Transactions on Image Processing Vol. 16, No. 5, May 2007
- [16] S.Zulaikha Beevi, M. Mohamed Sathik, “A Robust Segmentation Approach for Noisy Medical Images Using Fuzzy Clustering with Spatial Probability”, European Journal of Scientific Research, Vol. 41, No.3(2010), pp.437-451